Artificial Intelligence Across Borders: Transforming Industries Through Intelligent Innovation

Sibaram Prasad Panda

DeepScience

Artificial Intelligence Across Borders: Transforming Industries Through Intelligent Innovation

Sibaram Prasad Panda

DeepScience

Published, marketed, and distributed by:

Deep Science Publishing
USA | UK | India | Turkey
Reg. No. MH-33-0523625
www.deepscienceresearch.com
editor@deepscienceresearch.com
WhatsApp: +91 7977171947

ISBN: 978-93-49910-52-2

E-ISBN: 978-93-49910-25-6

https://doi.org/10.70593/978-93-49910-25-6

Citation: Panda, S. P. (2025). *Artificial Intelligence Across Borders: Transforming Industries Through Intelligent Innovation*. Deep Science Publishing. https://doi.org/10.70593/978-93-49910-25-6

Preface

This book explores how artificial intelligence is revolutionizing healthcare, finance, agriculture, education, and more. A practical, research-backed, and accessible guide that explores how AI is reshaping multiple sectors. Each chapter focuses on a different industry, illustrating real-world applications, use cases, benefits, challenges, and future trends. The book balances technical insight with real-life impact.

Sibaram Prasad Panda

Table of Contents

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 1: Introduction: The Rise of Industry-Agnostic Artificial Intelligence

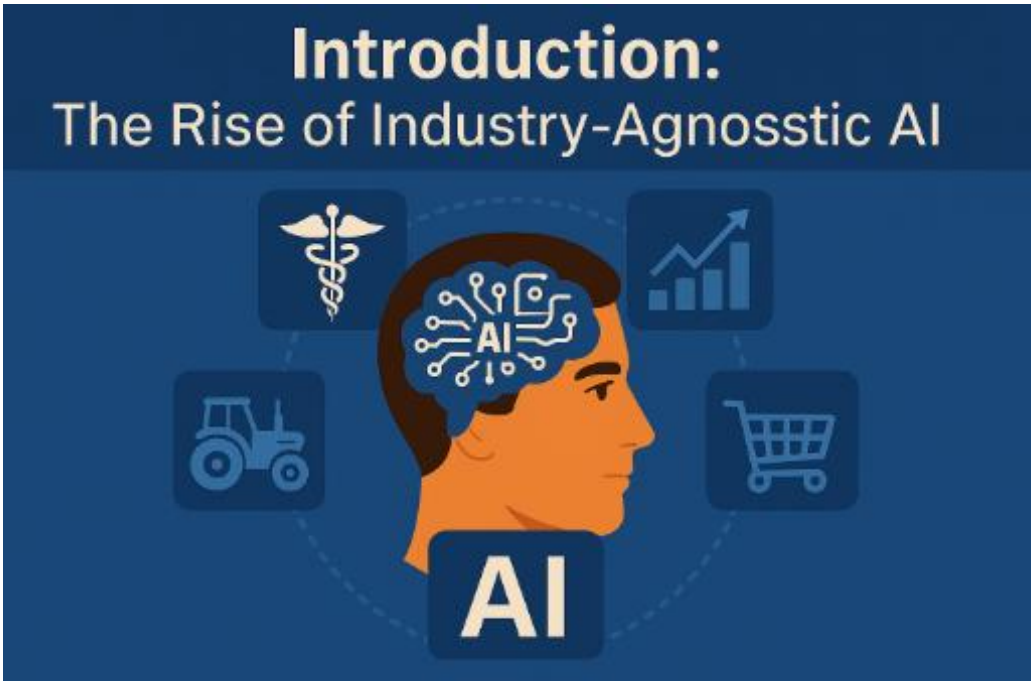
1. Introduction to Industry-Agnostic AI

The concept of Industry-Agnostic AI refers to general purpose, adaptable and open models for kernels of artificial intelligence available to everyone, created, modified, and improved repeatedly. The premise is that specific industry use case models take so long to build and often deliver so little, that it makes more sense to build a general-purpose kernel of the use case allowing organizations to adapt it for their specific needs than to build thousands of models for industries such as finance, insurance, healthcare, and supply chain. Indeed, with a few guiding examples in many "knowledge worker" use cases such as writing, classification, summarizing, extracting, agent-based interactions etc, adapted implementations of a model can create reasonable quality results – and with guidance and supervision, approaches can create industry specific AI tailored for enterprise needs.

The work is divided into 4 parts. We will first explain the concept of Industry-Agnostic AI, its motivations and its premise, how it is manifesting itself today, and its future evolution. We then give one-page summaries of a dozen "Industry-Agnostic AI" companies working in different domains and use cases but with the same basic premise, that of lowering the cost of producing and deploying AI solutions. We finish with a few words about the future of Industry-Agnostic AI.

2. Historical Context

It can be helpful to first place the latest, most capable forms of AI in the context of prior, influential technology waves centered around PCs, the Internet, mobile, and the cloud. Each of these earlier waves radically increased the breadth of technology's applicability, as well as the generality of the "types of problems" that technology could help address — and, by extension, the number and diversity of companies that needed to use technology to innovate to survive and thrive. Prior waves, especially the last three, made computing and networked, connected interaction increasingly personal and embedded: the computer became a pocket device for each person, and the network was embedded into every product for ease of use. In doing so, the waves created enormous demand for technology. Every consumer or enterprise product needed software needs to connect with other products and services; and needs to get better and more secure with time. What undergrounds these prior innovation waves? The two forces are both evident in the immense breadth, capability, and accessibility of the AI power at hand. AI lowers the cost of reasoning for every type of task that requires reasoning. There is really no task that cannot be or ultimately won't be automated, to at least some degree. People have long known of this potential: it is why AI was the first use of the term "artificial intelligence."



3. Defining Industry-Agnostic AI

In recent years, we have seen tremendous growth in the development and adoption of AI technology in all major industries and economic sectors. What was once a narrow band of systems built initially for academic research on specific tasks has now been extended across innumerable markets, products, and services. A new line of technology companies is emerging to address the myriad use cases and challenges, applying AI in finance, technology, manufacturing, retail, real estate, healthcare, transportation, agriculture, and entertainment. While many of these specialized models built for unique jobs may rely on original architecture, they tend to stay within industry-specific boundaries over time. But models such as ChatGPT and Midjourney are already demonstrating the potential to leap across industry borders.

A new theory is needed to better explain what makes certain AI technologies truly useful in more than one setting, allowing them to serve as turning points for different entities across various sectors. This theory would be an advance over existing technical ideas or design principles, illustrating the surfacing new capabilities of these models built by different companies in distinct markets. Naturally, a key hurdle to defining Industry-Agnostic AI is how to identify the few truly original systems among the thousands of AI products being released on a rolling basis. After all, it should go without saying that industry-agnostic models should be useful to professionals from different fields whose basic job functions differ. Industry-agnostic AIs should be verifiably capable of working in widely divergent specialized areas—such as the mass production of steel and heavy crude oil extraction—without any prior experience.

4. Key Technologies Driving AI

Three key technology areas are driving AI today: machine learning, natural language processing, and computer vision (Zhai et al., 2021; Dwivedi et al., 2023; Ouyang et al., 2022). We briefly summarize these capabilities here, but there are many more capabilities in the AI ecosystem that we do not cover in this chapter. Ongoing innovation in semiconductors, algorithms, inference engines, and frameworks will continue to expand the AI toolkit.

4.1. Machine Learning

At its core, the field of AI requires three main elements, namely algorithms, data, and processing (AI, 2022; Dwivedi et al., 2023; Zhai et al., 2021). Machine learning is used somewhat interchangeably with the term deep learning, but deep learning is, in fact, a subfield of machine learning and within the field of AI. The invention of neural networks lay dormant due to the critique of the people who were to become the giants in the AI field. They saw some problems for which the neural network could not give the correct solution.

With respect to the other two critical elements of modern AI, data and computing resources, advances in both these areas have been paramount in driving modern AI. The internet explosion has made copious amounts of data available in areas such as image recognition and natural language processing, both critical areas in AI, but also equally in modern industry and society. With respect to computer resources, advances in GPU parallel processing are the main empowerment reason for modern deep learning; without GPU processing parallelized over tensor computations the progress in applying deep learning to key areas of AI would have been impossible. The recent ubiquitous increase in the use of neural networks in AI applications, such as computer vision and NLP applications, owes its existence to the previously cited three elements in AI, namely algorithms, data, and processing resources.

4.2. Natural Language Processing

Artificial Intelligence has several subfields that help machines mimic human intelligence. One such field is Natural Language Processing, which allows machines to obtain a high-level understanding of human language. At the crux of NLP is the idea of comprehension—comprehending raw text, comprehending user intent, or deriving structured information from unstructured data. NLP lies at the intersection of Computer Science, Artificial Intelligence, and Linguistics, and involves many complexities that typically humans take for granted. For example, any two sentences that speak the same thing but are worded differently have substantially different representations in the vector-space that models their semantic meaning.

One of the earliest applications of NLP was in Machine Translation, the task of translating text from one natural language to another. MT has a long and tumultuous history, which saw the development of systems needing explicit linguistic rules of grammar and syntax, statistical systems that inferred transfer probabilities from large corpora, and finally the use of LSTM networks and then Transformers. With each passing phase, the quality of machine translation was improving, and today, MT systems rival or outdo human translators in some domains! This provides support for the undoubted potential of Natural Language Processing and Understanding as successful AI-enabled automation in the industry. Today, NLP is not only used for MT, but also for other access systems for human knowledge, such as chatbots for customer service, for extracting insights and summaries from human-generated documents, and text intelligence that infers possible near-term emotions, sentiments, or agendas that people might have. Understanding emotions and sentiments also finds its way into important security applications.

4.3. Computer Vision

Over the last years, we have witnessed several breakthroughs in how we use natural language to code applications for the computer, be it systems commands, website building, or software applications. It was only a matter of time before the same breakthroughs for working with pictures and moving pictures were available, allowing the creation of serious-quality code. In this particular area, however, the utilization in regular consumer products looks set to move faster than the utilization in coding or programming for commercial applications – the reason being that the final use of this technology realization for computer vision is expected to be for consumers in their person-to-person involvement, rather than for workstation-to-workstation interaction in enterprise organizational involvement. The question of utilizing computer vision could be as simple as solving the question of whether to send or stop sending that picture to the friend. Whether it is a static picture or a video is not relevant. It is to be sent, or played, and whether to send is the judgment call driven by emergent AI.

Over the past two years, there have been major releases of commercial products that address and solve problems users encounter with computer vision. These technologies have quickly scaled up into big technology platforms. But these are general-use applications. Are they industry-agnostic-specific enough for business-to-consumer support in flight? Not quite yet is the answer since branding of your product is an issue with AI applied to generic images. More exciting for us is that the utilization for specific use-cases has taken off, focused on certain capabilities such as upscaling and attention modeling or driven by vertical-specific tasks such as product annotation or photo retouching. There have been commercial companies providing these and related services.

5. Applications Across Industries

The implications of industry-agnostic AI are broad, leading to innovations in almost every sector of the economy — effectively, every industry that has data on what it is doing, why it is doing it, and how it could do it better is dusting off the toolbox that includes machine learning to make more money or spend less money, or both. We highlight a few of them below.

Healthcare

AI, big data, and machine learning offer game-changing innovations in healthcare treatment, delivery, and costs. Much of the impetus comes from the growing availability of large datasets on both outcomes and treatments, but these technologies are also being used to identify the best subpopulations to give a new treatment and a better way of organizing and monitoring treatment in patient care that take advantage of new modalities like telemedicine.

Current applications include disease detection and prediction systems for clinicians and support tools for patient interaction; patient data analysis platforms and diagnostic models for local medical facilities; and personalized medicine approaches — oncology is at the frontier, but genetic disease, cardiology, immunology, and others are advancing rapidly — like prediction of therapy response and toxicities, genotype-based treatments, immunotherapy optimization, and clinical trial enrollment guidance and support.

Finance

AI has transformed finance, making many activities cheaper and faster. This was happening before machine learning arrived, but with its emergence, the scale of finance's task has made it a logical application for ML: financial data is available in near-infinite quantity — forex, equity prices, real estate transaction prices, derivatives of real estate, the factors behind them. Supermarket prices and sales volume, interest rates, rents, loan losses, default rates, corporate profits and losses. Bank defaults, demand deposit balances, stock and market margins, all four countries in all stages of economic development. Losses and trade volume for economies impacted by climate change, and all of it defining the resilience of supplies of goods and services to the country's economy.

5.1. Healthcare

Artificial Intelligence, especially Foundation Models and modern generative models, have found their way into the healthcare realm, both raising hope and gathering skepticism. With a patient exposed to 46 petabytes of data, with genomics and multi-omics at the forefront of technological breakthroughs, there is dire need for novel and effective tools that can help medical experts process this information. Starting from areas that are considered “low-risk” for deployment compared to others, such as clinical data augmentation, language understanding and generation in clinical contexts, or medical imaging, systems have been proposed showing remarkable success in-house and in controlled settings, prompting regulatory bodies to publish guidelines on how to test future models and put their safety by design at the forefront of research.

In this context, the question of to what extent can these systems generalize to out-of-distribution data, or on clinical tasks that have not been benchmarked or supervised by experts, remains open. These concerns are magnified in the clinical space given the stakes and the potential negative effects of wrong predictions and suggestions in clinical settings, prompting AI safety researchers to focus on the distinctive aspects of the healthcare domain and devise solutions, whether these take the shape of model distillation, calibration, in-context learning, or supervised adaptation. Another fundamental aspect is the type of data that the models consume and on which they provide their predictions. The available clinical datasets, whether these are expert-annotated or real-world data, are typically limited in size and difficult to access. The class-imbalance and distribution-shift problems, present in almost any healthcare context, become even more critical in the case of language models—recent studies report little to no adaptation of these systems to such data-centric issues.

5.2. Finance

Finance is one of the most prolific industries in terms of the amount of content produced daily, mostly due to the sheer number of financial transactions and activities performed daily. The Services sector of financial activities in the US economy produces around $5.5 trillion in Gross Value-Added yearly, out of which around $1.2 trillion comes from the Services sector of financial and insurance activities.

Handling every problem that can arise in the Finance industry is paramount by being able to automatically clean, label, classify, analyze and act upon trillions of events that happen daily. Finance is probably the industry that the most research papers have been written about, since the advent of algorithms that allow for very sophisticated analysis and actions taking, using AI techniques, such as trading high volumes of stocks, financial assets or cryptocurrencies at real-time speed and accuracy for high-frequency trading and arbitraging systems, analyzing firm’s financial reports for risk, performing credit scoring and detection of possible fraud, or monitoring any movement to or from possibly “dirty” crypto wallets or exchanges. Even crime solving or detection and prevention tasks, such as money laundering detection, have seen developments in how to build monitoring systems to catch and punish illegal economic activities. And those are just a very small sample of the broad array of application problems.

5.3. Manufacturing

Traditional factories produced bespoke products, say embroidery, that took a long time to produce, the cost was prohibitive, and the output was small. Mass manufacturing in the industrial age meant producing large quantities in a factory, operated by machines, for the lowest cost. Creativity lay, however, beside the designer's office. The art of manufacturing lay in producing more in less time at the lowest cost, with acceptable quality. This is the Newtonian age of manufacturing — work done based on plan, do, check, act. The templates for all processes and activities were laid out in advance so that maximal efficiency would be obtained from the labor force, which did the processes without an exercising agency.

Which makes today's manufacturing act unique? The Quantum age of manufacturing stands for the act of making that converts any form of material into a finished product that delights the customer. All of nature's matter is available for use. The new manufacturers work with materials that are available as by-products of other processes. Creating products that delight means the products are unique or solving a problem that is not currently being addressed means providing a solution that stands for a paradigm shift in the industry. Come to think of it, the quantum manufacturers are not really manufacturers as they are creators. Creation assumes high levels of exploration and invention. This is unlike the Newtonian age manufacturing controller who designs templates for every work activity to optimize the cost of output, with little agency deployed into the system by the worker — templates that must be adhered to if an efficient factory operation is to be achieved.

5.4. Retail

Retail is a very–public–facing business; the Internet has made that very clear. With everybody connected to everybody, we can easily communicate the good and the bad. Retail has been at the forefront of AI adoption. At the inception of the field, retail was one of the only industries to have high–quality catalogs of their product offerings, allowing for natural language processing capabilities to emerge. Supervised learning is expensive because of the amount of data that needs to be labeled, but AI's capabilities can be utilized to reduce the costs. In fact, purchase data is one of the few clear labels we have on our datasets. With recommender systems in retail, especially when coupled with customer browsing history, we can convert users from lookers into buyers. By firmly establishing what the expected future behavior is, we can use AI to enhance this experience. For example, AI can determine the summarize the reviews made by a customer about products in a category. When a user is browsing a category with a huge number of options, summarizing the reviews based on the user's profile will significantly reduce the time taken by the user in deciding. Elicit user preferences in specific product aspects and provide detailed comparison charts in order to make a decision are also practical. Being able to optimize the next best offer or recommendation to a user. Use propensity modeling to help understand the set of all possible users.

5.5. Transportation

There is no there, again, there should not be any mistake, so don't talk back. Creating a smart mobility ecosystem is one of the biggest tasks of the modern smart city. The partnership comprised of various companies is doing all of this with the support of the City of Helsinki and its transport authority. Seamless troubleshooting for your vehicle when an unknown problem occurs is important to minimize your downtime. A car service utilizes Automated Diagnostics System to resolve a significant percentage of customer complaints without the car ever going to the Service Centers. This significantly reduces the overhead of service visits. The intention is to further improve this by enhancing the system towards Aftermarket Service Support capability. Predicting arrival times for transport services, such as buses/subways can seem like an easy task; however, doing this accurately and consistently can be very challenging. A major player partnered with another company to utilize AI to predict more accurately the arrival time for their services in a manner that beats any legacy prediction capability. A map showing the quickest route from source to destination is often not an easy thing to accomplish. Also, routes taken by mapping programs are often the ones with the minimum ETA while there may be other reasons to prefer a longer route potentially with the least number of inconveniences during the ride. Usually, it is difficult or even impossible to produce a map that optimally indicates the shortest ride. An app uses AI to predict the optimum route personalized for each passenger. For e-mobility solutions to truly create a positive impact in areas suffering from congestion and pollution, the emission-free vehicle fleets need to be made more utilitarian. Using AI to predict at what times the available fleets are more likely to be either underloaded or overloaded can help guide the availability and type of vehicles in these fleets to help minimize such problems.

6. Benefits of Industry-Agnostic AI

One of the greatest benefits of the wider adoption of industry-agnostic AI is that it will democratize access to the power of AI, from companies that have an abundance of resources to those that have very few. At present, most businesses in sectors at the bottom of the productivity barrel – hospitality, agriculture, and retail – can’t use AI to boost their productivity. This is because creating custom AI solutions typically requires vast sums of money, that have traditionally only been within the reach of a few scant corporations at the top of the economic food chain. And much of this custom technology has been developed to make innovative companies even more innovative – improving efficiency, decreasing costs, and increasing profit margins. Many AI algorithms in use today are industry-specific, such as those that predict the next likely trading action for traders; AI developed for a particular sector that takes unique problems into account. If we want to create a truly level playing field, we need to create AI that improves the productivity of every industry, not just the daringly innovative and wealthy.

Industry-agnostic AI solutions can be developed much more quickly than industry-specific solutions – for use across a wide range of companies and applications. This reduces the time and skills required to tailor AI engines to specific business problems. But industry-agnostic solutions can also be deployed much more rapidly, as organizations have discovered. Using automation, organizations can set up decision systems that can be used for applications across multiple industries. The benefit of the industry-agnostic systems that check whether applicants are creditworthy or not is that they can be rolled out rapidly, because the data has already been anonymized, so the applicant's privacy can be preserved, enabling a democratic flow of money.

6.1. Cost Efficiency

Industry-Agnostic AI solutions can reduce the cost of creating domain-specific practical AI by making a larger portion of the process cheaper, faster, and accessible to more developers. Building a domain scheme is very costly. The first of its kind is generally the most expensive, and some domains never had one developed. This is an opportunity for Industry-Agnostic AI, which can create a pretrained domain scheme and thus greatly reduce the cost of that effort. The cost of labeling datasets remains a major obstacle to growth – and any methods that can reduce that are highly valuable. It has been shown to dramatically reduce the cost of labeling datasets needed to finetune LLMs, and other tools are likely to be similarly cost-effective for other modalities and tasks.

While LLMs and other such developments would primarily reduce the cost of existing methods, Industry-Agnostic AI can also reduce the cost of adopting new practical methods that do not yet have any domain-specific implementations. The area of neural architecture search is an area of active research and promising initial success, and it may soon be possible to automatically develop domain-specific methods that perform better than general-purpose models. This would allow domains with no domain-specific methods to benefit from the innovation and performance increases of using model architecture pre-trained on large datasets.

Another strategy for Industry-Agnostic AI is preparation, the process of planning or scoping out a domain-specific area so that capabilities can be utilized in a highly optimizable way. Preparation is different than what we traditionally think of dataset or prompt engineering, that is modifying inputs for an existing general model or building auxiliary datasets.

6.2. Scalability

The deployment of AI on a massive scale has usually needed technical know-how, legal expertise, and financial resources, all of which deterred small actors from benefitting from AI. But the rise of low-code and no-code AI tools illustrates that with some guidance, even the smallest of actors can use AI systems for a range of applications. Moreover, services can automate many of the preprocessing steps that previously kids would have to perform themselves. The incremental advances in AI efficiency made by the entire community benefit even those who are not heavily invested in AI.

If there is standardization in the probing tasks, and domain knowledge already built into the industry-agnostic models, it becomes easy to plug-and-chug once again and drive down costs for extremely high-value use cases in the world. A careful and judicious balancing of domain knowledge embedded in industry-specific products, and the synergy made possible by the large-scale models makes for the best outcome for society. It is likely that the roadmap for industry-agnostic models looks like Intelligent Search did, or the web business did; for a long time, existing industry products combined with semantic search gave the best outcome. But slowly Large Language Models started to be integrated into various industry workflows.

6.3. Innovation

Innovation can be defined in various ways. Indeed, the earliest formal conceptualization characterized it as the "doing of new things" (or "doing things that others are not doing") and a unique and rare ability to break down framework conditions in a society. This distinction is echoed by others who perceive innovation as the "easy part" of economic growth. Some take a more demonstrative perspective and explain it rather as a fascinating destroy-and-create mechanism. It drives and perpetuates movements into periods of underlying strength with powerful new technologies or entrepreneurs and leads societies with easy power as well as declining industries into crisis.

However, innovation in a broader sense is an essential determinant of growth and higher prosperity and a ubiquitous source of improvement and change in societies the world over. It applies to developed and developing as well as resource-rich and resource-poor economies. Firm-specific innovation generally involves the application of knowledge in creating novel goods and services as well as new or improved ways to perform activities more efficiently. Additionally, it necessitates for business enterprises that are the sources of innovation to share the resulting rents adequate to stimulate the bloodless creative revolution and protect and promote a continuous flow of innovations. Thus, the lifeblood of virtually each innovation is brainpower, embodied in people who are creative in varying degree. Indeed, in recent decades, economic thought and policymaking have recognized increasingly that innovation is a systematic, core economic process and has a major effect on achieving faster economic growth, at least in wealthier, open-market economies.

7. Challenges and Limitations

As with any emerging technology, there are several challenges that need to be overcome before this trend can be fully realized. First and foremost, most industries have deep investments in systems and processes that are optimized for their business. For example, logistics companies are experts in how to deal with carriers, shipments, orders, etc. converting those concepts into a format that sends them to a general purpose, industry-agnostic AI model is a non-trivial task. Consider, for example, trying to integrate the concept of shipping freight from point A to point B at a certain time in a way that a model understands. Or a hospital trying to use a general model to write clinical notes when there are so many specific nuances that a hospital's model-based system would need to figure out.

Secondly, many companies have specific data privacy and confidentiality requirements that must be adhered to when deploying any kind of AI solution. These requirements may inhibit the use of smaller, more general models that are readily available for public use. For companies that want to fine-tune these models or that have strict data security requirements, licensed products or on-prem solutions may be necessary.

Lastly, there is a problem of the skill gap. Many companies are struggling to hire people with advanced AI skills. The workforce that is ready to implement and maintain these AI models is still small compared to the demand. Training and upskilling the workforce will be critical to close this gap. While generative AI lowers the barrier to entry and accelerates the ability of companies to adopt automation more broadly, using the technology itself is not a panacea; these models do require a degree of proficiency to integrate and build on top of.

7.1. Data Privacy Concerns

AI technologies take and massively compute on data to provide insight, and act on behalf of their owners. This is the desired result behind the purposes of many companies, the logic that this process itself is the business model and value sharing becomes tangential, is false because AI will embed in every business process soon and without sharing value across society and workers who develop, apply and guide technologies like these that concern us all, capital ownership income concentration will increase exponentially and eventually backfire against capital owners. It is a parasite-collate logic that results in parasitic corporations, thoughts and action. Americans, led by those who should lead, not following corporate orders, should lead dissent about the major privacy concerns regarding the excesses that industry agnostic AI can create against personal data.

Data privacy concerns have always been there, but now they come in volumes, mass and with a multitude of input vectors. Companies must be prepared to take the debate seriously and define urgent policies that reflect both user preferences regarding its data, corporate responsibility and transparency. AI large models create compounding concerns among the public and society overall, in many aspects since the first time AI was invented back in ancient Greece, hence the first imperative is to educate around this concern, within the company, to elucidate to the public, who should be the true final user of these technologies. From making decisions not to go into space exploration, we educate and build resources for everyone alive. The goal is to make normal that people that add knowledge, lead people who stir using AI, which in the future could very likely be, just like sharing is currently what we consider the right thing, to make people who apply AI lead and decide for people who teach to be good, not skill nor reveal.

7.2. Integration with Legacy Systems

One of the most cited limitations to the proliferation of AI technology is its inability to be deployed for use cases that also demand integration into existing processes. In many cases, such processes are automated, use low-code technologies or a combination of both and account for the vast majority of business-critical operations. Industry vertical AI has come into its niche because adoption – however narrowly limited to a vertical or industry use case – comes with the promise that after an initial investment, integration with such processes and systems can be achieved.

Generative or industry-agnostic AI on the other hand frequently sit outside of such process flows, integrated into existing systems through chatbots or the like, i.e. with no automation. However, in the case of industry agnostic AI, this limitation still holds. Many enterprise corporations have already embarked on digital transformation initiatives to modernize their age-old legacy systems, and to varying levels of success. Companies who have attempted the full replacement of what are known as "legacy systems" – IT solutions typically utilized for the longest duration by a business unit, department, or organization, – know that it can be a lengthy and difficult transition.

While legacy systems are often seen as complicated spools of outdated code that don't play well with more modern tech stacks, it's important to note that, for some organizations, legacy systems are simply time-honored tools that do precisely what they were designed to do. However, integration into existing automations or processes formed by these "legacy systems", even if they might still provide business value today, is most likely not easy given that they often use outdated code, languages, or configurations that simply don't "talk well" to current tech stack offerings and proven, cloud-based tools.

7.3. Skill Gaps in the Workforce

Despite the immense potential of AI, there are several challenges to be overcome in the deployment of AI solutions in the manufacturing sector. One major challenge is the current skill set of the manufacturing workforce, which is insufficient for the adoption of new AI advancements. The manufacturing industry has the second highest shortage of workers among major industries. But unlike Construction, which largely depends on untrained manual labor, the manufacturing industry notably experiences a growing deficit of skilled workers. Workers with tech-savvy skills are the most difficult to recruit. Organizations are increasingly looking for candidates with strong programming skills, functional knowledge of manufacturing processes, knowledge of industry 4.0 technologies, data analytics skills, and experience with robotics, automation and control systems, as well as programming expertise with AI and machine learning. It is estimated that by 2030, three and a half million manufacturing jobs will need to be filled, but 2 million of those jobs may go unfilled due to the talent shortage.

This shortage of talent is further exacerbated by lack of training programs for upskilling existing employees until they catch up with the latest technological advancements.

Manufacturing executives ranked an upskilling, under-invested and outdated workforce as one of their major concerns in AI operationalization. To address this widening skills gap, manufacturing organizations need to prioritize proactive reskilling initiatives funded by the organization, as well as develop partnerships with manufacturers and educational entities to institute programs that provide students with hands-on, experiential training. Organizations must also ensure that human workers have an opportunity to learn about AI and how it works and make an effort not to demean or devalue the humans in the workforce when advertising or promoting AI systems and their functionalities.

8. Case Studies of Successful Implementations

Examining these successful implementations uncover useful lessons not just about how to effectively generate and incrementally improve product, service and solution capabilities but also about the business model at work. With such a model in place, the most difficult hurdle, achieving distribution, becomes much easier to clear. None of these companies are competing within the existing industry boundaries. The capabilities of AI technology are so transformative that every company can become a competitor or partner.

8.1. Company A in Healthcare

An unnamed early-stage company is building an AI platform to use patient outcomes to help personalize the drug prescription process for physicians. Some of the current practice includes factors such as diabetes, cholesterol, blood pressure, and family history. Information about side effects, response-free survival, and tumor toxicity would help doctors select which drugs are best for each different combination available. The problem today is that patients with similar attributes could be very different, i.e. a drug might work for her but would kill him. As healthcare becomes more personalized, having better tools in place will be critical to clinical success.

8.2. Company B in Finance

An unnamed company has built a reputation within the finance industry for using Natural Language Processing to identify breaches within regulatory documents. The financial industry is one of the largest industry verticals today, and with increasing scrutiny from governing bodies, the ability to identify and mitigate risk has never been more important. The problem today is that compliance institutions have huge amounts of document data. Faced with limited resources and increasing amounts of information, these offices are still responsible for monitoring, reviewing, and processing document submissions, cease and desist orders, regulatory compliance requirements and penalties, investigation reports, and policy statements. This company focuses on an area that has been very profitable for a long time. With new regulations coming out, it is only a matter of time before negative sentiment starts to impact the stock and bond markets.

8.3. Company C in Retail

Another unnamed company headquartered in New York City is creating a tool that bridges e-commerce brands and social media. Clients upload a photo, video, or blog post, and the company identifies products within that media file to then serve relevant recommendations at checkout. E-commerce companies are seeing increases in conversion rates of about 10% just from tagging with this tool. One source of frustration is that traffic brought to the brand's site is not always converting. Helping to relieve that pain point is a massive opportunity. Currently, these companies are going after a niche of direct-to-consumer lifestyle brands, but as the offering becomes more robust it will become available to a host of online retailers looking to convert more customers.

8.1. Company A in Healthcare

Company A is the largest healthcare consulting firm in America. It does business under a common name that is known to every person with any affiliation to medicines. In short, it is a household name. The consultants apply Company A-led solutions to the internal problems of the largest, most prestigious, and most profitable healthcare providers and innovators in the market – and receive exorbitant payments for doing so. The problems are the kinds of decisions that internal teams could handle themselves: Should we buy Acme Medical Equipment Company? Should we build a new hospital in Charleston? Should we invest in this research? The firm specializes in high-visibility and high-stake decisions that can be made once every ten years.

Supposedly, there is no AI that could help a monitoring consulting team to reduce costs. For years, Company A's inside teams have sold, mostly to enterprise clients, hundreds of data analytics and "shop floor" solutions powered by various analytics vendors. The projects, however, barely lead to any results compared to more complex projects for internal teams to make evidence-based decisions. This seems logical, given that data is only as good as the educator within the internal team that requests it. What shocked the entire industry was something called the "data tsunami." Pretty much all the company's digital transformations during Datafication consisted of implementing expensive BI layers that quickly became obsolete and incapable of providing data for complex decisions.

8.2. Company B in Finance

We show the effectiveness of EDA on financial data modeling by applying it to calibrate neural density estimators for intraday financial data based on contextualized representations, which we call CoCalib. CoCalib leverages narrative context models based on pre-trained Transformers to build time-varying maps of the risk-neutral average quadratic loss associated with the density estimated by an intraday price process for a given asset. This can have a variety of applications in risk management, option pricing, and forecasting, where practical advances are specialized on asset class or geography. Presently, the calibration of neural density estimators for intraday financial price processes is obtained without using any contextualized information. Given the well-documented stylized facts of financial price evolution, it is our conjecture that embedding time-varying contextualized information can improve neural density estimation methods. Our contribution lies in proposing a plug and play solution that can easily be implemented on top of any state-of-the-art option-pricing neural density estimation architecture.

Datasets commonly used for intraday financial price density estimation are based on near risk-neutral equity returns due to the impressive number of options traded every day. Such a stance limits the interpretation of density estimates doing a small area. Our objective is to enable contextualized modeling of these equity price processes associated with high volatility, low trading volume, and options market illiquidity. Indeed, basing the proposed solution on non-centrally weighted density estimation allows for capturing structures associated with widely selling options from the average surface computed by interpolation.

8.3. Company C in Retail

Company C is the first global retail company offering a unified shopping experience – both online and offline – across 100 countries and regions. Guided by technology, its mission is to deliver the best customer experience through the unparalleled fulfillment capability and global supply chain network, and its technology capabilities have led to other enterprises tapping into its technology infrastructure to transform digitization and improve operational efficiency. Operating the world's largest retail e-commerce business, Company C is never short of data but has struggled to deploy it on a scale as it built its internal data-driven tech capabilities. The company had historically relied upon hundreds of third-party vendors who created add-on solutions across multiple business functions, whereas the internal tech team focused on building its own tech infrastructure. The first challenge was that the tools did not communicate with each other, creating silos. The other challenge was that these solutions did not utilize real-time data for decision making or require the data to be fed into them manually, delaying analyses and hampering operational efficiency. Company C turned to a partner to solve these challenges.

Instead of working as an add-on tool, Company C integrated the partner's platform into its own infrastructure with endless amounts of third-party data across functions that the partner has access to as it scaled. Hundreds of Company C's internal team members across functions have begun creating data-driven business solutions for every aspect of Company C's business. Inspired by the campaign object detection models – the same models from the partner's computer vision department that fueled the burst of productivity Company C experienced for launching its campaign – the multi-task company team adopted them to join multiple computer vision tasks together and utilizing the large-scale high-quality data. The result – computer vision models that accurately visualize 3D information using retail shopping pictures.

9. Future Trends in Industry-Agnostic AI

The outline of the discussions presented in the other chapters have laid a foundation for expressing some perspectives and opinions with regard to the future development of IA-AI. It is opined that the following three trends are likely to be seen as important in the future. First, there will be a demand for industry-agnostic AI solutions that adhere to ethical principles as determined by the appropriate stakeholders, comprise human-centered designs, and stand up to public scrutiny. Technology nor its developers are not immune to society's institutions and processes that contain nor control it, and there will be increasing pressure for appropriate oversight. This leads us to discuss the second trend, namely the potential for enhanced personalization possible with IA-AI. AI has been and is likely to be used for increasingly granular levels of personalization that are enabled using the rich, heterogeneous personal data available in the consumer economy. This development is expected to be possibly supplemented by the collaboration between large technology platform providers engaged in pushing the personalization envelope and industry players that have access to an abundance of customer data generated by their interactions with their products and resources. The third and last trend cannot really be called a trend but is the inevitable necessity for involving IA-AI solutions in helping the world combat the dangers and fallout from climate change and resource depletion. There is a realization in the corporate world in India and globally that it is imperative for businesses to limit and counter their negative impact on the environment and be net carbon zero by a particular year. Technologies are required that can help these business resources their impact and take concrete steps to implement positive change.

9.1. Ethical AI Development

Concerns regarding the ethical development of AI have emphasized the need for collaboration across multiple sectors and clear governance of technology development and deployment. The current hype surrounding generative AI has drawn attention away from many of the longstanding concerns that society has had about AI. There is currently no coherent global coordination mechanism to ensure that AI is developed for social good. Furthering our understanding of best practices on how to adopt, deploy, and develop responsible AI technology to drive social good is critical for its ethical and sustainable development and deployment. Critically, technology companies should be led by mission-driven experts genuinely interested in solving social issues standing in for the wider public interest when it comes to developing AI governance. Companies should consider their wider remit beyond simply developing and monetizing the most advanced AI products. Academics and third parties should also have access to proprietary AI architectures to ensure that analyses and audits can be performed to ensure technologies are ethically deployed.

A starting point would be to increase the transparency of technology developers by releasing impact assessments of the different AI products being developed. They should also invest in the ethics departments in their companies and fund external academic research into the impact of their products. These companies would also provide a service to society by funding journalism endeavors looking into the social effects of the newer AI products by utilizing the revenue they get from these products. In addition, national governments need to take steps to develop the regulations and appropriate institutional capacities that can set the parameters for AI in different domains and sectors. Industry-academic partnerships can generate safety measures to prevent amplifying dangerous errors, and negative biases present in data training models.

9.2. Enhanced Personalization

In recent years, there has been a growing demand for personalization in products and applications. Industries have leaned heavily into message targeting to improve customer engagement, while companies have differentiated their offerings leveraging vast amounts of user behavior data. The need for personalization has intensified with the advent of the pandemic. With limited ability to socialize, the demand for content consumption has exploded. This has led to a rise in popularity for technologies such as recommendation systems and personalized news feeds. AI has been a key enabler of the personalized experience that people get nowadays. However, using AI for personalized user experience is not without challenges. Building models present to a user based on their data needs to check the boxes on ethical AI, to avoid amplifying biases and inhibiting free will.

Today, a majority of the messaging and content presented to users through recommendation systems and personalized feeds continue to be relatively simple: a generalized attribute model built from past data patterns. The future of industry-agnostic AI, however, is that this personalization will become deeper and better suited for the individual. The future of personalization is multi-modal, based on who a user is, what the user has expressed interest in for different tasks and workflows, where the user has been and what context they are in currently, and when those preferences change. This richer view of user coordination can allow companies to offer deeper personalization, tailored to the tasks users want to perform and better suited to be as helpful as possible.

9.3. AI and Sustainability

Among the many applications of AI, its use for ecological purposes is becoming prominent. Global technology firms agreed to partner with a non-profit organization that aims to monitor greenhouse gas emissions to a finer level of detail than government agencies and solve problems of economic disparity. More companies are using AI technologies to leverage their existing data to develop solutions that will in turn create new opportunities for responsible economic growth. Wind energy companies are now deploying customized AI analytics to enable faster, more efficient turbine planning. By reducing the time to design and install a new wind farm, the technology could help meet net-zero ambitions sooner.

Ocean researchers are developing summertime marine heat wave forecasting with historical satellite data and AI. Marine heat waves are warming shallow coastal waters, affecting local environments, economies, and food security and increasing chances of regions experiencing extreme climate events. AI would help inform such forecasts and how they might change due to climate change conditions. Ocean scientists are using AI methods to sort through massive amounts of satellite data for red tides, harmful algal blooms that threaten public health with toxins, exacerbated by climate change. Faster detection will help warn people in time about contaminated shellfish and the necessity for closed beaches.

10. Regulatory Considerations

Introduction Regulatory considerations can dominate conversations about AI. Geopolitical dynamics are making the idea of AI primarily military technology rather than a consumer-facing opportunity more acceptable. As commerce-driven machine learning was beseeched by narrow regulation and hard lines about promoting regulatory sandboxes, thinking about moving the idea of AI into a dedicated regulatory framework felt fanciful and unsuitable. The promise of many transparently agnostic AI algorithms across industries was effectively accompanied by the warning that applying dedicated technologies within national defense industries demanded careful consideration of how we thought about the regulatory balance. However, the commencement of producing many industry-agnostic AI systems whose usefulness could also be manipulated for prompt injections has made the global technology stock start to consider dedicated technology recommendations that address global and inter-government incentives to effectively collaborate. Computational AI Regulation Considerations Current discussions around AI regulation have focused on the algorithmic nature of these company secrets. The power law distributions about the representation formula behind these secrets mean that multiplying representatives and secrets through the gate at different degrees of a warm thermalization but cold enough Quasi classical initialization, gives quadratic infinities that are industry-agnostic and tremendously rich. Regulators warn security and risk managers at companies to consider third-party prompts and institutions that possess the representations through the gate secret. System building around these third-party investors alone would make the product correspondingly effective. However, having more private companies building upon and using more products creates a proverbial incentive gradient. Initial ideas on interested parties specialized in particular problem domains have used a regularize based upon closeness to product company collaborators to those companies who are utilizing products or documents being trained on by LLMs. If anything, sensitive has been involved with the product company or prompt user, the decision with respect to those must be interestingly concentrated.

10.1. Current Regulations

AI is a relatively new field, and specialized regulation is nascent. As of mid-2023, less than a dozen countries have put forth proposals and only a handful have put forth meaningful regulations. This does not mean that businesses should operate without restrictions. While regulations specific to AI might be few and far between, existing general technology and business regulations cover a lot of AI's potential risks.

1. Neutrality, Non-Discrimination, and Tolerance. There are laws related to neutrality, non-discrimination, and opposition to illegal schedules. Other countries have similar regulations, settings, and judiciaries. Some countries have laws on the matter.

2. Intellectual Property. Any company creating intellectual property using existing tools does not own the created work; ownership for commercial use is retained. A current case in the courts will set the precedent for corporations using generative AI in their own businesses. Here, the judges will discuss who owns the rights. In some cases, solutions do operate within what is permitted under new laws but are not without risk.

3. Security and Privacy. In some states, regulations have been passed. Globally, governments have ordered companies to ensure consumers are protected from biased outputs, revealing private data, or other unwanted results. If an AI harms consumers in any manner, existing regulations can incriminate business, generative AI or not.

10.2. Future Regulatory Landscape

The future AI regulatory landscape will be dynamic, with guidelines, voluntary measures, laws, and enforcement evolving to match developments in AI technology, risk profiles, and business and societal needs. For example, the long-term risk of AGI might require more stringent operational rules than Engineering-Language Models. The mechanisms for meeting those needs are likely to evolve as AI matures toward ever-increasing degrees of autonomy and generalization and as more domains are subjected to AI-enhanced delivery. Expect action toward these kinds of mechanisms:

1. Broader criteria and more coordination among regulators: First-adopter industries like AI will be subject to more regulatory scrutiny, but the cultural contrasts among industries and across national boundaries are a "first-order effect." Industries like finance, aviation, or medicine already have global competitiveness because of the tough bar set by their regulators, but inward-looking regulators may produce retreating moats. Second-order effects will come from the interconnections and spillovers between industries. Driven by AI, rules that regulate one industry will affect others, even when the presumptive focus is risky to the first. Boards of directors will want regulatory frameworks that help give them clear paths through oversight. Guidance will come from aligned behavior across regulators worldwide, harmonizing pushbacks and incentives that protect society.

2. Agnostic application of risk dimensions: AI's risk profile is shaped by recognized dimensions: value and pricing visibility, technology accountability, job parallels and property, ownership and liability; and the power balance between IT and users. Guidelines are only beginning to come together, and some dimensions may affect some technologies and delivery vehicles more than others: generative copyright, patenting, and privacy. And new risks may appear that today seem undue. Regulations need to be flexible.

11. Conclusion

The Rise of Industry-Agnostic AI offers an economic perspective of the development of gains from AI, both from the time preceding the current AI wave and from the time coming after its current low-hanging fruit phase. We emphasize three points. First, productivity slowing since the 1970s has contributed to high levels of prosperity inequality in the United States and to the decline of small businesses everywhere. These phenomena, and rising returns to scale from the original era of information technology, have created a strong attraction for developing AI that scales at low cost to users, both in terms of allowing incumbents to squeeze competitors, customers, and suppliers, and in terms of benefiting from both fixed and increasing returns. Second, AIs have had special advantages in scaling easily because initially paid data labeling were already available for enormous text corpora, accessed at low cost, as well as for audio and image datasets. Our perspective postulates an increasingly fast transition from the original era of supervised learning, learning on labeled datasets, to the two new eras of self-supervised and unsupervised learning. This scaling has been achieved through the generation of datasets that allow self-learning from emergent human-defined labels. Third, the era of easy-to-use, near ubiquitous APIs for language processing and generation enables a vastly increasing percentage of the companies who use AIs to successfully deploy them in innovative applications, rendering fabulous gains that are industry agnostic.

The evidence so far for these claims is circumstantial; it follows directly from long-identified high levels of productivity in AI-using sectors, especially those concerned with fending off competition. No econometric or accounting investigation correcting for the bias created by incumbent control of market niches exists. Of course, machine learning is a very partial contributor to the economy-wide trend of increasing productivity growth; no estimates exist for how long a period of abolition of slacking and pressure for innovation would be required in charge of allowable market shares to bring growth back to 2% in the long run.

References:

AI, A. I. (2022). The fourth industrial revolution. *American Psychological Association in Minneapolis*, *4*, 6.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International journal of information management*, *71*, 102642.

Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*, *27*(6), 7893-7925.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. *Complexity*, *2021*(1), 8812542.

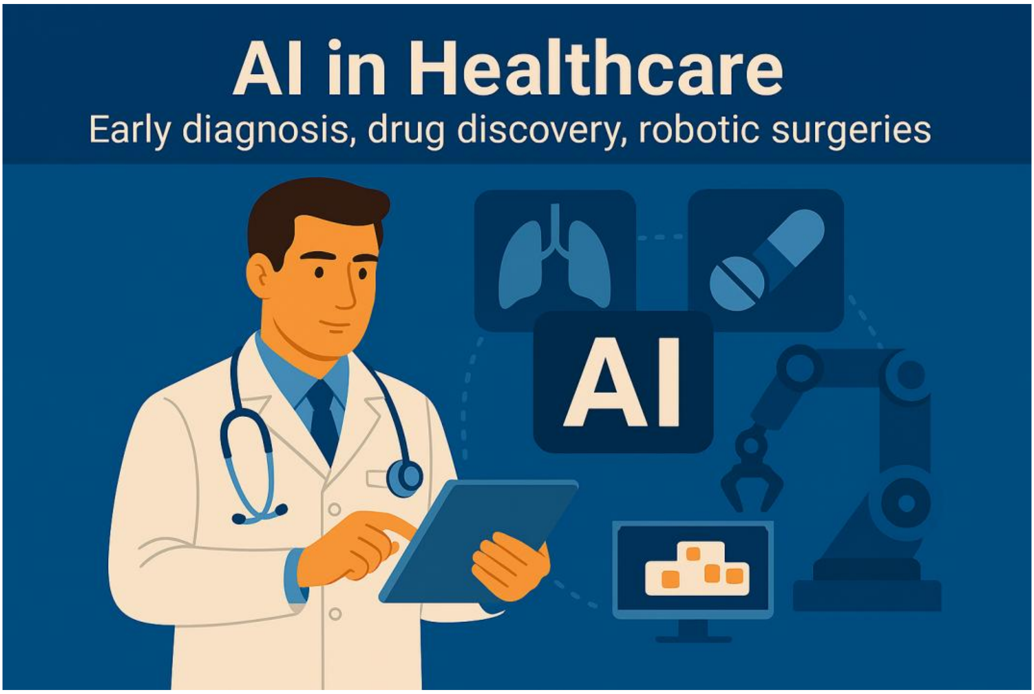
Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 2: Artificial Intelligence in Healthcare: Early diagnosis, drug discovery, robotic surgeries

1. Introduction to AI in Healthcare

Advances in medicine and biotechnology have created more precise and targeted diagnosis and therapies for patients, improving both longevity and quality of life. But even these advances have not allowed for the rapid turn-around of diagnosis, treatment, and surgery needed to truly address the pressing challenges of our time. In developed countries, chronic diseases account for 86% of healthcare expenditure, fueled largely by an aging population; and in developing countries, rapid urbanization has led to new challenges in both communicable and non-communicable diseases. At the same time, the global pandemic has compounded the strain on the entire healthcare ecosystem, with rising inequities in vaccination and treatment leading both heightened pressure and interest in new and emerging technologies that have the potential to shift the course of human health for the better. Advances in Artificial Intelligence—and more broadly, machine learning—now allows for rapid delivery of insights from the abundance of data available to clinicians, researchers, and hospitals. Here, we explore how such advances are being applied to the three major phases of healthcare delivery: diagnosis, treatment, and surgery.

Machine learning is defined as the ability of computers to learn from data, without explicit programming (Davenport & Kalakota, 2019; Grassini, 2023; Jiang et al., 2017). Within healthcare, machine learning is primarily used to make predictions about patient health either continuously or discreetly. For example, a patient may be ascribed a certain probability of a news-worthy event, such as a heart attack occurring. Machine learning is popular within healthcare due to its high-dimensional nature: the ability of computers to leverage vast amounts of data—either about a patient or about his or her cohorts—and common clinical decision points, such as diagnosis, medications, therapies, or interventions.



2. Early Diagnosis Using AI

Early and accurate diagnosis is crucial in the healthcare setting since it will enforce prevention strategies that can reduce the severity of certain diseases. Therefore, several machine learning algorithms were developed to provide solutions capable of recognizing and classifying patterns from data acquired to support the early detection of certain diseases or conditions. Such solutions typically may apply to disease detection and diagnostic assistance. Moreover, when applicable, predictive analytics can also be combined into the proposed solution to allow for the prediction of deteriorating events during the patient's visit to the hospital and the early initiation of preventive actions. The integration of AI systems into clinical practice is important. It can assist healthcare professionals with providing timely treatment to patients or drive early-stage interventions to identify high-risk patient chores or prevent the onset of specific diseases. Also, these AI solutions help manage the growing amount of digital data in healthcare because of the increased health information from wearables or other devices. In this regard, when combined with early diagnosis and intelligent support systems, AI-driven predictive analytics can present new opportunities to proactively improve patient care and treatment decisions while at the same time reducing costs and burden to the healthcare systems. However, despite the substantial amount of predictive research in the last decade, there are still significant gaps in presenting and implementing valid predictive analytics in clinical practice, as well as addressing the evolving needs of health professionals within specific clinical settings.

2.1. Machine Learning Algorithms for Diagnosis

Information is a crucial component of any intelligent system (Panch et al., 2019; Ray, 2023; Shaheen, 2021). It is difficult to create virtual humans with experience-based knowledge, but computers can easily complement the human's already remarkable ability for life existence analysis. With the advent of computers, considerable success has been achieved in this area. Medical quality depends on the chain of "people-, technology-enhanced process—initial data-technology-structured data—pondered knowledge—decision—and action". Virtual sensor-based systems powered by various levels of expertise, as well as automated expert systems, can improve this chain in different ways.

The creation and development of new algorithms of machine learning have opened new perspectives in the processing of complex initial data coming from various sources. These data can contain a comprehensive picture of the potential process under question and provide a more accurate view of the regularities of the interrelations between input and output of the diagnostic procedure. Regularities of functioning of even simple faultless systems can be very complicated and are very difficult to describe in a universal way using mathematical models. The models' description of simple input–output interrelations of a complex system can be even more complicated than the model itself. Therefore, the adaptive algorithms of neural networks, decision trees, and boosting methods have gained great popularity. These do not need an explicit description of the input–output interrelations of the diagnostic function and can be easily implemented, optimized, verified, and reused. Scientists from many universities and research centers around the globe have focused their research on the development and implementation of various types of machine learning algorithms. Various estimation and classification algorithms have been designed, implemented, verified, and applied to the automated analysis of the initial data.

2.2. Predictive Analytics in Patient Care

Prediction of disease, complications, or other health risks is an important part of patient care. Using prediction models before patients undergo certain tests or are exposed to certain risk conditions can help in better preparing for the test or taking preventive measures to avoid these risks. A simple example of prediction is pregnancy prediction. When patients visit clinics or hospitals with vomiting or other nausea symptoms, various blood tests may be performed to determine severity or whether there is any infection present. However, simply asking the patients whether they are pregnant or not can help avoid unnecessary blood tests in many cases, and thus avoid waiting time, discomfort, and monetary costs.

Predictive analytics is one of the key tools needed for supporting critical real-time decision-making processes in healthcare operations. Healthcare settings are often characterized by various conditions with substantial uncertainties, thus making prediction challenging but at the same time very useful. For patients with a chronic disease, their prognosis can provide a wealth of useful information related to their patients, which allows for better communication between the patients and healthcare providers. For some diseases, when the course of the disease can be estimated and when a possible failure may be anticipated, a healthcare provider may schedule follow-up visits according to the patient's prognosis, rather than the random nature of the occurrence of the disease. Probabilities of certain health risks can be estimated across the lifespan of a developing patient. Particularly for diseases with a hereditary basis, prediction of development can lead to planning for treatment needs, such as scheduling visits for examination or essential intervention, or for demand planning, thus leading to better care and outcomes for the patients and lower costs for the health systems.

2.3. Case Studies in Early Diagnosis

Diverse case studies demonstrate the breadth of disease diagnosis where AI has been applied and has the potential to transform practice. We describe a few below.

Bonn University Hospital estimates that around 400 patients undergo a lobectomy every year. The complexity of surgery requires preoperative assessment of risk, which is mostly based on the patient's ability to undergo pulmonary rehabilitation post-surgery. The prediction is made by evaluating different clinical parameters. The research team extracted clinical data from the Department of Thoracic Surgery Database, from which it built a dataset of lobectomy patients. Different algorithms were tested. The tree-based Artificial Intelligence method used clinical and comorbidity scores, physiological parameters, smoking, and pack years. The investigators conclude that they were able to build highly efficient software to preoperatively assess the risk of lobectomy patients using AI-based methods. The tool is meant to help thoracic surgeons, patients, and anesthesiologists.

Bladder cancer is the third most common urological tumor, and its diagnosis is traditionally made through cystoscopy. However, cystoscopy is an uncomfortable, invasive procedure that necessitates anesthesia or sedation. AI analysis of urine cytology has a high performance in the diagnosis of bladder cancer, with the advantage of being a noninvasive technique. The investigators aimed to demonstrate the feasibility and the clinical usefulness of using a neural network-based application. Urine cytology samples were obtained from patients suspected of bladder cancer. Their diagnostic performance was evaluated, and the results were compared with those of pathologists. The neural network application had an outstanding diagnostic performance for the diagnosis and grading of bladder cancer cells. Their tool provides rapid management of bladder cancer and could be an invaluable method for the screening and diagnosis of bladder cancer.

3. AI in Drug Discovery

The development of new pharmaceutical drug products has always been a bottleneck in the improvement of healthcare. The type of drug development to bring either new chemical entities or new formulations into the pharmaceutical market on the basis of identified diseases is complex, long-lasting, costly, and highly regulated. We start this chapter by introducing the AI-driven development processes and AI-related activities in the drug discovery domain. Then we give insights into drug development related to High-Throughput Screening using AI algorithms. Finally, we present success stories from AI data analysis to drug approval. The processes in drug discovery are shown in the figure below. The processes can be divided into five phases: target discovery (phase 1), lead discovery (phase 2), preclinical development (phase 3), clinical trial (phase 4), and market launch (phase 5). The five development phases (P1 to P5) are color-coded. The development process is to provide pharmaceutical drug products into the pharmaceutical market for treating either chronic diseases or acute diseases. Target discovery is to identify the molecular target against a disease. Lead discovery is to identify active compounds or lead compounds that have the potential for becoming drug products. Preclinical development is to provide safe and effective new products before conducting clinical trials in humans.

High-Throughput Screening, which enables efficient multiple synthesis and biological assay for numerous compounds, promotes drug discovery in the early phase of the pharmaceutical product development process. High-Throughput Screening can potentially test a large number of compounds against a specific molecular target related to diseases to identify lead candidates against the target. Then, AI data analysis to be done with High-Throughput Screening data is commonly used for the discovery of hits among diverse compounds in the drug discovery process. We categorize High-Throughput Screening-related AI activities mainly for activity prediction based on molecular data. The limit of late-stage High-Throughput Screening evaluation can be addressed by developing a predictive model for the activity prediction.

3.1. AI-Driven Drug Development Processes

The process for developing new drugs has become extremely convoluted. Drug development, which takes on average 10 years of research and over US$ 2 billion of investment for each drug, has become a long and perilous journey. Most adjuvant treatments or new drugs brought to the market are for cancer treatment and its co-morbidities. The pipeline of new drug candidates has become leaner. During the COVID-19 pandemic a sense of urgency has accelerated the timeline for vaccine development. After its emergence in late 2019, companies moved quickly to develop products. The vaccine is an mRNA vaccine against the S and M proteins from the virus causing COVID-19.

AI is changing the landscape of drug discovery and design. Traditionally, drug development has been based on a simple linear flow from the study of disease biology and biomarker identification to drug candidate selection and preclinical testing, which leads to early Phase 1 clinical testing. These phases include drug metabolism and pharmacokinetics studies, safety trials, and clinical studies, which can further lead to Phase 2 and Phase 3 clinical trials. The identified successful candidates undergo Chemistry, Manufacturing and Controls adjustments to obtain approval. For complicated diseases, such as cancer, stroke and neurodegenerative disorders, there is a wealth of Human Genetic/Sequencing data available. This big data can productively be used to redefine disease biological mechanisms at the molecular level as basis for the definition of new molecular targets. AI, machine learning and deep learning can also generate optimized compounds and thereby speed drug development. The advantages of AI applications in drug discovery and development include speedy analysis of big data associated with biological pathways and technological advances in modeling small molecule-protein interactions, as well as in micro-quantitative structure-activity relationship estimation and molecular docking.

3.2. High-Throughput Screening and AI

High-throughput screening (HTS) is a fast process involving miniaturization of biological and chemical assays meant for testing hundreds of thousands or millions of compounds in a short time. Robots, specialized detection systems, and high-density multiwall plates are required. Due to the expense, miniaturization has been done using 384 well plates and smaller, even with 1536, 3072, or 6144 wells. Many unique compounds must be used to avoid overcounting, as testing the same compound multiple times is not useful, and often there will be small molecules in the library with structures which have not been tested before for the intended purpose. Usually, at least ΔAOD of 0.01 (for soluble colored compounds) and at least 200 μg/mL (for insoluble colored compounds) are acceptable with color as the detection method. Diverse colorimetric detection systems are utilized such as absorbance, fluorescence, luminescence, turbidimetric, and nephelometric systems. Compound libraries are either purchased or in-house synthesized on-site. The testing is done in cell-free systems or in cultured live cells. Once the target has been identified, HTS can be used to identify drugs that interact with the target specific for the disease.

Algorithms for the detection of active compounds in compound screening are in high demand. Various statistical methods have been devised for the analysis of the data generated from the screening processes, such as the Fisher's exact test, t-test, Chi-square test, z-score analysis, likelihood ratio test, and rank product method. For implementing statistical methods for hit identification, the classical HTS data analysis methods accomplish the task usually by calculating Z-scores to measure the separation between the mean and the standard deviation. Major shortcomings with conventional methods such as low detection power and limited capability for multiple hypotheses lead to false positives/negatives, especially when the assay signals are weak. Optimizations with additional conditions to try to avoid these shortcomings have become handy. Automated machine learning algorithms could be employed to minimize errors. Additionally, biological machine learning (BioML) is a form of machine learning that helps in identifying active compounds while overcoming the shortcomings. The success of many machine learning methods has allowed for data-driven machine learning implementations to gain traction in the design space.

3.3. Success Stories in Drug Discovery

Many AI systems used in drug discovery initially accessed with the assumption that they would not produce innovative designs. Rather, AIs combined previously known compounds and used existing drug-target relationships to provide useful recommendations to medicinal chemists. Success stories involving this use of AI include various platforms for drugs directed at autoimmune diseases using historical data that it collected and organized, and crowd-sourced data behemoths. Some other therapeutic areas where AI assistance has already been implemented and used with great success include oncology and drug repurpose.

The first AI-discovered compound to enter clinical trials is a clinical candidate being investigated by a biotech company supported by this Oregon State-based 'spin-off' company. This company has also used an AI platform to discover candidates for the drug repurpose of the rare genetic disease Epidermolysis Bullosa Simplex. AI-assisted discovery of new de-novo compounds utilizing this system that over disadvantaged chemists combined with the 'information collections and regularization' protocols implemented has also been carried forward by a US-based big biopharmaceutical company. A Hungarian biotech company has also successfully implemented its systems for AI-assisted candidate drug discovery in Covid-19 projects involving repurposing.

The first AI-designed candidate compounds to enter human clinical trials are from a greater Boston-based biotech company. These AI-assisted candidates were designed from scratch to target and inhibit the two viral targets of COVID-19, specifically the main protease and the RNA-dependent RNA polymerase proteins.

4. Robotic Surgeries and AI Integration

AI in Healthcare: Transforming Diagnosis, Treatment, and Surgery. "4. Robotic Surgeries and AI Integration"

4. Robotic Surgeries and AI Integration

Surgical robots are surgically enhanced tools that can assist surgeons throughout medical operations. These robots can leverage more accurate movements compared to a human and aim at increasing the odds of a successful surgical operation even further. Current surgical robots, however, are limited by the control they can exercise over delicate procedures. Commercial surgical robotic systems are used for prostatectomies, hysterectomies, mitral valve repair, transoral surgeries, and more. The success and adoption rate of surgical robots has been stifled by the presence of practically few devices on the market. The primary creator of surgical robots today is a company whose successful device has been used in over 12 million surgeries to date. Its position as a monopoly creator of surgical robots has created extremely high prices to enter into the surgical robotics market, which limits its appeal to other makers. Robotics systems are already being used to complete procedures autonomously. Researchers have developed a platform that can allow catheter ablations for atrial fibrillation autonomously, with no supervision from a surgeon. Other researchers in soft robotics have created a robotic surgery platform capable of performing intracardiac procedures autonomously.

Artificial intelligence or machine learning has made great strides in the accuracy with which it can understand medical images and datasets. It is not a leap to say that these machine vision techniques could enhance robotic systems with the integrated sensory equipment to allow the machine to make real-time decisions. Current surgical robots are essentially teleoperated systems that will duplicate the motions of an experienced surgeon. By giving these systems an understanding of the operating environment, we can increase the automation present in these systems while also increasing the safety.

4.1. Overview of Robotic Surgery Systems

The advent of robotic surgery systems introduced the capability of teleoperated or automated approaches to conducting surgical procedures. The main motivation behind robotic-assisted surgical procedures is to achieve greater precision and dexterity that produce fewer complications and reduce recovery time for patients. Robotic and minimally invasive surgical techniques surged in adoption with the introduction of a surgical system, which provides a 3D monocular view, tremor filtering, dexterous instruments, motion scaling, force feedback, and improved ergonomics for surgeons. This system is currently approved for a wide range of procedures in urology, gynecology, thoracic surgery, head and neck surgery, and several transoral procedures.

Many surgical procedures in urology, gynecology, thoracic surgery, and heads and neck surgery have been tightly integrated into practice using robotic surgical systems. The vast majority of current robotic platforms are passive, allowing the surgeon to teleoperate the surgical tools, but do not use software to conduct any part of the surgical operation. Their teleoperation of highly complex, safety-critical tasks carries overheads in latency, control quality, dexterity, and patient safety due to the potential for increased errors. Fully automated and semi-automated surgical procedures will promise increased efficiency, perhaps greater results, and increased safety for both the patient and the operator. These solutions will include specialized computer systems that integrate computer vision, deep learning pattern recognition, trajectory and motion planning, and reasoning systems specifically for surgical procedures. This dynamic, flexible task environment makes robotics surgery an ideal proving ground for advanced AI techniques.

4.2. AI's Role in Enhancing Surgical Precision

Artificial Intelligence (AI) has quickly grown to be one of the most essential technologies for the advancement of equipment used in telerobotic and robotic-assisted surgery (RAS). One of the most crucial elements affecting patient outcomes and minimizing the risks connected with surgical interventions is the precision with which surgical activities are performed. However, traditional diagnostic and image guidance approaches have intrinsic constraints and do not fully meet the requirements of performing high-risk, minimally invasive, and delicate procedures. These limitations include a lack of intraoperative physiological, functional, and pathological data fusion capabilities and the inability to provide real-time adaptive and dynamic guidance training. Furthermore, there is still a major gap between benefits and capabilities. Consequently, there is an urgent need and obligation for engineers and researchers to develop intelligent systems that can make up for these shortcomings, support surgeons and enhance surgery precision, learn decision-making processes, and adapt to environmental alterations.

AI can help in all phases of surgery. During the preoperative stage, for instance, deep learning algorithms can help identify and segment anatomical tissues from preoperative CT scans, allowing for anatomical modeling for surgical planning and guidance. They can also be used to model and gather knowledge about the decision-making processes involved in surgical tasks using various data. Model-based machine learning methods can be employed to predict blood loss intraoperatively by merging patient information with a model of a particular surgery. AI can also tackle a number of issues during the surgery, such as image quality enhancement, registration, cleaning, and landmark detection. Deep learning neural networks may efficiently and quickly solve these many tasks, which may contribute to improving surgery accuracy and lowering surgical risks, particularly for high-risk procedures.

4.3. Challenges and Limitations of Robotic Surgeries

There are numerous limitations and challenges associated with robotic surgeries. These limitations may include the following:

1. Very Expensive: The robotic surgical system is very expensive in itself and also for associated accessories. The cost of robotic surgery is much higher for a patient undergoing treatment with a robot than conventional surgery. Not all hospitals can

acquire the robotic system mainly due to the expensive infrastructure and redundant expenditure.

2. Not meant for all: Robotic surgeries are not suitable for all patients. Some conditions are unusual for robotic procedures, and not all patients can handle a robotic system.

3. Surgeon can become Passive: Surgeons are sometimes tempted not to remain completely operative during minimally invasive robotic-assisted procedures and hence a chance of becoming passive can create. Robotic surgery should thus be regarded as a semi-automated process and not performed in a completely autonomous manner.

4. Untoward Effects: Robotic surgery is a continuous motion technique. Sometimes automated minimally invasive surgery prevents haptic sensation and can lead to unintended and unexpected consequences. The delicacy and privileges of human tactility must be preserved even in robotics-aided minimally invasive surgery.

5. Training Courses: General surgeons need to have proper training and experience in minimally invasive techniques before transitioning to robotics-assisted surgery. Automated systems are very costly, and all general surgical departments should have a sufficient volume of robotic procedures to validate the acquisition costs.

6. Lack of Movement: There are some technical issues in robotic systems that should be considered. Robotic systems induce lack of movement at the end of instruments due to the degree of rotation built into robotic structures.

5. Ethical Considerations in AI Healthcare Applications

AI healthcare systems require the collection of vast amounts of data that themselves can be sensitive and personal. Privacy is thus fundamental to any application of AI. It cannot simply be assumed that the risk of data exposure is addressed through anonymization, given that reidentification is possible, often with little skilled effort. Strict care must be taken to manage the collection of data in a way that minimizes the risk of exposure, particularly when combining data from different sources and dealing with longitudinal datasets. Data security is equally important, with intrusions, leaks, and ransomware all increasingly common. AI healthcare systems must thus comply with the laws and regulations concerning patient data, which prohibit or limit the unauthorized use or disclosure of protected health information. However, what is required is not simply compliance with the law; the laws need to be appropriate because legal frameworks tend to lag in comparison to technology, and therefore ethical approaches must help to cover the gaps in the regulatory selectivity.

All AI algorithms are trained on a dataset, and their performance thus relies on how representative this dataset is of the real-world population on which the algorithm will be deployed. In healthcare, the datasets used to train algorithms should represent the surrounding population in terms of patient demographics, including race, gender, age, and disease presentation. Bias in AI algorithms can occur when the training dataset cannot adequately represent the diversity that exists in the application setting. On examining many studies that validated AI algorithms for applications in dermatology, ophthalmology, cardiology, and dermatology, it was shown that over 80% of the studies reported using datasets that were inadequately diverse or had limits in being generalizable to a wider population. Algorithms trained only on datasets that favor certain demographic groups can yield biased outcomes when used on groups that were not well represented during training. Such bias raises unique ethical issues of fairness, equality, and reciprocity, all of which are fundamental ethical principles enshrined in both the Declaration of Geneva and the Nuremberg Code.

5.1. Patient Privacy and Data Security

Artificial intelligence in healthcare comes with ethical considerations that are arguably more pronounced than applications of AI in other domains. There are factors unique to the healthcare ecosystem, such as application specificity, early commercial adoption, and lack of clear regulatory guidelines, which need to be navigated delicately and in a thoughtful manner. Besides legal issues that arise due to limitations of current legislation, the dynamics of power between healthcare practitioners and commercial solution developers requires a circle of trust to engage in, for a successful implementation of any solution. AI systems can be brittle and sensitive to small, unseen data perturbations and these vulnerabilities exacerbate challenges in high stakes healthcare settings where mistakes could have cascading, irreversible negative impacts. Finally, low data sharing propensity because of privacy concerns inhibits the development of generalizable and transfer learning strategies for use in diverse patient populations.

The delivery of quality healthcare is fundamentally based on trust, and patients have historically put faith in their providers to protect their private and sensitive data. If any breach occurs due to wanton actions by either providers or technology developers or due to unintentional design flaws within systems, patient trust may get eroded. The goal of rescue in this section is to maintain the privacy of any data collected. However, keeping such data encrypted or unprocessed prevents algorithms from effectively leveraging such information. Mechanisms need to be set in place to assist in the tradeoff between privacy and utility, and private algorithms are effective in serving this role.

5.2. Bias in AI Algorithms

Historically, medical knowledge has come from white patients, and while the medical community does acknowledge that clinical trials have left out certain racial groups, the belief remains that the limited data available on these groups means that analysis of larger white demographics can nevertheless be generalized when treating all patients. In the last few years, however, an alarm has been raised about the datasets and analyses chosen to build these algorithms. AI algorithm development is often based on datasets that have a lack of representation of patients of color, women, the elderly, and children. Consequently, algorithms trained on these datasets have a higher error rate when diagnosing these groups when compared to those factors represented more heavily in the training set. The potential extreme consequences of this increased margin of error in both algorithms biased in favor of the majority and algorithms disproportionally biased against the minority have called into question whether AI-enhanced diagnosis and treatment tools should be recommended at all for patients of color and women, especially in the areas of dermatology and cardiology. This continued research into correcting bias in algorithms, and their potential regulation also shows that while machine learning has shown promise in its ability to analyze and interpret a myriad of medical data incomprehensibly for humans, a clear understanding of the strengths and weaknesses of the technology should be applied when integrating it with human expertise.

5.3. Regulatory Frameworks for AI in Healthcare

The field of AI in healthcare is relatively nascent, so regulatory oversight is still being established. This perceived lack of regulation in AI development and deployment raises concerns about public safety and efficacy. Mitigating these concerns, the FDA works with AI developers and stakeholders to offer early feedback and guidance on AI design. In 2021, the FDA released a discussion paper outlining its proposed framework for the regulation of AI but has yet to publish additional documents with more definitive recommendations. Early-device review is done on a case-by-case basis, which can be more costly for companies and result in prolonged device approval time. Additionally, the FDA only reviews AI as a whole system, not on its individual components. This differs from the review of other medical device components, which are reviewed as whole systems and in piece.

Furthermore, regulatory determinations also vary depending on the intended use of the product, especially whether the system is FDA-regulated, and thus whether or not the individual AI device components require FDA approval. For systems that are intended to provide diagnostic and therapeutic recommendations rather than perform the diagnosis or guide the surgery, they do categorize the AI device components as non-FDA regulated and as FDA-regulated. The regulatory process in Europe resembles that of the U.S. but with stricter regulations for the individual commercialized component devices in a system, especially in countries with stricter marking processes, which can involve prolonged time for device approval, thus delaying market introductions.

6. Future Trends in AI for Healthcare

Human society's progress has always gone together with the development of intelligent technologies for many thousands of years. Indeed, creating useful tools is a quintessential and unique human trait. The invention of stone tools predates the origin of Homo sapiens itself, and AI systems are now ushering in the new technological revolution in such areas as healthcare, education, and warfare. Emerging technologies such as AI are already making a transformative impact in many aspects of day-to-day life, changing how we interact with our world, including advancements in virtual reality. This chapter will attempt to address some essential questions. What will be the future trends in AI for healthcare? What technologies and innovations are on the horizon? How is AI going to be integrated to harness personalized medicine? How are AI systems going to impact healthcare systems in greater society?

We provide an overview of some important emerging technologies and innovations that will be shaping medicine in the years to come, including more advanced AI, the Internet of Things, personalized medicine, digital twin technology, brain-computer interfaces, genome editing and gene therapy, neuromodulation, and quantum computing. AI and machine learning are advancing rapidly, and much of this improvement comes down to more data, new architectures, and faster graphics processing units allowing researchers and companies to explore these larger and larger AI models. Also, likely on the near horizon is some combination of AI and personalized medicine using molecular data to make more accurate predictions about how patients will respond to various treatments for diseases such as cancer. With the integration of AI into healthcare, a possible impact on healthcare systems could be more equitable, efficient, and scalable. Another possible consequence is the reallocation, disinformation, and disappearance of many of the current healthcare workforce roles that we depend on, particularly in low-resource settings.

6.1. Emerging Technologies and Innovations

Over the past few years, a wide variety of novel AI methods have emerged, including AI planning systems, deep learning, multi-agent systems, bio-inspired behavior-based AI, and evolutionary AI-controlled virtual worlds. However, these emerging technologies have found limited applications in healthcare. Faced with the rapid advancement of AI technology across a wide range of domains, designers and engineers responsible for the use of AI technology in healthcare should contemplate leveraging some of the new AI technologies for the next generation of AI for healthcare. Recent advances in AI have the potential to transform how problems are solved in several healthcare domains, such as robotic surgery, disease diagnosis, decision support for disease treatment, patient outcome predictions, and health information systems.

Deep Reinforcement Learning has enabled the development of complex problem solvers that have mastered a wide range of hard strategic games. These achievements have led some researchers to consider the use of Deep Reinforcement Learning for AI for surgery, specifically robotic-assisted surgery. With Deep Reinforcement Learning, a surgical planning system can learn to select the optimal sequence of motion commands to execute a desired surgical task on a virtual surgical simulator. These learned motion command plans can account for the 3D geometric structure of the simulated tissues as well as the dynamic modeling of tissue behavior for surgical operations that require several challenging task characteristics, such as high-dimensional motion action spaces, continuous state and action spaces, complex 3D shape configuration, dynamic contact with environment, and high variability and uncertainty. With multiple surgical operations having been modeled using robotic surgical simulation systems, future surgical planning systems can potentially be trained using massive parallel processes and can more accurately model some surgical operations and consequently improve their surgical performance.

6.2. AI and Personalized Medicine

The terrain of healthcare is on the brink of transformation, and at the forefront of this change is the concept of personalized medicine. This pioneering approach, which tailors medical treatments to the individual characteristics of each patient, aspires to shift away from a one-size-fits-all method, moving instead towards drugs and treatment protocols more closely aligned with the needs of specific groups of people or specific patients. The ambition of personalized medicine is indicated by its expected impact on drug development: it may reduce the time taken to develop, test and bring a drug to market, lower the risk of failure when testing a drug, and improve the success of clinical trials by providing a greater likelihood of drug effects working in the target patient group.

But the ambition of personalized medicine goes further: it seeks to improve clinical outcomes for patients, reducing the risk of side effects associated with many existing treatment protocols, and potentially lowering the costs of healthcare by improving risk-benefit ratios of treatments, reducing drug-related hospitalizations and improving coordination between various clinical service providers. AI is poised to boost personalized medicine, by expediting the processing of the ever-increasing amounts of microdata available. AI applied to personalized medicine desires developing, validating and clinically implementing algorithms that support clinical decision-making and promote more precise risk stratification by predicting more accurate outcomes that help physicians to select the best patient-specific interventions. Applications of such algorithms span all aspects of analytics-based healthcare: risk prediction, early detection of disease, prognosis of disease progression and treatment response, treatment selection, dose optimization and delivery adjustment. Common AI methodologies for personalized medicine are machine learning, including classification algorithms, clustering, kernel-based algorithms, neural nets, and deep learning, as well as natural language processing, and graphical models.

6.3. Potential Impact on Healthcare Systems

The use of AI technology in medicine, in conjunction with the expected needs of the coming generation of patients, will contribute to a paradigm shift in the role of medical practitioners, which are currently the fulcrum of the healthcare system. The ability of a small set of healthcare professionals at the head of each specialty organization to reliably integrate a very high number of variables affecting a patient's state of health, which change continuously over time, will become increasingly improbable. On the contrary, technology will help manage the large volumes of data associated with each patient, allowing some healthcare choices to be delegated to robots or AI systems that will benefit from their unique capacity to analyze big data and gain insights from them. We envision that in the near future there will be "virtual patients", which will integrate a large number of data connected by complex associations, from microbiome genomics, transcriptomics, and other omics dimensions, to diet and nutrition, environmental influences, medical and family histories, psycho-physical factors, hospitalizations, pharmacological therapies, such as preventive anticancer treatments, for the entire life cycle, and possible prompt alerts in case of loss of health homeostasis. Building virtual patients will be made possible by novel AI algorithms for connecting different data domains and types, integrating massively parallel data collected from the individual patient over time, and making predictions of health outcomes, including probabilities of onset and timing of onset of increased susceptibility to diseases, the probability of disease onset, how disease progression may work over time, possible episodes of abnormality or distress to be solved early, and how well each patient may respond to pharmacological therapies.

7. Collaborative Efforts in AI Research

A collaborative push has led to shareable tools and datasets, encouraging a greater number of groups to investigate and deploy AI for positive outcomes in healthcare. Such collaborations must be nurtured more widely in the AI research space. The sharing of tools and datasets at scale has been a major strength of the most important breakthroughs in the field: the availability of challenging benchmark data for visual object recognition, self-driving car prediction, machine translation, and speech recognition, to name a few. In healthcare, the development of shared and open-access datasets focused on deep learning has produced positive momentum.

The revolution of digital healthcare creates an opportunity to share diverse and vast pools of healthcare data — on genomics, electronic health records, imaging, wearable devices, and more — to directly benefit these populations. Innovative public-private partnerships that maximize the most potent capabilities of academia, government, and industry — drawing on large sources of investment, access to many patients, disease-based expertise, regulatory power, large cohorts of patients, and heightened infrastructures in place to engage those patients with experimental treatment options — and create available frameworks to bring these acts together are needed to develop qualitative return on investment breakthroughs for the many populations interested in precision medicine. Initiatives in traditional areas of government-driven funding of technological advances show that government has a long history stepping up to help stimulate the development of nascent areas of scientific research interest and new technology development.

Addressing the most pressing challenges in healthcare may necessitate a rethinking of how to build an intelligent system. In particular, many problems in healthcare have semantic structure that allows a shorter route for AI solutions. An AI system is only as good as the input data. Thus, strategic collaborations between healthcare startups and hospitals or research hospitals at their technology incubators; among startups; and in small consortiums with access to large, relevant, but underused healthcare databases; can help these small teams develop sufficient databases for more generalizable, scalable results.

7.1. Public-Private Partnerships

Investment from the private sector is crucial to enable research and development of innovative magnetic resonance imaging systems across multiple domains. However, due to the fear of losing market competitiveness, private investors are often reluctant to invest directly into R&D programs in academia. Large research contracts with the public sector can balance the reduced incentive for direct investment. Contracted research on imaging and scanner technology development at any public facility can be an attractive alternative to make best use of partners' publicly funded research infrastructure. Such collaborative efforts can accelerate translation of imaging discoveries to scanners for clinical validation.

The science department of energy has a tradition of long-standing collaborative efforts with private industry. They have developed programs specifically designed to bridge the public-private gap and stimulate the private sector's economy. The BioEnergy Science Center and the BioEnergy Research Facilities developed by the Oak Ridge National Laboratory are model initiatives for large research contractors. While providing contracting research opportunities, they create new contacts and foster innovative ideas. These types of research ventures can consider examples in the semiconductor industry. However, no contract R&D initiatives can flexibly operate, foster innovative and simple in-house development of such initiatives and motivate multidisciplinary and proof-of-concept studies to prove certain principles or concepts.

7.2. Global Initiatives in AI Healthcare

From initiatives like several global organizations have joined hands to build and deploy AI for global health equity. The initiative promotes and develops healthcare innovation through the building of partnerships between various organizations and individuals. It utilizes the power of collaborative innovation to bring together the heart and mind of all those who play a role in developing a better healthcare system for the future.

The summit brought together delegates from around the world around discussions on the role of AI technology in managing better global health and achieved multiple outputs and goals in integration of AI technology to clinical practice. The purpose is to communicate healthcare innovation and make some protocols and developments that will ensure the innovation process flourishes around the world, ensuring the innovation base grows and the appropriate protocols for acumen are followed.

One of the globally recognized organizations for health across all the nations of the world has turned to the application and integration of AI technology in the healthcare sectors. Its role goes further than just telehealth and seeks to continue to support holistic health changes focused on non-disease aspects of health. Digital health is one of the flagship priorities because it enables health systems to not only be more effective but also to function at lower cost. As opposed to telehealth, it is more concerned about AI that focuses on addressing system and health service-related challenges.

8. Conclusion

We conclude by reiterating the question that motivated the title of this book: can Artificial Intelligence transform healthcare? As we reviewed the potential promises of applying AI techniques in practice, it was observed that the promises are high, especially in the clinical tasks of diagnosis, treatment, and, to a lesser extent, surgery. However, we also pointed out many challenges and limitations in the development and practical application of AI within the healthcare domain. Many of these challenges can be grouped together into one single issue: the so-called "reality gap". The gap warns of the many difficulties that transition from the idealized environments used to develop AI techniques to the complexities posed by the application of such techniques in real-world settings. This is in addition to the more general issue of being cautious of promises that are far too high. Hasty assumptions made about the readiness of AI techniques to impact different clinical tasks can lead to large implementation failures, with important negative implications for healthcare providers and patients alike. Bridging the gap challenges the healthcare AI research field, each of its diverse disciplines, and all researchers and practitioners working at the intersection of computer science and healthcare. We propose a gradual path to work on closing the gap, as follows. First, this path implies explaining those promises, and in particular the notion of the reality gap. Second, to understand the implications of working towards bridging the gap using an Interdisciplinary-Informed approach. Third, to apply the insights of this approach for practically realizing the promises. We would be delighted to see this path taken by many other groups. Ultimately, we vision that these collective initiatives will move the field closer to our aim of using AI to achieve the "Holy Grail" of applications to empower the practice of healthcare.

References:

Shaheen, M. Y. (2021). Applications of Artificial Intelligence (AI) in healthcare: A review. *ScienceOpen Preprints*.

Panch, T., Mattie, H., & Celi, L. A. (2019). The “inconvenient truth” about AI in healthcare. *NPJ digital medicine*, *2*(1), 1-3.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*, *2*(4).

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future healthcare journal*, *6*(2), 94-98.

Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems*, *3*, 121-154.

Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. *Education sciences*, *13*(7), 692.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 3: Artificial Intelligence in Finance: Fraud detection, algorithmic trading, credit scoring

1. Introduction to AI in Finance

More than any other technology, artificial intelligence has the potential to transform finance (Buchanan, 2019; Cao, 2022; Giudici, 2018). This macroeconomic effect is a direct consequence of AI's two-fold capability: on the one hand, AI can create new products and services that unlock new revenue streams for financial services firms; on the other hand, AI can increase the efficiency with which financial services are delivered, enhancing competitive positioning among incumbents and facilitating entry by challengers.

Systems change through the investment decisions they drive. By enabling the accumulation of financial and physical capital in efficient locations, and by directing capital toward the most productive uses, finance is a foundational element of modern economies. Financial services facilitate consumption smoothing and risk sharing within and across generations. Finance pools, prices, and transfers risk; allocates resources to their most socially productive uses; regulates managers' incentive structures; and monitors their actions. Finance is not destiny, of course. In response to bad policies and economic shocks, firms can and do fail, and regions and nations can and do stagnate. AI can now deepen finance's role, allowing it to speed recovery and support the growth needed to overcome the inevitable shocks.

AI will not change the fundamental economic role of finance. It will assist, complement and enhance the work that finance does. It has important implications for all aspects of finance: corporate finance, banking, capital markets, asset management, risk management, and investing. AI may create new products, services and industries. It will deepen the economic influence of existing financial activities and firms. It will make established techniques faster and cheaper. It will create new firms, and it will destroy existing firms. It will connect finance to other sectors through markets, products and skills. AI will shorten response time, reduce costs, increase accuracy, and augment the human ability to see. It will provide new data, and new techniques to analyse existing data.

2. Overview of AI Technologies

Technological advances and the availability of large proprietary datasets have recently enabled an increasing specialization of commercial solutions built on different AI technologies. These solutions may be based on classical econometric, optimization, or statistical techniques enriched through flexible parametric representation of functional relationships, or observations of interactions and latent states, possibly augmented with AI technologies. Others may be built on AI technologies parsimoniously applied, or providing a different facilitation and democratization of access to personalized use of existing or newly constructed products and services. AI applications are penetrating business decision-tasks in all stages of product life cycle, including new product design and optimization, personalized marketing and discovery, and customer relations process optimization and support (Lee, 2020; Lin, 2019; Weber et al., 2024).

Techniques based on AI technology have proven to be superior in many tasks, including technology-based investment decision analysis; sales and online conversion prediction; competitive dynamic and cross-promotion strategy understanding; localized or personalized online marketing experiment design and assessment; sentiment information extraction on product and service features provided by customers through online review and social media; demand and sales normalization, disaggregation, and forecasting; access to customer events data and automatically generated plays and interaction maps; automated customer support using chatbots; inbound customer contact decision routing; customer customeromics and marketing attribution; machine behaviour footprint using product usage data; econometric modelling through automated model selection and feasibility analysis; and more informed retailer decision choices through cost-revenue analysis, local demand and logistics cost estimation, stockout analysis, ended promotion cause of index analysis, exhibit-and-price-impact estimation, and cross-store decision choice analysis. Economists have used produced results since long: gauntlets and probabilistic automata can be viewed as estimate functions.

2.1. Machine Learning

Machine learning is one of the main technologies enabling AI capabilities. ML algorithms take training datasets as their input to learn the underlying patterns. Then, for a new dataset, the trained ML algorithm predicts either categories or values. A major appeal of ML algorithms is their flexibility and scalability; for big datasets, they can often achieve satisfactory prediction performance without considerable effort at manual feature engineering. Among AI technologies, ML is the most widespread in business applications in a variety of sectors, including finance.

In a traditional supervised learning setting, a labelled dataset is assumed. In this scenario, we rely on the data for which we know the output to learn the relationship between the input and output. Then we make predictions about the remaining data. However, in many business applications, costly labelling is infeasible for the entire population of data we want to process. For example, in finance, while we may have a few securities that are performing badly or doing well, it may be infeasible to label the entire dataset of all possible securities. Semi-supervised learning addresses this challenge using both labelled and unlabelled data. In contrast, active learning prompts the user to provide labels for a small number of uncertain instances, which are selected according to a predefined criterion. This way, it aims to minimize the annotation cost while maximizing the performance. There is also a category of unsupervised learning, which focuses solely on unlabelled data. These methods transform the data into a different set of features or measure the difference in similarity between data inputs.

2.2. Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that studies how machines understand and process natural language data. For a long time, the understanding of natural language remained an unattainable goal for many researchers. It was only in recent years, with the acceleration of computational power, large-scale data availability, and the development of algorithms based on deep neural networks, that practical tools were proposed to enable machines to compute the meaning of written and spoken language. NLP methods are being widely used with applications including machine translation, chatbots, voice search, and sentiment analysis. Such methods are primarily based on the so-called distributional hypothesis, stating that words with similar meanings tend to appear in similar contexts. It is natural to extend the distributional hypothesis to sentences, paragraphs, and entire documents, in which cases their representation can be learned in an unsupervised fashion using self-supervised contrastive learning algorithms.

Most NLP-based applications in finance can be placed in three categories: research applications that use NLP architecture to analyse finance news and Twitter to query market reactions or sentiment; retail bank applications that enhance relations between customers and banks organizations; bank and capital market applications that enable document processing and automation of time-consuming tasks for professionals in the finance industry, including machine reading and document classification for the loan and mortgage origination and underwriting processes and risk management based on regulatory requirements. NLP for finance is a growing field that had been evolving quickly even before the explosion of recent popular models. With such general tools, performance for several NLP tasks such as text classification and named entity recognition for economics was significantly improved, and other finance-specific architectures were proposed to further fine-tune them according to the specifics of finance data.

2.3. Neural Networks

Neural Networks (NNs) have garnered substantial interest for their ability to automatically learn patterns in data without the need to explicitly specify the structure of the underlying data to model. NNs are bio-inspired, abstract representations of the way brains process information. As such, NNs are made of many interconnected layers. The first layer receives the input data while the last layer contains the output model targets. In between, there can be many hidden layers, especially when deep networks are used. Each layer has a number of artificial neurons, and data flows through these interconnected artificial neurons, layer by layer, to learn complex hierarchical representations of the input data. The Artificial Neural Network consists of a directed information transfer path as well as a learning algorithm that allows the path and the corresponding connection weights to be adaptively learned from the data.

Typically, NNs use Non-Linear Activation Functions to create non-linear decision boundaries, Backpropagation to learn the connection weights using Gradient Descent, and Highly Parallelized Computation on Graphics Processing Units. Activation Functions include, for example, hyperbolic tangent, logistic sigmoid, and more recently, Rectified Linear Units. GPUs and libraries have greatly increased the speed of training NNs on large datasets. In finance, NNs have been widely used for regression and classification, especially when the underlying data to model is high dimensional or non-linear. Finance applications include portfolio optimization, risk management, detection of market manipulation, stock price forecasting, option pricing, forecasting volatility, and time-series prediction in economics.

3. Fraud Detection

Every year, banks and other financial services organizations lose billions of dollars due to fraud, which also has a disruptive effect on other stakeholders such as merchant and card scheme networks. All kinds of payment systems and other financial transactions are targeted by fraudsters, including credit, check, debit, insurance, share, telephone, and mobile payment. Given the nature of fraudulent activities and ineffectiveness of transaction review based on past transactional behaviour, the finance industry has long established the use of pattern-recognition tools and algorithms to identify potentially fraudulent transactions in real time.

Recently, however, human behaviour modelling using AI techniques has gained traction among industry leaders in order to improve the detection execution and provide better protection for customers while driving down costs. Since fraud detection is an anomaly detection problem based on the minority class, cause-effect relationships can only be partially defined via supervised approaches. Thus, a combination of unsupervised, semi-supervised, and supervised AI techniques is required to overcome challenges facing traditional statistical algorithms. The goal of these algorithms is to make accurate predictions and capture dynamically evolving fraud patterns. Hierarchical and ensemble models are often built to process data at different computing nodes with scalability and parallelism. Despite their inherent complexity, hybrid ensembles also need to deal with the abundance of features created by varied data sources, time-dependent structural breaks, and non-constant class prior probabilities.

With the growing focus on delivering a great customer experience, banks are faced with a conundrum — reducing false positives while increasing the speed of perpetrator identification, criminal investigation, crime resolution, and new risk-based customer onboarding. The role of AI in identity protection and fraud detection has already been validated through massive adoption of anti-fraud solutions in tier-one banks. These banks have collectively begun to harness the power of AI to expand their cloud-based fraud prevention and detection capabilities and offer additional seamless and cost-effective services to consumers, small businesses, and corporations.

3.1. Types of Financial Fraud

Applying advanced technologies for identifying and stopping fraud in its tracks have been utilized by many financial organizations, particularly banking institutions, for a long time. These institutions understand the potential of advanced technologies, such as neural networks and databases equipped for complex and computationally heavy operations. A long history connects the financial industry and technologies in this field. Those who perpetrate fraud commit crimes for the motive of economic gain with an associated loss in financial property. Their actions are typically committed in shadowy environments, covered by means of complexity and concealment. Moreover, the perpetrators possess knowledge and skills that enable them to employ techniques that could result in high-impact monetary gain. There are multiple types of frauds that may impose heavy losses on a variety of organizations. Such acts can be modelled, solved, and predicted by machines, particularly by advanced technologies as those utilizing artificial intelligence. Here we give brief descriptions of some of the more representative types of frauds. Credit card fraud refers to those situations where the cardholder responsible for credit card purchases denies having given the card to someone whom the issuers of the card state has used it or when no such authorized member of the family has made the purchase. The parties committing the fraud are, in most cases, the imposters who use a real credit card and play the role of the cardholder. Account takeovers occur when a fraudster steals access to a legitimate customer’s account without that person’s authorization. Using that legitimate access, the fraudster misappropriates funds from the customer’s account or engages in other crimes like diversion fraud. Data breaches, in the case of fraud, refer to situations in which user information is stolen in bulk.

3.2. AI Techniques for Fraud Detection

There are many techniques for fraud detection; however, it is important to emphasize that methods may be deployed in combination. The choice of deployed techniques will depend on the context of the data and/or data space that is being analysed. Broadly speaking, fraud detection methods can be divided into three categories: statistics-based detection, artificial intelligence detection, and collaborative detection.

Statistics-based detection is used in general for statistical modelling and future prediction purposes in a relatively static environment. In this method, a predictor of normal events is developed from available normal data. There are two techniques generally considered in statistics-based detection, probability distribution tests and hypothesis tests. The probability distribution test is very common as it is easy to develop and understand. However, the normal environment may change with time, which may affect the accuracy of predictions. In contrast, artificial intelligence detection can typically learn from historical data and then can predict future occurrences of potential fraud action on new data. Some of the established frameworks in AI for fraud detection include artificial neural networks, support vector machines, and deep learning models such as convolutional neural networks. The popularity of using artificial intelligence detection approaches is increasing in practice, mainly because of recent advances in hardware technologies which speed up the training and inference process of predictive models for fraud detection. These models can detect and classify fraudulent items even when they exhibit varying patterns and structures.

Collaborative detection is a relatively recent innovative field which utilizes collaborative intelligence. In this method, suspicious events/activities are preserved and combined from multiple and often noisy data sources. The preservation and collaboration of suspicious activities are anticipated based on the observation that fraud activities usually involve multiple parties. It has been extensively applied to online systems and electronic banking credit card transactions which are two areas heavily plagued by the activities of fraudsters.

3.3. Case Studies in Fraud Prevention

COVID-19 has forced many people into isolation around the world. Automobiles turned into repositories of personal and business items. Historically, fraudulent personal and corporate tax returns are among the top five hottest confidentiality breaching areas. A change in our typical habits exercised by now, together with the heightened vulnerability of our emotions, may result in tax fraudsters surging to the top electromagnetically.

Taxpayers and taxing authorities around the world are exploring untapped data opportunities on Individuals and Corporates. Authoritative sources such as Bank Account Balances, Foreign Deposits, and Business Product and Services Capabilities must be incorporated in real-time machine-readable data pools. Previous successes in enterprise profit analysis have proven that Business Data Modelling can forecast the likelihood of cyber tax crime. Probabilistic Link Analysis will allow taxing authorities to use AI fraud detection techniques to serve taxpayers proactively and as a matter of urgency.

To assess business resource hire, utilization, and share with greater accuracy, APIs will need to connect data held captive across disparate taxpayer systems. With greater visible access to taxpayer connections, opportunities, resources, and bricks and mortar, tax risks can be detected with efficiency. Collaboration must be achieved with other able tax authorities, including those responsible for Corporate Tax, Tax Treaties, Withholding, Value-Added Taxes, Health Care, and Privacy. Integrating such disconnected hierarchies can detect tax violation deviations regardless of industry.

4. Algorithmic Trading

4.1. Introduction to Algorithmic Trading Algorithmic trading (or algo-trading) is regarded as one of the most successful applications of quantitative trading strategies, enabled by advances in mathematics, computer engineering, and communications technologies. The notion of algo-trading has been widely used in the finance literature to refer to the trading activities when computer programs are used for controlling market operations, replacing human trading. Algo-trading employs explicit quantitative trading strategies that have been pre-defined by the user and thus the timing of the trade and the execution of the orders are done by the program with minimal human interaction. A distinguishing feature of algo-trading compared to pure automized trading strategies is the availability of explicit trade execution strategies. These trade execution algorithms offer a mechanism to control the execution of the trade by using market orders or limit orders contingent on the current market conditions. Approximately 40% of all trades are executed using algorithmic trading strategies, and in some market segments, this ratio exceeds 90%. Since the market shares of many institutional investors have become excessive, they usually must trade proportionally over the market hours in order not to distort the order book, which is improper to pay the full trading commission to the brokerage. Moreover, since the expense of monitoring the market has been reduced dramatically by high-speed internet providers, the trading commissions paid to the brokerage have also been reduced to a fraction of the market impact cost.

4.2. AI Strategies in Trading Using artificial intelligence techniques, some algorithmic strategies have become more adaptive than classical execution strategies and have the capability of coping with time-varying market conditions. Recently, several financial institutions and professional investors have adopted semi-automated trading strategies by integrating rules developed from market experience with pre-defined execution strategies. By doing so, they can benefit from the consistency of algorithmic trading while avoiding pitfalls with a purely algorithmic solution such as creating market impact through executing large market orders. The need for highly sophisticated algo-trading strategies has led to the establishment of quant-houses, institutional investment firms that specialize in the development and implementation of algorithmic trading systems. Significant rounds of innovations in cutting-edge algorithmic trading systems are delivered on a regular basis through collaborations between software engineers, mathematicians, and experts in finance.

4.3. Risks and Benefits of Algorithmic Trading Despite the numerous advantages of algorithmic trading, it also has become one of the most criticized components of global market microstructure. It has been accused of contributing to many high-profile market manipulation cases and damaging market stability. The so-called flash crash that happened in the US stock market on May 6, 2010, has revealed the shortcomings of the algorithmic trading systems adopted by major institutional investors and the potential negative impact on market stability. Given the overwhelmingly increasing market impact from algorithmic trading, it is vitally important to develop robust and pristine algorithmic trading systems to exploit arbitrage opportunities while alleviating the detrimental effects on the overall market microstructure.

4.1. Introduction to Algorithmic Trading

Algorithmic trading (AT), also known as automated or algo trading, refers to using automated systems to send orders (buy or sell) in markets based on predefined rules. Many times, these rules involve technical analysis, indicators, or other datasets, such as news or social media sentiment. Algo trading has been increasing in popularity over the years, partly due to the ubiquity of easy-to-use trading platforms and of low commissions or even zero commission models. AT is now commonplace among retail traders, hedge funds, and market makers alike. Algorithms have been improving in sophistication and reliability, and there are many enablers that allow us to create better trading strategies. However, trading systems are notorious for being easy to build but hard to make money from during live trading. In this chapter, we explore the world of algo trading going from simple rule-based systems to advanced machine learning systems. The goal is to gain an understanding of what works and what does not, and to learn practical skills that we can apply to building our systems, from back testing to live trading. We share insights learned from years of trading experience, and from academic literature. This chapter is organized as follows: in this section, we introduce the world of algo trading, we explain what the different style of trading are, and how do algo trader make money. In Section 4.2, we describe the different type of AI models and techniques we can use for predictive modelling, and then we delve deeper into the details of how directional predictions translate to profitability in Section 4.3. In Section 4.4, we summarize lessons learned from both practical and academic perspectives. Finally, in Section 4.5, we discuss the risks and benefits of algo trading. It is hoped that this chapter will help shed light on the world of algorithmic trading, what works, what does not work, and how one can build a successful trading career.

4.2. AI Strategies in Trading

In finance, an automated trading system is a clear set of instructions on how to make trading decisions; it is defined over time as a set of rules without human intervention but rather by a machine. These systems would collect relevant information about the security from its history, analyse it, build or revise the rule, make a decision, and then execute the trade based on the instruction set; managing its risk exposure by employing predefined parameters. Most of the time, both open-source and proprietary software packages are used, which make the implementation of the program more systematic. Following this methodology, different setups of rules can be easily implemented, combined, and put back into live trading with better performance. AI is being employed in the world of algorithm trading to break through the limitations of rule-based systems that seem to underestimate risk and have, until today, struggled to cope with the massive amount of data to respect the multitude of systemic and specific risks. Analysis of market sentiment, news, announcements, and macroeconomic variables through NLP tools becomes a feasible goal to pursue for trading desks.

Factoring in behavioural finance paradigms that traders have bypassed via exploiting the inherent characteristics of markets is a major step toward returning higher profits consistently. Neural nets are then increasingly being used to decide price movements or detect multi-asset correlations that would signal an imbalance, while reinforcement-learned neural nets are employed to implement optimal allocation, execution strategies, or volatility and market impact estimation in a life cycle of microstructure trading.

4.3. Risks and Benefits of Algorithmic Trading

The potential risks and benefits of algorithmic trading systems to financial markets were difficult to ignore. The ability for AIs to process diverse datasets beyond human capabilities, their 24/7 availability, instantaneous communication across global markets, speed at which they can execute trades, and functions such as latency reduction, could lower market costs, enhance market liquidity and efficiency, smooth short-term volatility, and improve the functioning of core market processes. However, algorithmic AIs could respond rapidly to major events or economic indicators and then act in concert across multiple markets in milliseconds in ways that regulators or financial institutions with a human factor could not stop, monitor, or mitigate, and thus be responsible for flash crashes, herd behaviour, and negative externalities. The potential for negative or unexpected externalities from AI algorithms and AI-hedged strategies operating simultaneously across the global market was a focus of recent academic studies. One of the first applied studies found evidence of AI algorithm impacts such as large price inefficiencies, as high as 70%, and thus the potential for significant arbitrage profits, as well as the emergence of new cross-validation methods to test AI performance and price efficiency and their ability to merge high-frequency and low-frequency data of varying quality for a given market. Recent additional studies have also expanded the investment focus to investment clustering. They found that densely invested clusters of mutual funds and long-short equity pairs investing in long-short equity portfolios demonstrated herding risk and systematic long-short equity risks.

5. Credit Scoring

Estimating the creditworthiness of customers is a fundamental task in the finance sector. Lenders have long needed to quickly, accurately and at a low cost assess whether individuals will repay their loans. With their propensity to automate decision making, financial institutions are often at the forefront of the use of statistical methods to help in their activities, particularly in risk assessment at the loan approving stage. Credit scoring models help lenders to take the articulation of such problems and translate them into simple quantitative tools: the parameters of the model allow for a concise summary of the diverse factors that determine the risk of an applicant, and, in the simplest case, the decision of the lender is to accord a loan or not according to an established cutoff value. Credit scoring models must be prudent in their decisions since they need to balance the conflicting requirements of enforcing discipline among their borrowers while continuing to lend to solvent borrowers and thereby earn interest income.

The earliest credit scoring models targeted home loan applications and initially originated in the 1930s with the introduction of numerical credit reports by the national retail trade. The creation of national banks thereafter required the establishment of a systematic and uniform means for evaluating mortgage loan applications and thus banks laid the foundations of a scoring approach for credit risk assessment. Other sectors of the economy soon used similar scoring techniques. Subsequent developments in the area included the introduction of credit bureau data, changes in the composition of the loan applicant data, and the ensuing refinements and many variations of the original idea. The refinement of credit scoring models particularly exploded in the 1970s with the creation of new national credit bureaus and the widespread adoption of credit scoring techniques across the world by banks, insurance companies, and retailers.

5.1. Traditional Credit Scoring Models

Credit scoring is one of the earliest and most wide-ranging AI applications. More than half of the world's adult population is presently credit-inactive, while around 1.5 billion people are borrowing constrained. This figure is defined in terms of personal loans extended by publicly traded corporations, banks, and government-affiliated enterprises. Establishing a credit score allows financial providers to ascertain the risk of a loan default and determine the terms of loan repayment, including interest rates, collateral pledging, and loan duration, among others. Credit scoring serves to condense a great deal of both hard and soft information into a simple, comparative numerical index.

Machine learning can offer substantial improvements to credit scoring for both consumers and lenders in terms of efficiency and risk optimization. Logistic regression was a popular approach to credit default propensity modelling prior to 2020. Supervised algorithms used several consumer variables to predict past defaults. Logistic regression utilizes a logistic function to model a binary dependent variable. One implementation in credit scoring is the FICO scorecard. A common method to evaluate the logit model is McFadden's pseudo R2, although it is an imperfect measure of model fit. While logistic regression results may be interpreted relatively easily, ML methods deployed for credit scoring are less commonly understood by lenders. Although aspects of these methods' loss functions are sometimes interpretable, the most reported performance metrics are problem-specific.

5.2. AI-Driven Credit Assessment

In recent years, credit scoring—an integral part of banks and financial intermediaries' operations—has undergone a profound transformation driven by the widespread adoption of artificial intelligence techniques. Credit scoring models leverage traditional information and/or non-traditional information from alternative data such as social media, financial transaction data, e-commerce data, smartphone-based data. While traditional credit scoring techniques mainly rely on logistic regression, classification trees, and similar strategies, due to their robustness and simplicity, AI-based models have shown promising improvements in predictive accuracy and business performance when dealing with very rich, innovative, alternative datasets. Deep learning models, along with ensemble strategies, can achieve particularly strong performances.

A study highlighted the improvement in prediction accuracy achieved by the AI-based models, at the time still early implementations. Since then, various advancements in the algorithms, availability of large datasets, and capable computing power have led to successful implementations of AI across functions, products, and industries, including the field of credit scoring. Besides the flourishing fintech landscape, features of the pandemic have strongly affected the implementation of AI in credit scoring. The social distancing measures introduced to contain the spread of COVID-19 have accelerated the shift toward entirely digital, automated experiences across various areas of the economy, including financial services. Consequently, major banking institutions have been under pressure to keep up with their rapidly digitizing competitors.

5.3. Ethical Considerations in Credit Scoring

The widespread adoption of AI in finance has led to remarkable improvements in credit scoring systems in both the developed and the developing world. More than any other area in finance, the AI-based approach has led to unprecedented breadth and depth of access to credit facilities for people in all walks of life. Especially in developing economies, these systems have enabled the financial inclusion of individuals with little or no financial history – and thus typically excluded from traditional credit scoring. The associated benefits of democratizing access to capital also have important positive repercussions in terms of poverty alleviation, economic stability, and growth. Investments in education and health, business creation, and the mitigation of the effects of calamities and shocks are all enhanced by easy access to credit and generally contribute to more developed and resilient economies. However, the deployment of machine learning for credit scoring also raises several ethical concerns. Some of these are rooted in the general properties of any supervised machine learning approach. One challenge for all predictive models is the lack of transparency about why such models generate a specific prediction for any given data point. Despite recent progress, explaining the predictions of complex supervised learning algorithms is still a frontier research area in ML. Indeed, in the case of credit scoring models based on deep neural networks, there are serious difficulties in interpreting and decoding how the model "thinks". The problem concerns not only academic research but is increasingly coming to the attention of regulatory authorities. Prior items of legislation already require any entity reviewing a loan application to inform applicants of the criteria used to evaluate their applications. This would include algorithmic credit scoring systems.

6. Regulatory Framework

In comparison with other fields, regulations in AI applied in the finance space are very regulated. However, this regulatory framework is only concerned with risk mitigation. These laws ensure that the risks associated with these automated AI processes are negligible. However, there is still a lack of concrete regulations in place that look at the ethical ramifications of using biased AI in Finance. In the European Union, there are ongoing efforts to outline specific provisions on different classes of AI systems. Additionally, there have been draft guidelines on the use of AI in the Financial Sector, specifically about the prevention of consumer detriment and financial crime. In the United Kingdom, there has been a discussion on the approach to the regulation of AI and machine learning used in Financial Services.

In the United States, there is no specific Federal law directly regulating the use of Artificial Intelligence in Finance; however, there are some general laws which can be applied to the use of AI in Finance. The most notable of these is the Fair Lending Laws. These laws work to prevent discrimination when it comes to the terms of lending. Certain State Laws require regulators to conduct an ethical review of proposed laws prior to their enactment. Governments and local agencies in several states are considering formal policy proposals for the regulation, evaluation, and use of AI models in various spaces. There are also motions from some groups within the Federal government to promote the prioritization of ethical usage of AI systems and their dos and don’ts. There has also been expressed oversight to regulate the use of AI as it may exacerbate issues relating to discrimination, fairness, and privacy.

6.1. Global Regulations on AI in Finance

Creating AI technologies and applying them in financial services requires balancing a huge amount of innovation with safety and soundness elements. Globally, there are four distinct regulatory approaches: pre-emptive action by technology specific agencies; pre-emptive action by domain specific agencies in selected countries; permissive regulations by domain specific agencies; supervisory principles and guidelines by domain specific and pre-emptive technology regulatory agency. Pre-emptive approach by TSPAs protects innovation much more compared to action by large tech companies. The primary TSPA plays at least four roles: commoditize AI by providing guidance; create demand for responsible AI systems by articulating federal expectations; and support low resource organizations in AI roadmaps and AI guidance. The ‘Innovation’ is happening mainly in the private sector making products and services based on AI research - the creation rules must be conducive to productivity and low barriers to entry into the AI market. All these policies must be oriented towards strategic competition with other countries especially in the field of AI.

Domain specific regulators prohibit harmful outcomes. Simple policies left to the regulator’s discretion may just require regulators to explain if any AI product or service has been prohibited. Companies must ‘validate’, ‘disclose’ and ‘mitigate’ issues in their product or services like being inaccurate or amoral. If the AI system impacts consumers or business or governmental outcomes, even indirectly, then large tech companies believe pre-emptively verifying and validating these impacts with domain specific regulators may lessen the chance of subsequent harmful incidents. These rules and regulations may come to the bank board level by way of corporate governance. Financial institutions must be familiar with regulators AI policies, integrate them into enterprise risk management, new product approval processes, and analyse transactions and make assessments for high-risk customers or products.

6.2. Compliance Challenges

AI algorithms are increasingly utilized in a myriad of decision-making processes, adequately reflecting the high expectations of the technology. The concentration of risks often located within the AI-finance systems can lead to significant externalities and public interest’s damage. Given the proven incapability of market players in self-regulating, the institutional reaction to regulate has taken place on the two fronts of: 1) Control over how AI is employed by firms – imposing restrictions on the usage of such technology and applying penalties. 2) Mandating how firms disclose the use of AI, externalizing, and potentially amplifying the risk. It constitutes the “comply or explain” approach, impacting the informational quality and efficiency of the AI-influenced decision-making process.

The adoption of the first route tends to decrease the propensity for the use of AI-based systems and thus counteract the positive contributions attached and linked to its usage. It can take the twofold form of an outright prohibition over the use of AI technologies in critical areas – such as decision-making functions which are involved in the algorithm-guided influence over vulnerable borrowers or allowing the application of punishment for improper exploitation of AI algorithmic governance. On the contrary, privileging the second route, favouring the activity disclosure allows customers, clients, and the market in general to gauge the impact of AI on the control and decision-making structure. Adopting a “comply or explain” regulation fulfils two main purposes: 1) alleviate information asymmetries, thus ensuring fairness and protectionism. 2) Favor a soft regulation approach that may reduce the chilling effect of prohibitions on the adoption of advanced technologies.

7. Future Trends in AI and Finance

Despite what has been said, the impact of AI in finance is still in its infancy, and we are already seeing exciting developments in critical areas that bodes well for the future of AI in finance. A critical trend in AI in finance and technology in general, is the emergence of new novel technologies. Companies are investing heavily into Research and Development, and emerging critical technologies are often interconnected. For example, large language models are a game changer in terms of how AI is being deployed. Sample efficiency of these models has drastically improved with the introduction of Reinforcement Learning from Human Feedback. Previously, fine-tuning large language models were extremely expensive and done in a one-shot manner. This drastically limited experimentation and creativity. The availability of these models has now created a surge of interest in Natural Language Processing tools and Deployment in other specific industries. Furthermore, Large Language Models are also general tools for multitudes of NLP tasks, and the demand of deployment has also unleashed a new wave of fine-tuning and applications on SMEs. This is just one of the flavours of what companies call Foundation Models. Foundation Models are usually pre-trained on lots of data or compute, but there are also other ways evolving like the use of Contrastive Learning for Zero, One and Few shot Learning. Other emerging technologies also include Diffusion Models for image generation or Speech Generators. These models are also providing experimental and novel ways for Generative Models on other domains.

These foundational technologies will reduce the barriers for smaller players to enter the market. Smaller fintech startups will now tune these large models and tools to their niche sectors, capture their data and create their differentiation moat through a growing flywheel effect. As a result, these fintech's have the potential to compete with incumbents in providing tailored services that these larger players cannot replicate or react to fast enough. Moreover, in addition to capital, Governments and Incumbent players must also rethink their attitude toward providing and building partnerships with these smaller upstarts. These smaller firms have also brought innovation into the financial markets, and financial institutions should build vertical collaboration on multiple fronts with them and invest longer term.

7.1. Emerging Technologies

Artificial intelligence technologies are rapidly evolving, becoming more intelligent, and increasing in variety. Soon, miniaturization and inventive combinations of existing technologies such as the Internet of Things, blockchain, and augmented, mixed, and virtual reality will increasingly act as catalysts to the enhancing growths of existing AI technologies. Investment in invisible AI technologies will accelerate dramatically, which will in turn enhance investment in products such as controllable AI-based natural language engines and knowledge engines. Hence, finance will see an acceleration in the investment in invisible AI-based products, including controllable AI-based natural language engines and natural language-based knowledge engines. AI-based augmented reality products, which overlay virtual visual information through glasses, visors, or contact lenses on an individual's view or field of vision to either enhance, enrich, or give context to what they are seeing, will develop rapidly. Already initial products are enhancing the view of mechanics and technicians repairing machinery. As the technology improves, the applications will proliferate.

In the future, emerging technologies are expected to redefine how finance professionals live, work, and interact with their financial universe and with one another. The merging of humans, machines, and organizations will demand deep philosophical explorations to help determine a better path forward. Technology is an enabler, and combined with sensitive human intuition embodied in organizations, it can manifest future possibilities. Blockchain may grow from igniting a trust less and permissionless financial infrastructure to connecting the economic activities and values of people across the globe into a creative circle economy to realize the interdependency and leverage the comparative advantages of different regions to serve one another in their supply chains. How the wide-ranging trends of these emerging technologies are integrated into our everyday lives will determine the next phase of our evolving partnerships and our relationship with AI.

7.2. The Role of Big Data

The development of AI in finance is also supported and fuelled by the rapid generation of large amounts of data, thanks to the wide availability of sensors and devices connected to the Internet. A widely quoted definition of big data is the 3 Vs: Variety, Volume and Velocity. The number of devices that can provide a quantity of data, such as smartphones and sensors, is constantly increasing, thus providing larger information sources. The use of social webs, phone records and/or interaction with e-commerce sites can provide very valuable data covering various aspects of one individual. New algorithms can aggregate, classify and cleanse data related to specific areas as e-commerce, flight, mail, payment or social actions, and can use patterns extracted from this data to predict user behaviour, patterns that can be used for fraud detection, marketing campaigns, credit scoring, and many more.

Big data contributes to the development of AI in another way as well. Supply or deep learning approaches embed the idea of data-driven learning based on very large training datasets, and besides the amount of data, its quality is an important factor affecting the performance of models. The complexity of current AI algorithms, increased also by the rise of deep learning, provides the capability of training predictive models able of recognizing patterns or inferring correlations present in the data, supplied with a proper training dataset. Systems can learn from data, but this does not mean that they understand the problem as humans do. AI has produced great achievements in solving applied research problems, but it is still hard to understand its internal mechanisms. The so-called explainable AI is an attempt to bridge the gap, with the development of techniques aimed at producing more interpretable output from black box systems, especially required in sectors as finance, healthcare and security.

7.3. Impact of AI on Financial Services

Already today, organizations across different industries are investing considerable financial resources to innovate their products and services by applying AI technology. Research reveals that a significant percentage of financial technology firms were planning to invest in AI, and investment in cognitive computing and AI technology across different industry sectors, including finance, would grow substantially by the year 2021. It is believed that AI will create additional value in the global financial system, and the effect of AI on the investment banking industry is projected to be significant with annual savings of up to a certain amount. AI has arrived, and the effects, processes, and procedures of what computing technology change from average to excellent human productivity will be radical in its impact.

Presently, the impact of AI on the finance sector extends well beyond robot-advisors and algorithmic trading applications that have been in existence for years. AI, specifically subfields of machine learning and natural language processing, are being used in multiple applications across several areas in the industry that include service delivery, advisory services, risk assessment, loan underwriting, compliance and regulatory reporting, process automation and optimization, trade processing, anti-money laundering, and detecting and mitigating cyber threats. Investment firms are employing AI to assist in portfolio and wealth management. Companies have taken on the mission of providing investors tailored investment strategies and recommendations based on their personal preferences and machine learning analysis of voluminous traditional and alternative market sources of data.

8. Challenges and Limitations

The development of effective applications is a precondition for AI’s success. However, there are numerous challenges preventing it from achieving its potential. While the actual needs for improvement vary widely depending on the need, successful releases so far are usually in partnerships with early adopters and where the high development costs compared to traditional techniques are deemed appropriate, given the innovations at stake.

AI’s development relies on data to generate requirements. In finance, the data, especially regarding historical prices, is abundant. It is obtained from trade data, as well as self-generated research and ratings feedback data. Other kinds of data either on internal or external control often demand specific contractual arrangements. Examples are access to customers’ sensitive private data for purposes, provisioning of their transaction history with the bank. Talks about credit scoring. Given the nature of financial services, there is increased demand for data privacy protection from customers as implied in regulations. Regulations must ensure that any AI application does not lead to increased discrimination by different types of customers. This is especially true about lending, where there is risk of worsening financial inclusion. Furthermore, models need to be regularly back-tested, which is extremely sensitive because some businesses are low volume compared to their impact on an economy.

8.1. Data Privacy Concerns

Recently, interest in data security and privacy has stimulated the development of new technologies for sharing sensitive data without immediately revealing it. Our topic is federated learning, a novel approach to data modelling in which the model is trained by multiple entities collaborating locally on their private data, which is never shared or centralized, using a global model and communication that preserves the privacy of the data. Federated learning allows for the development of a privacy-conscious collaborative training approach which leverages distributed and independently owned data. A key use case is in the case of fintech partnerships in which banks make use of sensitive data from other fintech's in order to train models for use on bank customers, but in which sharing the data in order to collaboratively train models is too risky. Federated learning makes it possible for participating companies to refine a global model over time at their own pace. The global model is stochastic: It is not necessarily the same as the locally computed models, which are also maintained, but represents a consensus among companies over the "best" model over the most recent communications. Moreover, federated learning is incremental and parallelizable—subsets of participants can choose to run one step of the training communication at a time, while other participants make no changes at that moment and choose to share or update the global model later. Thus, the model can be improved iteratively and shared across participants.

8.2. Bias in AI Algorithms

The algorithmic design of AI applications is often being criticized for introducing bias into outputs. Content bias refers to an AI's training input to alter the product. In finance, financial data, including loan records, credit scores, and bank statements, can reflect complex structural biases against marginalized groups. This might result in disparate impacts during model training. For example, if a creditworthiness model discriminates against low-income non whites by rejecting their loan applications based on insufficient historical credit records, the model could reflect and strengthen an underlying structural bias that makes these people credit invisible. Algorithm nontransparency makes the issue worse. Especially if an algorithm uses subtly different denial rules for applicants from different racial groups, racial profiling is inevitable, with consequences ranging from customer dissatisfaction to legal repercussions. Such issues have become critical for AI application designers because industry practitioners are committed to building ethical AI systems.

Another important direction is on product evaluation. AI products may not be evaluated the same way as traditional financial services. The human-centred design principle guides the creation of human-centred AI products. Financial service companies consider whether to include humans in decision-making or product use. Just like most loan applications are not reviewed by loan officers, humans currently have little say in the approval or denial of loans using AI models. AI service providers now prioritizing evaluating algorithm outputs based on user experience metrics, such as inversion time, accuracy, and fairness, allow questions about product fairness of algorithmic decisions to be addressed. Developing fairness, accountability, and transparency criteria for product evaluation should minimize design bias and ultimately improve AI outcomes for marginalized groups.

8.3. Operational Risks

A considerable part of the global financial market operations has been thoroughly automatized. Although automation decreases the costs of human workforce, increases productivity and at the same time improves accuracy and reliability, the interactions that computers have and the effects that those have on market prices can result in effects that are unknown to trading companies. These effects may result in considerable losses. If an AI system is proficiently developed, the risk of operational incidents can be decreased by allowing less human-involved decisions and trades. However, as a paradox, abnormal risks can be created by forgetting to manage the potential residual behaviour.

Armed with some historical surprising cases related to algo-trading, we can analyse how AI trading goes wrong and how cognizant all operators should be. On May 6, 2010, the US stock market experienced an extraordinary drop: in a little more than 15 minutes, the indexes fell around 996 points (almost 9%). As fast as they fell, they were also recovered. The market did not crash. It was a flash crash. In brief, this phenomenon can be described as a price declining very quickly without any reason, falling well below the value of fundamental equities. It is an important event, because small stocks were almost neglected by the system; their prices dropped until they were suspended while stocks with high liquidity were not affected. So it is a strong market and an arresting event in its shape, location and speed. The nature of its speed is caused in part by the existence of High-Frequency Trading.

9. Conclusion

This book has provided an extensive survey of the many applications of AI-related methods in various areas of finance. We have discussed how classical statistical techniques are used to address many financial problems. AI methods, such as supervised and unsupervised learning, reinforcement learning, and novel heuristics proposed in the new AI paradigm, have been used for data analysis, model construction, decision-making, optimization, and many more tasks, often outperforming classical methods. Liquidity forecasting, asset and market volatility modelling, stock, bond, and volatility index price prediction, portfolio management optimization, risk estimation, credit risk assessment, quantitative trading strategy formulation and construction, as well as insurance underwriting, have benefited from AI-related algorithms and heuristics.

The survey presented in this book can be very helpful for research industry practitioners who want to address practical problems in finance and trading or model-related prediction tasks, such as time series forecasting, sentiment prediction, and risk estimation. In addition, financial experts or quants interested in developing or fine-tuning preexisting AI-related tools can find ideas, examples, and motivations in the presented applications. Modelling, analysis, and decision-making activities in finance and trading can greatly increase their effectiveness with the help of AI-related methods. We hope that future research will help shed more light on these topics and develop new computerized tools for financial experts.

References:

Weber, P., Carl, K. V., & Hinz, O. (2024). Applications of explainable artificial intelligence in finance—a systematic review of finance, information systems, and computer science literature. *Management Review Quarterly*, *74*(2), 867-907.

Cao, L. (2022). Ai in finance: challenges, techniques, and opportunities. *ACM Computing Surveys (CSUR)*, *55*(3), 1-38.

Buchanan, Bonnie G. "Artificial intelligence in finance." (2019).

Giudici, P. (2018). Fintech risk management: A research challenge for artificial intelligence in finance. *Frontiers in Artificial Intelligence*, *1*, 1.

Lin, T. C. (2019). Artificial intelligence, finance, and the law. *Fordham L. Rev.*, *88*, 531.

Lee, J. (2020). Access to finance for artificial intelligence regulation in the financial services industry. *European Business Organization Law Review*, *21*(4), 731-757.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 4: Artificial Intelligence in Agriculture: Crop monitoring, precision farming, supply chain optimization

1. Introduction to AI in Agriculture

Food and water scarcity are important challenges facing the world today. The world's population is expected to reach 9.7 billion by 2050. World population growth demands a 70% increase in agricultural production to ensure sufficient food for all. With deterioration of agricultural land, it is vital to increase food production with a limited amount of land. Improving farming practices is a key factor in tackling these problems and ensuring sustainability of the economy, the environment, and society. The agriculture sector is focused on producing crops that meet international standards, feeding the growing population. The recent trends in agribusiness require better crop production with more efficiency, better quality, and lower costs. AI plays an important and transformative role in agriculture today and in the future.

The agriculture sector is one of the sectors where AI has had a significant breakthrough (Bannerjee et al., 2018; Eli-Chukwu, 2019; Javaid et al., 2023). AI is becoming increasingly popular in some niche areas of agriculture, such as crop monitoring and management, precision farming, traceability in the supply chain, and soil monitoring and management. Modern agriculture is becoming increasingly reliant on technology, and farmers embracing this new methodology are becoming digital farmers, part of a new, high-tech Agri-supply chain (Jha et al., 2019; Liu, 2020; Smith, 2018; Vincent et al., 2019). Digital farming aims to enhance productivity, profitability, sustainability, and the stewardship of land resources. Improving crop yield is essential for food security and economic stability, and crop monitoring and mapping systems are the first step toward achieving this goal. Crop surveillance can benefit farmers by eliminating production losses and planning for potential production shortages. Monitoring enables farmers to assess crop maturity, and detect risks such as disease outbreaks, pest infestations, and drought or flood damage.

2. Overview of Agricultural Challenges

Agriculture is a significant driving force for any economy due to its capacity to generate essential resources such as food, cotton, and oilseed. Agriculture plays a very important role in influencing the economic and social development of a country. It is the science of cultivating the soil, growing crops, and raising livestock. Agricultural products are the basic requirements for all people. The animal and plant products are consumed for food; the cotton, wool, and leather products are consumed for clothing; the jute, wool, and leather products are consumed for packing and promotion; and the sugarcane, wood, paper, rubber, and medicinal plant products are consumed for industrial purposes. Agriculture serves as the fundamental industrial system for other industries by supplying raw materials and commodities. Agriculture is regarded as the backbone for improving the country's economy. The precursors of economic development in developing countries are labour surplus and high agricultural dependence.

Improving agricultural productivity is the way to escape the rural poor from poverty and satiate the demand for surplus labour in the overall economy. Regarding exports, most countries are net exporters of agricultural products. Like their major developed partners, developing countries must invest heavily in the agricultural sector. There are several challenges in current agriculture practices. The situation becomes severe due to the increase in the population and the climate conditions, which make people rely on modern agricultural procedures. These challenges include food security, overuse of resources, land and water scarcity, wastage of resources, unpredictable climate, impact of climate change on crop yield, global warming, soil erosion and salinity, crop yield loss, declining productivity, pest attacks, insufficient labour availability, food wastage, demand, and effective supply chain.

3. The Role of AI in Crop Monitoring

The improved development of new technologies has provided agronomists with various tools to monitor crops remotely. Satellite imagery is currently used to identify crop types, make initial predictions regarding crop yields, and assess the health status of crops. However, the current spatial and temporal resolution of satellite imagery is insufficient for operational precision agriculture services designed for smallholders, including crop forecasting. Furthermore, satellite data links are either very costly, with long waiting times, or are affected by cloud cover. In the last decade, both UAVs and drones have been used in agriculture to collect high-resolution remote-sensing data in a timely manner, but their cost is still restrictive. Airborne multispectral imaging has been applied for many years in the precision farming sector; however, to be economically feasible, the flights have to be planned for large geographic extensions and conducted for large agricultural areas with a very high parcel density. However, they are still much more expensive than satellite or UAV technologies. Furthermore, sensor miniaturization and the development of light-weight spectral sensors and hyperspectral sensors, as well as improved platforms, are needed to guarantee optimal conditions for operational UAV flights for data collection over smaller agricultural areas.

Machine learning techniques can also be combined with portable hardware technology for on-site data collection and processing in practical field applications to detect plant and fruit diseases and predict their status. Moreover, the use of cellular and cloud technology may provide solutions that are less costly than present precision agriculture implements. Sensors using plastic optical fibre, multispectral, or thermal imaging have been used for imaging crop health status and to detect pests or diseases. The recent development of spectral cameras has made it possible to use Near Infrared Spectroscopy, an optical active sensor, for real-time prediction of plant response variability, providing a big data set for cellular and cloud data collection. By integrating customized model plants of the same genotype and age directly planted in the field, the effects of abiotic stress can be assessed to calibrate the sensors to be used when monitoring the field data. In addition, to improve prediction accuracy, artificial neural networks can be used.

3.1. Remote Sensing Technologies

Introduction

Monitoring the growth status of crops, identifying cambial injuries or losses, and diagnosing diseases, pests, and nutrient element deficiencies are all important parts of pre-and post-harvest timeliness decision-making support. Scholars from various disciplines, along with engineers, have developed a multi-level and multi-scale system of crop growth status monitoring and decision-making system. The spatial-temporal data for monitoring crop growth status come from remote sensing, unmanned aircraft, real-time astronomical satellites, and other resources, and are integrated with many geo-information data in the research area. These techniques facilitate the intelligent identification of crop growth features at the landscape scale and the timely and effective detection of abnormal crop status changes, and then automatically trigger the decision-making system and output useful information for decision-makers.

Remote Sensing Technologies

The low service cost and real-time remote data transmission system of the Internet of Things boost the development of crop growth status remote monitoring. The satellite, drone, and UAV have been widely applied to monitor various types of crops. These types of monitoring systems can optimize the demand for data acquisition, maximize the value of various monitoring data, expand the fields of application, lighten the research workload, and meet the needs of multi-level and multi-scale crop research. Various types of optical remote sensors have been researched and are at different operational levels for crop monitoring. These operational sensors provide many remote images and data products, such as surface reflectance and normalized difference vegetation index, which have supported hundreds of crop growth status monitoring applications on a range of agronomy scales over the past few decades.

3.2. Data Collection and Analysis

Remote sensing alone is not sufficient to enable reliable monitoring or assessment of the current health of cropland. While remote sensors may be able to detect certain conditions themselves, they are not designed to assess the true health of a given crop by providing definitive answers. The inability of remote sensors to ground truth their observations necessitates additional efforts toward data collection and validation via on-site assessment. However, new sources of data beyond on-site survey for data collection are emerging in technology terms that use advanced communication systems. These new technologies aim to both facilitate quick response times during major events and support large datasets, giving users the ability to deploy multi-sensor platforms.

Some existing data collection systems have largely adopted new technology sectors involving small tent-based systems based on multi-spectral aircraft or satellite observation, available in short periods, that significantly decreases surrounding costs. These data, as well as data collected using high-definition 3D unmanned aerial vehicles, have been used to estimate the biochemical properties of plants. Such UAVs enable continuous monitoring of research plots, improving estimates of high temporal variation of plant biochemicals, and reduce reliance on land-based sensor systems that may saturate during large events. Other sensors have also been used to estimate response due to resource use efficiency and energy exchange across agriculture landscapes. Drones with information-gathering capacity also serve as monitoring systems; examples point to drones equipped with near-infrared sensors capable of observing viral infection in crops, and colorimetric detection devices used on crops to provide temporary ground truth for assessments of remote sensing datasets. Other integrated devices with added thermal sensors promise to be used on horticulture crops.

However, such sampling systems on their own as employed presently may not yet be sufficient to create high-confidence maps for scaling up to large areas that would allow for a mass response to a virological threat or crop nutrient deficiency. Such sustained data are needed, especially, at community levels, to allow at least some difference in the control-data relationships.

3.3. Predictive Analytics in Crop Health

Predictive analytics utilizes the attribute data derived from remote sensing to calibrate and validate advanced process-based models. Crop health monitoring techniques can be implemented to forecast the timing of critical events in crop production as well as the variation of crop growth traits, such as aboveground biomass accumulation, leaf area index, and yield. To predict plant health and yield throughout the growing season, long-term continuous data collection is needed together with the application of machine learning algorithms.

Different stages of crop growth are influenced by several environmental conditions. For instance, meteorological factors such as temperature, humidity, solar irradiance, precipitation, and wind speed trigger flowering, and abiotic stressors, including drought, salinity, and cold stress, might delay flowering. Environmental events such as ash from volcanic eruptions or application of fertilizers over agricultural land are also factors influencing different growth phases. Remote sensing can provide information on such important environmental parameters, and based on the available data, machine learning models can be successfully applied to predict plant health. Remotely sensed data can also be utilized to estimate the amount of the most important nutrients needed in each crop growth stage that could help optimize the number of fertilizers applied for crops, ensuring good yields while preserving the environment.

4. Precision Farming Techniques

The principles of precision farming involve managing spatial variation in farmland on a field-by-field basis, thus shifting agriculture from a broad-spectrum approach to a more site-specific one. With precision agriculture, resources are accurately applied in variable amounts to match crop production and resource need, resulting in increased farm profitability and a reduced environmental footprint. Furthermore, precision agriculture has taken major leaps forward with the increased access to new sensor technologies such as UAVs, soil health sensor, ground and aerial multispectral imagers, and satellite and aerial radar.

Traditional crop management and monitoring systems, largely based on satellite imagery and farmer experience, cannot accurately measure variations in plant growth and conditions within fields. The demand for real-time management information to make timely decisions is increasing too for farmers to optimize crop production practices. Ground-based, rapid-acquisition remote sensing can reveal within-field variation and changes over time. Remote sensing data at high spatial resolution can help understand the dynamics of crop growth and responses to variations in soil and nutrient conditions. Sustainable management practices can be measured and monitored from the soil to the atmosphere. In this section, we will present some of the precision agricultural tools for soil health assessment as well as for crop and yield prediction, from UAVs to VRT technologies.

Soil is a dynamic resource whose properties and processes are continuously changed when subjected to the effects of climate, cultivation, and in some locations, even contamination by anthropogenic activities. Soil health monitoring is of great significance to ensure crop productivity and sustainability. However, traditional monitoring methods can be laborious, expensive, time-consuming, and non-repeatable. New sensors including those mounted on UAVs and ground machines have emerged that provide continuous data for soil health assessment. These tools, combined with soil health indices and statistical databases, may help identify disturbance areas in fields where soil conservation practices may be needed.

4.1. Soil Health Monitoring

Introduction

Soil health is paramount in the sustenance of agriculturally productive ecosystems; the relationships between soil microbes and animals with those who grow food is crucial and desired in many ways. On one hand, we cannot live without the food produced using soil. On the other hand, the soil itself is being depleted and polluted by agro-chemical fertilizers and pesticides, overuse of the same and increasing land demand for agriculture and the increasing demand of crop and animal production for the world population. Its healthy soil and ecosystem services regulate water, nutrient and energy fluxes; and prevent pollution, pest incidence and other diseases.

Traditionally, soil health issues were identified through discrete on-site sampling, expensive or time-consuming lab analysis, and qualitative assessment of soil's chemical, physical and biological properties, resulting in limited spatial coverage and infrequent updates. In recent years, Unmanned Aerial Vehicles and satellite imagery have been increasingly utilized for monitoring land cover, crop health, land-use and land-use changes at various spatial and temporal scales for relatively low cost. These approaches have offered opportunities to fill the spatio-temporal gaps of conventional approaches and enable more frequent and near-real-time pollution assessments.

More recently, examples of the use of UAV remote sensing for soil and land characteristics/health monitoring are surfacing. They include soil organic matter, nutrient and heavy metal contents, compaction degree, physical and structure characteristics, hydrology behaviour, vegetation indices, dust emission and soil biodiversity. This monitoring has been achieved through soil sampling, and satellite and UAV imaging, spectroscopy and photogrammetry techniques with different sensor configurations, and sometimes in combination with geographic information system and machine learning techniques.

4.2. Variable Rate Technology (VRT)

Variable rate technology (VRT) reduces production costs and environmental effects, thereby enhancing efficiency in precision agriculture. VRT involves the applications of separate inputs at different rates in a particular location, such as fertilizer application for cropland, pesticide application for specific areas of crop demand, and seed moisture management. The VRT techniques are more sophisticated, including site-specific optimum planting density, and depend on crop effects and soil variability. VRT has two components: adjustment of field inputs according to both field variability and individual plant demand.

Planting density protects crops during early growth that yields effective management of pests and enhances their protection. Planting density is the most important input used on all the agricultural lands across the globe. Managing planting density reduces crop yield and increases production risk. Planters traditionally lack the capability to change planting density at reduced-specific locations while manually managing fertilizer pressure, tillage depth, and planting depth. The appropriate procedure of VRT supports farmers with localized variables like soil properties, weather information, and crop genetics to maximize yield. In corn, more nitrogen input with a higher density of VRT results in higher nitrogen usage efficiency.

Most crops require inputs during a short period of time, usually a few days. Variable rate irrigation (VRI) improves deficit irrigation advice through the onset of crop water demand to provide crop and irrigation water management improved predictions. VRT capacities can be implemented in irrigation systems such as surge valves or VRT valves to increase rate modification zone sizes in surface irrigation or sandpaper for VRT management in subsurface irrigation. Applying VRT and micro-irrigation on vegetable crops may enable proper working or family working with a limited space or redefining a family choice or working day to provide an efficient and effective irrigation control system with an accurate prediction model.

4.3. Yield Prediction Models

Yield prediction/models have a great place in precision agriculture because they provide agriculturists with the ability to calculate what crop yield can be anticipated in each area. These calculations often depend on various variables that may impact the predicted yield, and they help identify zones within the field for which additional actions may be required. Further, farmers use crop yield models to ascertain the point at which the want of a resource limits yield to improve fertilizer/irrigation input to reduce possible yield wastage. Models are implemented in those applications with specific growth phases for each crop to monitor NDVI signals through growth and gain yield prediction accuracy, compared to other models.

Accurate prediction of crop yield is very important for proper planning of agricultural practices and food supply chain management. Artificial Intelligence (AI)-based techniques have offered many solutions to address issues related to crop growth, such as yield prediction or forecasting. These techniques can also help to understand crop behaviour and make forecasting more accurate. In AI, Machine Learning is an emerging technology that can be useful for data analysis in both track and prediction modelling. In the recent past, several Machine Learning-based yield prediction models have been developed, which are intended to foster ratio developments. These abundant research promote algorithms and predictive modelling accuracy evaluation for yield prediction at the year-next level, while only predicating the yield index for respective crops.

Computational Intelligence is an area of AI that deals with computing systems that develop solutions to problems by borrowing ideas from nature and human experience. It is not only popularly used in smart technologies but also applied to yield prediction; it can be also known that CI techniques are generally popular for their use in data mining technology; modelling of complex problems that need huge data usage and do explore the Relationships and Connectivity’s in data to make desired decisions, like yield prediction.

5. Supply Chain Optimization with AI

AI technologies can assist stakeholders in all supply chain stages, from manufacturing to delivery, in running their businesses more efficiently, making predictions, identifying new solutions, and mitigating risks. Supply chain processes are sensitive to external impacts and affect the market and economics of agriculture, which requires constant monitoring of the situation. Achieving an efficient supply chain requires unlocking the potential of the entire chain system. An AI tool managed metamodel of AI solutions is used to select and develop these solutions for the supply chain, regardless of the state of the physical product.

At the heart of every supply chain is the searching problem, which is to define the best configuration that allows to meet requirements for the product to be supplied at a minimum cost. The optimization processes involved in the product supply must constantly revise the operational decisions of the supply chain in response to the demand for its products. AI tools simulate the complete customer journey. They use predictive capabilities to prioritize and reach potentially high-value customers with personalized engagement to increase likelihood of conversion. These know factors that shave days off the supply chain clock, reduce working capital tied to inventory and cut transportation costs.

Infrastructure must continually update and agree allocation processes to prepare ahead for what inventory it will consume or need to add. The process requires forecasting techniques to predict actual consumption by allocation location. AI technology designs alternative forms of supply logistics to understand how to reduce transportation costs while satisfying product delivery requirements and install dynamic routing to gain lower costs and optimal utilization of available capacity.

5.1. Demand Forecasting

Several AI-based forecasting methods are already being used. Smart cubed forecasting systems utilizing neural networks which consider items featured in past and present promotional catalogues, time series analysis and hybrid approaches with expert judgment have been successfully applied to predict sales quantity. Neural networks can also model the weather impact on demand, while machinery learning methods can use sales data to create hyper-local store assortments.

AI technologies can enrich product information that is processed for demand forecasting, considering the information explosion in social media. Another machine learning-based method predicts the sale quantity assigned by retailers to a specific item for each branch of a supermarket chain over the next one to 52 weeks. Shorter-term predictions or stock replenishment can be enhanced from weather forecasts or scheduled events affecting demand. A forecasting model that can support transportation management systems, created with an adaptive Bayesian hierarchical artificial neural network model overcomes issues of high dimensionality. Using noisy demand data, it can model positive and negative demand cycles in a supply chain.

Finally, to forecast the short-term demand of produce food items with a limited supply and volatile demand, which is the case of many perishables traditionally ruled with push-based policies, a model based on a probabilistic exponential smoothing method has been proposed. The model learns from the realization of demand and the prices consumers pay, allowing the transition from push-based policies to enhanced push/pull policies, increasing the operational margin for these resilient-to-sale price items. It enables demand signal information that can be used to tune systems forecast into real time.

5.2. Inventory Management

Inventory management is the practice of controlling the amount of product already on hand in storage. An important goal of inventory management is to determine the optimum level of safety stock sufficient for continuous production to satisfy customer requirements, but not so excessive as to tie up capital in excess stock or increase holding costs. Such excessive stocking occurs, among others, due to an overprediction of demand.

Several AI techniques are available for correcting overprediction and are applied throughout the agricultural supply chain from farmers to customers. In agriculture, however, demand forecasting is actually not so easy, so crop failure or demand increase in other regions can occur. Here, we will discuss that AI can be utilized to optimize agricultural production practices in terms of manpower and capacity to smoothen the demand for a target agricultural product.

AI can be implemented to aid seasonal items with low-frequency demand in inventory management, typically, by reducing the level of safety stock. Given a long enough lead time, which is increasingly difficult for fresh food, demand for seasonal items with low-frequency patterns is predictable through time-series prediction. Overprediction on inventory of agricultural products is most serious in cold chain items with a relatively high infringement ratio, especially those sold in all seasons. Here, advanced but less common demand forecasting methods using AI seem useful. Yet even with a certain level of accuracy, overprediction is not avoidable, especially by popular items with relatively high-demand variability, sold in peak seasons.

AI may be, at least as a potential technology in practice, applicable also to fresh items for which the shelf-life is much shorter than lead time. Information provided to an AI engine and effective use of AI output depend on the required accuracy, either for supply chain optimization by all makers sharing the demand prediction results or only for retailers.

5.3. Logistics and Distribution

Presently, it is salient that logistics and distribution are some of the last parts of the supply chain to be digitalized, for several reasons. In general activities that take place within a company's walls are more easily digitally transformed than the activities that take place outside a company's walls. The logistics and distribution function is the step in a supply chain that designers have the least influence over. Logistics and distribution mean moving the product from the final point in the manufacturing step to the end consumer. The supplier and vendor networks are often overlaid following a fully connected model which leads to major complexities. For these reasons the exclusivity of these activities are more complex, there is an infrequency in the flow results in difficulties and are overtime-oriented.

Many solutions seemed quite effective at first, but they were often “flavours of the month.” The logistics and distribution companies were unable to completely realize the benefits that could be achieved for various reasons. Several algorithms were being offered to solve what seemed to be the potential solutions, i.e. optimize truck loads, optimize route planning, and find the best warehouse location. However, due to the complexities of global regions, the stacking of services, the ever-fluctuating demand mix, etc., it was extremely difficult to implement a solution with sustainability. Today, artificial intelligence has turned into an ideal digital strategy that would be able to develop significant internal and external supply chain efficiencies. Its presence exists in logistics and distribution. AI can support logistics and other related domains in several ways. First, through big data processing, machine learning algorithms use AI to create route optimization.

6. Case Studies of AI Implementation

In recent years, various companies around the world have successfully implemented AI and ML to address the challenges outlined in prior sections, capitalizing on the convergence of these economically viable technologies alongside modern ag-techs such as automated robots, satellites and sensor deployments. The following sections detail some of the most successful and prominent use cases of AI and ML in the major crop monitoring and precision agriculture areas.

6.1. Successful Use Cases in Crop Monitoring

To improve crop data collection accuracy, a company has developed drones that use thermal sensors to conduct aerial NDVI tests. To interpret data from the drones, the company has also developed its proprietary AI for high-accuracy data interpretation and making actionable crop recommendations to farmers. The drones allow the company to carry out NDVI tests at a quarter of the cost of satellite-based tests, while simplifying the process for farmers. This capability has allowed the company to monitor millions of acres of crops; as a result, numerous farmers have learned about under-fertilization, atypically dry crops, and other issues affecting yields, allowing them to adaptively manage their fertilizer utilization, accordingly, providing value to both farmers and investors through potential yield increases.

Another company has combined satellite imagery with AI to track agriculture supply chain metrics such as crop yields. Its platform provides intelligence services to growers, traders and investors regarding crop existence state, crop acreage, yield, quality, harvest time and actual harvested crops. By combining NDVI, EVI, NDSI and how these values vary with time and season, the company's AI algorithms can deliver accurate information on these state variables over entire fields from different satellites multiple times a week without needing on-the-ground validation visits. The algorithms are designed for local geography and crops and are trained on local historical weather and satellite data and local historical parcel-level harvested crop data, constructed by triangulating parcel-level farmer reports with national and state harvest totals, among others.

6.1. Successful Use Cases in Crop Monitoring

Agriculture is on the cusp of a technological revolution, with the power of artificial intelligence poised to shift fundamental production systems. Crop growth monitoring is important for timely information about plant diseases, crop growth staging, flowering forecasting, and fertilizer and water management. However, most monitoring systems rely on costly satellite images with limited spatial resolution and temporal frequency. Recent technological advancements allow small drones equipped with low-cost lightweight sensors to acquire high-resolution aerial imagery of small areas and downscaled information, yet their operational costs remain relatively high. On the other hand, the development of an ecosystem of autonomous low-cost sensors can trigger a technological revolution in the field of close-range remote sensing. The abundance of data provided by these novel sensors will help in the development of machine learning algorithms augmented with the use of convolutional neural networks capable of cracking the huge amount of data we will handle.

We will focus on the use cases of crop monitoring using AI-assisted computer vision techniques that deal with field-wide surveillance and decision-making. We will focus on different scales of crop monitoring. First, multi-spectral imaging for crop health monitoring at the plot scale. Second, the use of low-cost multi-spectral sensors and computer vision techniques to monitor crops at the parcel or farm scale for crop mapping, crop nitrogen monitoring, and crop harvesting, and plant monitoring models based on colour cameras. These advances have recently called for low-cost alternatives to satellite and drone images in the field of crop management. These developments are especially interesting for precise agriculture at the plot and parcel scales using multiple sensors embedded in precision agriculture machines, autonomous tractors, automated harvesters, UAVs, and remote-sensing satellites. These algorithms and models previously focused on the processing of high-quality data acquired by expensive and expert-operated satellite and drone systems.

6.2. Innovative Precision Farming Solutions

Farmers experience great challenges in predicting production yields. Therefore, they desired predicted results that were more precise and reliable. Furthermore, they also insisted that solutions should be simple and effective, with the least economic investment needed for the implementation. For their special case, the KitKom team has created a product called KitKom Cloud, which is the first intelligent and simple solution that uses multispectral imaging in UAVs together with a platform for processing and analysing the data. The proposed solution has reduced aerial data processing time by 90%, increased density of data analysis, enabled online processing of data on demand, cost-effectiveness, and boosted predictions for butyric acid concentration in grapes, which is detrimental for production, with a determination coefficient equal to 0.87 and a 10.83% error margin.

Recently, we had the opportunity to assist on a project where crop modelling and prediction of grape yield were performed. This work consisted of collecting UAV aerial data in traditional single images and multispectral, for different property areas in two geographical locations. Aerial data were taken in the flowering stage. After post-processing and analysis of the spectral data, the results obtained indicated that the best spectral models for prediction of grape yield were not indicated band relationships, but the extreme band values in the bands corresponding to 490 nm, 675 nm, and 850 nm, confirming the need to implement spectral models for each geographical positioning of the region of study. The UAV and KitKom Cloud system, proposed by the technical group, is the ideal tool for decision and assistance in precision agriculture in vineyards and other crops with similar characteristics. With regards to the decision-making process in agriculture, we can say that with such a combination, we had a narrow window on the full value chain.

7. Challenges and Limitations of AI in Agriculture

The agriculture ecosystem is slow when it comes to adopting any new technology. The farmers have become accustomed to the workflows, and they are not willing to risk it for an untried and untested technology. AI presents an incredible set of features to help the agriculture ecosystem. However, for it to be of real use, its impact should be as if someone just waved a magic wand.

AI, to be most effective, needs a significant amount of quality data to be fed into ML models for training. For AI to be completely transformational, data from all parts of the ecosystem – the supply chain vendors, transporters, and farmers themselves – will have to be made available. Because of this, the data will be fragmented and oftentimes with missing features for different players. Due to all of this, it will be very difficult to detect anomalies in the models and of course, farmers and agriculture stakeholders would be apprehensive to share their data.

Considering the above, agriculture-based AI implementations should be just as easy to use as any of the other apps that are omnipresent. It should be possible to obtain insights quickly after implementation, and any ML model should be useable with a minimum amount of training. It should be extremely easy to integrate any AI-based solutions into the existing software ecosystem that the farmers are using. Building specific mobile, easy-to-use apps for farmers and the participants in the supply chain can make this happen.

AI uses a significant amount of computing resources for its operations, including model training and inference. These resources are generally available as cloud services but use a fair amount of money and network bandwidth. More importantly, AI might provide some insights into various aspects of the agriculture ecosystem, but most of it has hardly been used by farmers and agriculture stakeholders. There are several reasons for this – the stakeholders are generally averse to change, and many of them are from rural parts and would not have even used normal desktop computers.

7.1. Data Privacy Concerns

The current collection and use of data privacy remain a challenge for many ongoing AI in agriculture efforts. Most of the decision-making is dependent on data collection services, research institutions, and agricultural sector industries, which is often of low security leading to privacy concerns for producers and producers' families. Various software and applications require information and biometric data, which they often provide, without assurance of proper security measures to maintain confidentiality. For small-scale farmers and farmworkers from developing countries, providing biometric information has many ethical issues, especially considering their lower socio-economic states, compared to large corporate entities for which these systems are developed to be efficient and artificially intelligent.

The fear and reality of data misuse expose producers, especially small-scale and low-income farmers to economic and financial exploitation such as price discrimination or rescue-aid negligence. AI technologies within agriculture must address data privacy and protection of producers at the individual level. Research investments toward assurance of technology privacy are especially important for sectors of the agricultural industry such as small-scale producers since AI applications that neglect data confidentiality are paving the way for AI to exploit people and their interests. Data privacy is one of the most challenging and under-researched areas in agriculture information systems and technology AI integration works and proposed three key areas on data privacy for AI technology in agriculture. With AI field operations, agriculture data privacy with sensors must address safety and security, data aggregation and sharing, and optimization and decision-making. In addition, providing equitable AI applications in agriculture for family farms of diminished size, small-scale producers and low-income farmers must have data privacy protection.

7.2. Integration with Existing Systems

AI solutions have been heralded for their potential to disrupt entire sectors with new and more efficient solutions to long-standing problems. However, the existing methods are built on years, if not centuries, of labour-and knowledge-intensive working of the processes. Make no mistake: we live in the age of integration, and while businesses are keen to take up solutions that AI can offer, they do not want to undergo a complete re-engineering of their entire processes to squeeze out the final few percent of efficiencies at exorbitant costs.

What this means is that any AI solution must be designed and implemented with the companies' existing systems in mind. This also speaks to the need for diverse testing datasets covering the variety of situations seen around the globe, and from which generalizations can be made regarding the efficiency increases which may be seen in applying them. Many times, companies may have invested into sensors or dedicated drones to ease the burden of data gathering but are not utilizing data-driven approaches to the steering and management of these resources to achieve the best possible outcomes. AI models can be easily integrated with these existing sensor-drone infrastructures to make the systems more intelligent.

Moreover, existing companies will likely have their own contours for input and output of information, for example, soil infographic data, pest damage rates, and cumulative financial cost data, which they may need to feed into their internal processes. AI models can be used as black boxes in embedded systems that accept inputs in not-generic formats, and produce predictable outputs, without being retrained each time, customizing the model usage to the specific company's requirements. Such integration of AI solutions into existing systems is the example of a low-risk high-reward development model that companies gravitate towards, and AI holds significant promise in enabling such integrations.

7.3. Cost of Implementation

AI technologies offer selected businesses the potential for stunning productivity gains. Implementing these technologies, however, requires a financial investment. There is no getting around the need to spend to improve margins, shares of the market and market attractiveness. The range of estimated costs is considerable. Companies belonging to the early adopter category could expect to be spending between 3 to 5 % of their total spend on AI in the early part of the 2020s, which would be slightly above that of companies on the next stages of AI technology adoption. By the mid-2020s, however, advanced user companies should be devoting 30% of their IT budget to implementing AI in their operations, including hardware upgrades, consultancy services, software licensing and talent acquisition. By 2025, global spend on AI software could exceed $100 billion, and spending on services could go over $60 billion.

Investments to be made at the level of the agri-food business vary according to the share of AI in their overall operating model. That is why only AI-ready businesses will see any improvement in the functioning of supply chains and in the performance of their main goals. The cost for becoming AI-ready depends on several factors including, the complexity of IT architecture currently used, the scale of data collection projects, the need of internal talent training, investments on external talent will have to be made and chances of transfer of unused tech infrastructure dedicated to data analytics projects. AI-ready businesses will probably reap the bulk of the investment cost burden, while the best part of the economic benefits will likely accrue to AI providers during the exploratory phase of any implementation process.

8. Future Trends in AI and Agriculture

The future of AI applications in agriculture is promising, with key design decisions that will likely affect the adoption of these systems including emerging heterogeneous use cases and models of how these technologies will be used overtime and in whom's resource and skill context. AI tools in Precision Intensive Agriculture will likely cater to a heterogeneous group of users. Farmers that are equipped with independent natural science knowledge, and that are able and willing to adapt and experiment with novel techs will likely act as spearheads of technology innovation and adaptation, nudging their local context, and those they share knowledge with, in new directions. Other users are less likely to produce or adapt cheap and income-generating tools by themselves. However, their natural and often social science knowledge will shape their interest in uses of AI technologies, for example in support of the sustainability of food production systems. Interactions between different user groups, as models for collaboration, will be crucial for the actual adoption of smart and intelligent tools in Precision Intensive Agriculture. Other than that, future trends are decreasing costs for AI in agriculture deployment systems and improved robustness and thus AI models for natural environmental conditions, and future trends that relate to alternative food production systems and the demand for sustainable or organic food. These technical developments will enable the integration of cheap AI-supported tools in the farm's infrastructure, but in an economic context that creates innovation cycles preventing rural space and farmers and local communities from losing competitive advantages of sustainable agricultural practices.

8.1. Emerging Technologies

The idea of integrating various technologies with agriculture is not new. The most discussed use of technology is automation, primarily related to labour shortage in traditional markets and the advances in robots and associated software. Agricultural robots can be deployed to automate various functions including planting, weeding, harvesting, crop monitoring, packing, and related activities to lower costs and increase speed and efficiency. A typical area where agricultural robots are deployed is in weed control with harvesting being the most challenging. But robots, at the current level of automation sophistication, are deployed in farms under controlled conditions over crops with sensitive and precise parameter requirements. The pervasive deployment of agricultural robots to create a collaborative ecosystem further deployed on demand through intelligent software modules is the next frontier. Additionally, the hard constraints of sensitive and precise harvesting conditions and current costs of robots may create possible roles for robotic ballets of drones in recognised use cases.

Crop monitoring is a vital but laborious function in the agricultural ecosystem. Drones are integrated with cameras to monitor farming areas. But the costs of drones currently deployed make them commercially not scalable. To overcome this, low-cost open-source air and ground-based observation platforms have been developed. However, persistent deployment of these cameras presently creates privacy issues. Integration of IoT into the agricultural ecosystem looks at deploying low-cost smart sensors that can operate in parallel, as a managed service, in farms with various smart applications that need to be deployed for a given window of time. Such a system can led to the collaborative concept of AgBots where each robotic device can be linked to a sensor network for collaborative data collection for different purposes. From this perspective, agricultural computers, computer vision, and IoT can enhance AI-enabled agricultural decision making at scale and at speed through Tedious, Expressive, Data-Demanding Artificial Intelligence.

8.2. Sustainable Practices

Investing in technology applications that will improve food production is essential in helping meet the increasing demand for food expected from the ever-increasing population growth while conserving global limited natural resources, such as land, water, and energy. Sustainable food production systems need to be employed to overcome the challenges that modern agriculture is facing, like meeting future demands or producing more food with less input while climate change is threatening food and nutrition security, health, and ecosystems. Sustainable practices should encourage the conservation of global ecological public goods and emissions without undermining rural livelihoods, and to contribute to boosting economic growth. However, providing public incentives to support global public goods generated on-farm is a costly, complex, and sometimes inefficient way to encourage sustainable agriculture. Creating and strengthening market incentives for farmers via specific product quality standards or agricultural insurance schemes that reward farmers for their risk-averse behaviour can also be done. Agricultural policies to support eco-friendly agricultural technology innovation are essential for achieving environmental sustainability and driving rural economy growth at the same time. Bio-based sustainable alternatives to fossil resources are needed to satisfy society’s needs without threatening future generations’ ability to meet their needs. Policy interventions will play an important role in stimulating, coordinating, and facilitating these investments and in enabling them to contribute to meeting the demand for products.

9. Ethical Considerations in AI Use

AI technologies are not ethically neutral. There are several important ethical concerns associated with AI use, particularly its impact on labour markets. Mechanization has displaced human workers across centuries. The Industrial Revolution was preceded by the labour-disturbing invention of the mechanical loom, but only after that invention became widespread was there social unrest from displaced workers. Displaced workers found it difficult to forge new identities and prefer long history. In the agriculture sector, AI has the potential to reduce the need for manifold roles including farmers, farmhands, crop inspectors, pest controllers, truck drivers, warehouse managers, and grocery clerks. Workers in these roles are often older, less skilled, and less mobile than workers in other sectors, making it improbable that they could adapt. Thus, an important ethical concern is whether the introduction of AI capabilities is liable to cause severe economic and identity-related harm for these people.

Education and retraining programs are important components of socially responsible incentive structures to support workers impacted by AI use. A second ethical concern is environmental impact. Further research is needed to address the potential trade-off between AI's worsening environmental budget and its use case in climate-friendly sustainable agriculture. It is generally understood that increased production and processing efficiency can result in decreased demand for natural resource inputs. However, short-term AI-enabled market competition may also result in lower prices, which can spur increases in production and processing in both developed and developing economies.

9.1. Impact on Labor Markets

Much of the excitement surrounding machine learning technologies relates to their potential for providing low-cost solutions to previously challenging problems. The fundamental question surrounding innovation is the question of substitution: whether machines will increasingly replace human labour and which tasks they will take on. In one respect, our discussion thus far has laid some of these questions to rest: for crop monitoring, AI is being employed to substitute human supervision for precise data about specific locations and specifications.

What will happen to conventional labourers performing the jobs displaced by intelligent machines? The displacement of labour has long been an effect of technological progress broadly defined, leading to betterment, and to wishes to impede betterment. In general, displaced labourers face a difficult transition period: they generally find it hard to shift into new jobs, even as the economy gears up towards replacing their lost output. This slow absorption can take many years. In agriculture, the answer has long been emigration, whether to cities or to foreign countries. These solutions have long been needed, since technological progress in agriculture is generally very rapid. Productivity growth outstrips labour-movement responses, leading to ever lower employment in agriculture. Thus, agriculture has been slowly changing relative to other industries, contributing a lower share of output for an ever-declining share of labour. It is claimed to be a permanent property of economies that rapid productivity growth alters the structure of output, increasing shares of services and manufactured goods, but lowering that of agriculture.

9.2. Environmental Implications

However, increasing crop yields with AI does not automatically imply decreasing emissions. For instance, when low-rate fertilizer applications combined with machine learning double the income from cotton production, greenhouse gas emissions also increase significantly. On the other hand, specialized high-yield maize production generates ten times the emissions per unit of GDP compared to the low-input high-yield production system, which is more skill-demanding. There is a wide consensus that precision agriculture is associated with reducing the environmental impact of crop production. For precision agriculture to benefit the natural environment, crops need to be produced more sustainably while maintaining high productivity. This is no easy feat in terms of implementation and requires long-term policy support. College-educated farmers with diversified income sources and enhanced promoting extension services enhance the adoption of precision agriculture, which, when realized at large-scale, has the potential to restructure the education system and innovate rural labour transfer, as well as promote rural economic development. Households need high levels of trust and reciprocity to adopt precision agriculture, which is concerned with reducing soil erosion, groundwater depletion, fossil fuel consumption, pesticide reduction, and, ultimately, the environmental impact. The spatial non-stationarity in the relationship indicates that the association varies significantly across regions.

Adoption of existing precision agriculture technology does not, however, guarantee a decrease in inputs. AI is expected to boost productivity but as mentioned before, growing demand for food could put pressure on growing environmental concerns, such as biodiversity and air pollution. It is still quite unclear how climate change will impact agriculture with higher temperatures, potential droughts, and extreme weather. Machine learning methods, on the other hand, might be able to answer questions of uncertain crop response to weather and its variability, altogether become a more robust tool to understand the natural environment.

10. Conclusion

The discussion on the conduct of supply chain practices in the exporting and importing nations on the planet came a long way from agriculture being a traditionally murky field suffering from low productivity, constant cycles of misery in the shape of famines and administration encumbered with issues of food shortage and food security, to the current days of science-laden agriculture that is responsive enough to meet the insatiable demand resulting from ever-growing global population. Economic growth in tandem with increases in disposable income led to a steady shift in demand towards convenience foods. Greater attention is being paid to the twin issues of food security and safety. Exporting nations must be able to prove the supply of a safe, high-quality produce on a consistent basis for sustainable growth in shipments. Failure to comply with these mandatory requirements would lead to a ban on shipments from the offending country. Such developments inflict heavy financial losses on exporters and ruin the country's reputation with trading partners. Whereas importers are generally more advanced in the field of agriculture technique, yet they suffer from the issues of high land costs and low productivity levels. On the other hand, developing economies, which still rely on the traditional methodology of production, suffer from constant fluctuations in output levels.

With the advancement in artificial intelligence techniques such as expert systems, machine learning technologies, and IoT along with the provision of better computing power and research in developments enabling cross-country movements of labour, supply chain processes promise to transform efficiency and effectiveness relating to all dimensions discussed above. Stakeholders need to identify tech readiness of local players and how these can be leveraged to improve management decisions or enable adoption of futuristic immersed happiness experience.

References:

Bannerjee, G., Sarkar, U., Das, S., & Ghosh, I. (2018). Artificial intelligence in agriculture: A literature survey. *international Journal of Scientific Research in computer Science applications and Management Studies*, *7*(3), 1-6.

Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research*, *9*(4).

Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem*, *2*(1), 15-30.

Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, *2*, 1-12.

Liu, S. Y. (2020). Artificial intelligence (AI) in agriculture. *IT professional*, *22*(3), 14-15.

Smith, M. J. (2018). Getting value from artificial intelligence in agriculture. *Animal Production Science*, *60*(1), 46-54.

Vincent, D. R., Deepa, N., Elavarasan, D., Srinivasan, K., Chauhdary, S. H., & Iwendi, C. (2019). Sensors driven AI-based agriculture recommendation model for assessing land suitability. *Sensors*, *19*(17), 3667.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

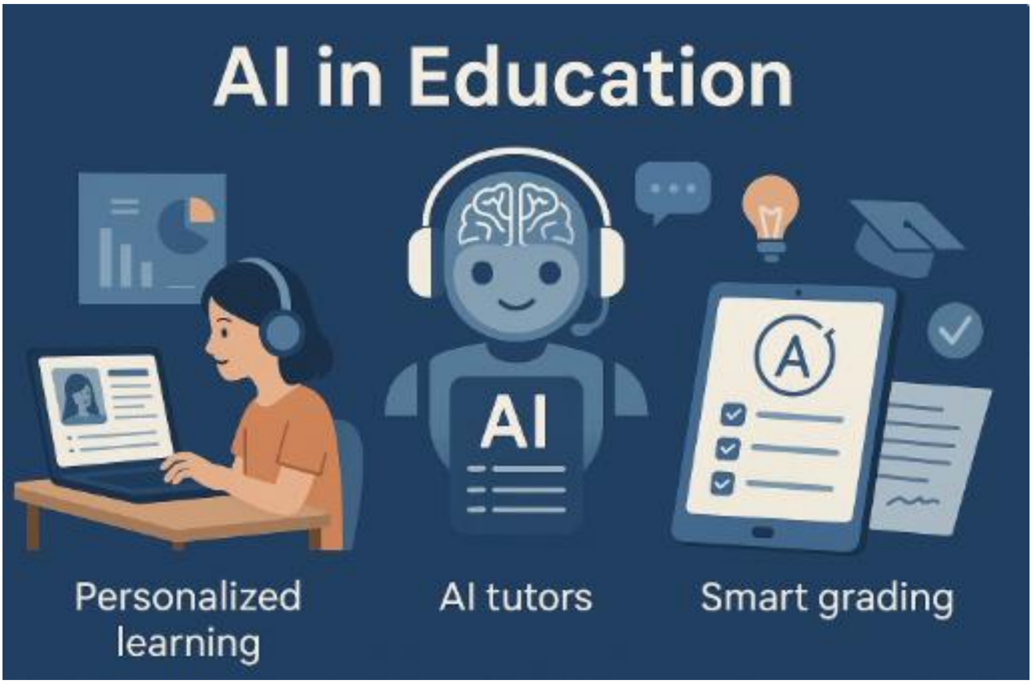
Chapter 5: Artificial Intelligence in Education: Personalized learning, Artificial Intelligence tutors, smart grading

1. Introduction to AI in Education

As the pace of development of AI tools, services and applications accelerates, inquiries from education professionals have surfaced: what role can or should AI play in support of educational institutions, teaching and learning; and conversely, in what ways can and should education prepare both citizens and professionals to leverage AI? These questions have led to a burgeoning sector of education-science research, contributions from education practitioners, and the emergence of AI-enhancement platforms and services. In this chapter, we start to draw the roadmap for what education must gain from advances in AI and also for what our rapidly evolving world, increasingly relying on AI for processes both simple and complex, needs from education.

In addition to an overview of the trends in the market, we outline and summarize directions for institutions involved in teacher training, in curriculum development, in educational software engineering, in education policy and even institutions outside the formal system: informal learning sectors, private actors who develop curricula, who develop tools for the education of the general public on what it means for our society, our economies, and education itself to have AI as a partner for the future. At first glance, one might think that the links between AI and Education are obvious and clear. Indeed, according to some actors in recent years, numerous services and tools of undeniable educational value have emerged using AI-based technologies.

To cite one of many examples, a service called Knowledge Graph has been incorporated into a search engine. By means of a short combination of queries, users can quickly get access to a huge amount of structured and semantically interconnected information. The purpose of this service is to enhance the augmented cognition processes of users to allow them to obtain associative dimensions which are not simply a composition of the individual queries of the search, but which also consider the semantic and relational values present within and beyond their individual keys or concepts.



2. The Concept of Personalized Learning

2.1. Definition and Importance Personalized learning is a process that is responsive to the unique needs, skills, interests, and cultural backgrounds of each student. Personalized learning aims to increase students' motivation to learn, thereby improving their academic achievement and long-term success. Personalized learning differs from individualized learning in that it is based on the entire school vision, while individualized learning is one specific approach. Personalized learning is a major education reform that emphasizes the active role of each student in their own learning, helping them to become lifelong learners. Personalized learning blends content, pedagogy, and technology into a unique learning experience for each student. In recent years, many other terms have emerged to describe variations on personalized learning. Individualized learning, differentiated instruction, differentiated learning, customized learning, competency-based education, student-centred learning, and mastery learning are just a few examples. Although these models differ in subtle but important ways, they all advocate recognizing the needs of individual students. Personalized learning allows students to take a proactive role in their own learning. It gives them a choice in directing their learning experiences, including how they learn and when they learn. Research shows that giving students some degree of autonomy leads to stronger motivation to learn and helps them develop higher-level thinking skills.

2.2. Benefits of Personalized Learning Personalized learning is beneficial for many reasons. Major benefits of personalized learning include the following: Addressing individual learning differences is often considered the goal of education, and personalized learning offers the greatest potential to achieve this goal; Students learn best when learning is relevant, so personalized learning capitalizes on student interests; Learning is more productive when students set goals and assess their progress, which is a central tenet of personalized learning; Students take more responsibility for their learning with support from teachers and parents; These benefits help create empowered, self-directed, and effective learners.

2.3. Challenges in Implementation The challenge lies in how to implement personalized learning in classrooms. Although some proponents see a future of computer-based instruction with little teacher involvement, most current implementations centre on teachers assisting students with learning paths tailored to their needs and preferences. This is often accomplished through differentiated instruction, formative assessment, and scaffolding, along with student choice. As many educators and district administrators can attest, achieving true personalized learning for students is difficult.

2.1. Definition and Importance

In education, many terms are used, sometimes indiscriminately, because of the nebulous character of the teaching and learning processes. Among these terms, are the following: Differentiate learning, Meaningful learning, Individualized instruction, Effective learning, Learning style, Learning enablement, etc. In addition, the personal dimension of the learning process is not necessarily visible, because its importance depends on the level of cognitive development achieved by students. Therefore, it is not uncommon to hear that learning cannot be personalized, not only for its complexity, but also for its difficulty of integration into the practice of teachers who must face a large and diverse number of students in the classroom every day. Personalized learning, however, appears today as a solution – or more precisely, as an answer to a need – for the educational challenges facing educational systems in an increasingly globalized, digital world with more unequal opportunities. Personalized learning is, above all, a broader concept that implies the active participation of students, their motivation and their desire to learn. This specificity of personalized learning is not always specified by other terms used in the academic literature such as individualization and differentiation. Consequently, personalized learning systems emphasize the active role -methodological, informative, formative, social and evaluative- that students take in learning. It integrates methods of differentiation, individualization and evaluation based on the different umbrella of student motivation and monitoring.

2.2. Benefits of Personalized Learning

Students have a wide range of learning needs that arise from their own cognitive capabilities, psychological condition, and cultural and social context. Personalized learning, also referred to as individualized learning, is a pedagogical approach directed to fulfil each student's specific needs, teaching style, aptitude, interests, and motivations. Personalized learning encourages students to learn in their way and at their own pace. Personalized learning has become the primary pillar of education in which teachers can motivate students to be responsible for their own learning since the early development of the cognitive and meta-cognitive skills of sense-making, analytic reasoning, problem-solving, and critical reflection.

Many scientific studies have highlighted the effectiveness of personalized learning along with its positive impact on students. Personalized learning improves student subject knowledge mastery. Students can fulfil a greater breadth and depth of knowledge, grow faster, and reach significantly higher academic outcomes, especially in the area of reading. Additionally, personalized learning increases student motivation and makes students feel competent. Personalized learning produces increased learning by focusing on the process of learning that motivates students toward high-level performance, enhances learning productivity, and sustains improvement in effort to develop the full potential for both high-achieving and low-achieving students.

2.3. Challenges in Implementation

The widespread adoption of personalized learning policies has however met some barriers, such as an absence of established practices, controversies around their precursors, and political resistance. These barriers are tied to technical difficulties, existing beliefs and attitudes, and traditional educational norms. Personalized learning requires providing an adequate learning environment adapted to each learner, but research is far from identifying an exhaustive list of how to achieve this goal. Related to this latter problem, but also to educators' attitudes and beliefs, is the fact that large parts of the education workforce and the public at large may strongly adhere to behaviourism and associated notions of effective teaching, such as predetermined learning objectives organized in a linear progression as a prerequisite for effective learning and teaching. Political resistance to personalized learning comes from an opposition to individualistic views of education that provide an intellectual backing for market-based policies. In fact, the implementation of these policies often leads to parental pressure to gain admission to the established hierarchy of schools. Personalized learning systems may also promote school choice and increasing use of school mobile applications.

The potential risk associated with the recent development of personalized learning systems through automation, big data analytics, machine learning, and artificial intelligence has led policymakers to take precautions. These precautions urge the education community to be careful when adopting personalized learning due to the risk of establishing a mirage of true personalization via software packages which collect data exhaustively for each learner across numerous topics and across standard assessments. These packages may be tempting, as they offer coaching and remediation guidance for each learner through adaptive branch logic algorithms.

3. AI Tutors: Revolutionizing Learning

Widespread use of AI in tutoring – currently dominated by text and instruction-based programs – has already started on a small scale, with some carefully managed applications of computational counterparts to human tutors (Chen et al., 2020; Holmes & Tuomi, 2022; Jeon & Lee, 2023). As intelligent conversational agents based on chatbots have developed, it has been possible to nearly commercial research work on intelligent tutoring systems which automate tutoring by AI. Research has shown that, for specific tasks and short dialogues, automated tutoring can even be superior to human tutoring. Applications of these agents have included tutoring in language learning, which many consider a sweet spot, allowing for scaffolded conversational practice, preparation for coding tasks, computer programming, health track for war veterans with PTSD, and generating valuable content on demand. We describe intelligent tutoring systems and define AI tutors as intelligent virtual agents performing tasks previously performed by human tutors.

Tutoring is a unique act of coming alongside another to help them see, understand and complete an otherwise challenging task. The combination of demonstration, guidance and feedback provided by the personalized relational interaction of a tutor with knowledge of both the domain and the learner's next steps are invaluable. The development and dissemination of research that examines the potential of intelligent systems to replicate the potential of tutors is how artificial intelligence will truly impact education for the majority. Tapping the resources of artificial intelligent motivation, engagement and monitoring, we put the new term of AI Tutors forward. AI, like a good tutor, can scaffold learning, provide low-level intrinsic motivation, and monitor and therapist when deep issues arise – maintaining a long-term relationship with the learner.

The first chapter on this topic explored the evolution of AI tutoring from early starter intelligent tutoring systems to a blended future, enriched by research, ethical systems design, creative tools to design unique learning paths, to the focus of this chapter. Perhaps the most exciting area of education is the use of chatbots for learning and instruction.

3.1. Types of AI Tutors

Artificial Intelligence-based tutors are emerging tools for personalized educational learning.

Intelligent Tutoring Systems (ITS) are perhaps the most widely-used educational AI, embedding rules or constraints to affect how a learner interacts with the tutoring system. Additionally, they can help mitigate the noise of learner signals by creating artificial structure to unstructured learning activities by introducing scaffolding, reeling learners back in when they wander off-task, and plugging knowledge gaps when necessary. In fact, research has shown salvaging "lost" opportunities can improve student achievement of intervention. Ai-Tutors are most frequently simplified to "AI" + "Tutors", defined within the context of this work as any instance of AI which serves to tutor or instruct but is perhaps less effective than an embedded Intelligent Tutoring System. Research on Constrained AI also makes a distinction between a rule-free and rules-based structure, where the AI Tutor is and isn't constrained, respectively. Rule-free models rely on black-box deep learning methods, while rules-based may present predefined corrective feedback or content requirements as proposed by the engineer. Foundational AI-Tutors warrant additional discussion; these utilize unsupervised learning to build a tutoring model and are not driven by a reward system that reacts to user decisions.

Decision trees are a good example of a model which is hand-constructed from input data, as it captures general and user-specific task-related knowledge but avoids the "symbolic regression problem" of node prediction while remaining easy to interpret. Programs like MATHia, Cognitive Tutor, and Design-A-Bike are rule-based intact Intelligence Tutoring Systems. Lastly, we should note that AI-Tutors also share features with other platforms, including medium agents like Chatbots and educational games. Scaffolding is also implemented in DeepTutors, to explain when not to use an "off-the-shelf" deep network randomly pre-trained on a vision dataset; its metaphorical "teaching" takes the form of push notifications to students.

3.2. Case Studies of AI Tutors in Action

The last few years have shown several AI educational infrastructure initiatives with interesting AI tutor implementations. Among these efforts we find an intelligent tutoring system for mathematics; a system focused on math, science, and humanities; and a system aimed at English composition. The first two have been in beta/testing versions/operations for a few years while the third is based on earlier implementations. Here we describe a few case studies.

An AI tutor for mathematics courses personalizes students' learning during independent practice, tailoring the content on-the-fly in response to student performance. This provides real-time feedback and helps students stay focused and engaged. Unlike math software that contains a single tutorial for each topic but operates by presenting static exercises, this AI tutor adapts its next prompt by dynamically selecting and constructing a task that makes the best use of what the student knows and how she is progressing. It also provides hints that address all aspects of a student's displayed approach to an exercise and delivers instructional messages that identify both the correct and incorrect features of her current process. Finally, optimized from years of AI action-selection research, it moment-by-moment selects what to present for the task's next step: a prompt, hint or feedback message, based on how the student has arrived at the current state.

3.3. Effectiveness of AI Tutors

The use of technology in education is not new. To identify studies related to the use of technology and the effects of this use, we conducted a systematic review of the literature. According to the reports, the first papers that presented a controlled study using technology date from 1997 and 2000. The analysis of the studies supported by technology shows that AI Tutors have been used in a variety of situations, such as to support the teaching-learning of students, either in person or at a distance, and more recently as aids for teachers. For us to understand the other possibilities offered by Artificial Intelligence Technology in the Teaching-Learning Process in the educational environment, it is important to analyse the effects presented in these studies. While the number of publications is significant, it can be noticed that they are much more concentrated in Computer Science than in the other areas of knowledge.

The AI-TLP was able to keep the students' learning, either through quality parameters or through learning metrics such as the grade obtained by the students. The AI-TLP was also able to increase the students' learning, either through quality parameters or through learning metrics such as the grade obtained by the students. In these studies, the AI-TLP was indicated to collaborate in the Teaching–Learning Process mainly in the Remote Education Model, especially in the periods of the pandemic. The AI-TLP was able to keep the students' learning, either through quality parameters or through learning metrics such as the grade obtained by the students.

4. Smart Grading Systems

Despite AI's limitations, recent years have seen advances in a wide array of functions and systems designed specifically to help educators reduce their grading workload. Oftentimes, these functions are combined with Learning Management Systems. As an editor that helps two or three college instructors every semester with set-up and maintenance of different Learning Management Systems, I see firsthand how tedious, time-consuming, and sometimes error-prone automating the grading of online assignments can be. With respect to traditional face-to-face class grading, the physical labour of grading is exchanged for the mental labour of designing rubrics and spending time in front of a computer, usually on a program that is less than user-friendly. With the recent advent of Generative AI functions, critics of AI in education cite academic integrity as a concern. While I do think these critiques are valid to some extent, we need to balance concerns about misuse with a level of reality about the degree to which such formulations have been used historically.

While Generative AI can help facilitate work that instructors have always had to do in some capacity, such as crafting a prompt that asks students to summarize a reading, present the author's argument, and assess its strengths or weaknesses, a more exciting possibility is that of developing learning experiences that allow instructors and students to personalize experiences and content by utilizing large language models (Kim et al., 2022; Luckin & Holmes, 2016; Zhang & Aslan, 2021; Zhai et al., 2021). Language models can be seamlessly embedded into existing systems to facilitate automatic grading and tutoring of student responses. While this might only be a small difference on paper, the reality is that most citations in introductory-level undergraduate papers have, historically, been neither grammatically coherent nor much better than average. So, if Generative AI can be utilized to develop activities and resources that take advantage of natural language processing tools, the ability to generate bad essays isn't so much a security concern as it is a ceiling that needs to be pushed up more innovatively than students have in the past.

4.1. Overview of Smart Grading

The aspects mentioned in the introduction motivate the use of smart grading systems for education. These AI systems can assist teachers in evaluating students' work. In general, smart grading is a discipline in Artificial Intelligence that concerns the development of models that automatically assign a "grade" to a student performance to allow evaluation or feedback tasks. Normally, the main application area of smart grading systems is computer-based testing on a wide variety of disciplines and domains. When being applied to natural language tasks in education, smart grading systems are usually designed to give feedback to students to help them improve their performance in areas such as second language acquisition, argument writing, or critical thinking, among others. From the teachers' perspective, smart grading alleviates their burden and helps them be more efficient, effective, and consistent during the evaluation process. Thus, smart grading allows teachers to focus on the development of learning activities, the students' learning process, and the provision of personalized feedback. Transparency, reliability, and consistency are some of the reasons why there is an extensive use of artificial intelligence grading in the education field.

Due to its objectives and functions, smart grading includes many different sub-tasks, such as assessment, review, and evaluation; it uses a variety of data sources: student answers to predefined questions or guidelines applied to their answers; a variety of input formats: plain text, structured text; graphic information; and a variety of performance types: multiple-choice, n-choices, cloze, essay, or written performance.

4.2. Technologies Used in Smart Grading

Several technologies can be utilized in the development of smart grading systems. The most common techniques are natural language processing, automatic speech recognition, and machine learning. For exam grading, functions as natural language processing, automatic speech recognition, and machine learning are very useful in extracting useful information from the input speech and text, such as keywords and keyphrases, and in the evaluation of the needed scores. In addition to these technologies, different techniques can also be used for achieving the expected grading result. For example, information retrieval, knowledge-based systems, expert systems, automated critical thinking assessment systems, and statistical analysis techniques can also be used in specific areas to evaluate the expected grading functions. Natural language processing is concerned with the interactions between computers and human languages; it has various functions to perform a useful interaction between a computer and a human being.

Therefore, it is part of the wider computer science domain of human–computer interaction. As natural language processing needs a good language model to simulate functions such as the generation of text, speech synthesis, words prediction, and parsing, the language model can be created using deep learning algorithms, which add a higher level of artificial intelligence to the whole smart grading system. Deep learning algorithms, which are based on neural networks, have driven recent advances in many AI sub-fields such as natural language processing; deep learning algorithms usually require very large datasets, usually using GPUs, specially designed computer chips for creating those datasets. In addition to assistive technologies, natural language processing and deep learning algorithms also facilitate functions such as information retrieval and summarization, sentiment analysis, and question and answering.

4.3. Benefits and Limitations of Smart Grading

While evaluating student work is an essential task for teachers, the evaluation process is certainly a time-consuming one. Even if the teacher has developed a rubric of grading, oftentimes, the evaluation of answers involves a more qualitative analysis. Smart grading systems can help overcome this problem by providing an automatic initial assessment to help the teacher in decision-making and speed up the whole process providing the first assessment draft. Students would gain more benefit from receiving timely feedback on their performance rather than having to wait weeks for their assignments to be returned. Studies show that students perform better when they receive quick feedback since they can act on it, allowing the instructor to teach more effectively. This process can be applied to different types of materials, such as essays, short answers, lab reports, programming exercises, quizzes, and multiple-choice exams, among others. Some systems also implement additional features, such as feedback suggestions, preference for penalizing or rewarding specific behaviours, or crowdsourcing the grading process. However, there are some limitations to using these kinds of systems that must be taken into consideration, particularly related to the human touch in the learning process. First, the results produced by the system are only possible if the training set is balanced, relevant, and specifically selected. Moreover, teachers that deliberately create ambiguous or difficult-to-score questions may not find an automated grading system useful.

5. Integrating AI into Traditional Classrooms

While the potential of AI to revolutionize education is vast, traditional classrooms are still necessary for many student groups. This section offers concrete examples of how to implement AI-based learning strategies in such an environment. While AI is the focus of this book, we aim to be as platform agnostic as possible, allowing educators to innovate regardless of the specific AI tools they have access to. To this end, the following section draws on learning sciences research on agency, motivation, assessment methods, social classroom conditions, and challenge-reducing learning environments as a set of guiding principles for effectively integrating AI in education.

5.1. Strategies for Integration

Agency is viewed as a central construct of the learning sciences yet tends to be underexplored in AI strategies. Promoting learner agency fosters autonomy, competence, and relatedness, which in turn promotes engagement and a successful learning experience. Ideally, AI tools help learners provide evidence of their learning, such as through original essays, creative assignments, and exams, which they create independently or with the help of AI. AI can also lower barriers by offering intelligent adaptive features that scaffold learners in the agency development as a "one-per-student tutor." This includes generating example projects and providing feedback and keeping track of the component parts of tasked projects to reduce the learning load. Additionally, when students choose an AI tool aligned with their values and design the curriculum creatively on their own terms, it can be an unparalleled project-based learning experience. The key challenge remains that traditional assessment methods and their focus on a single product often exist in parallel to this more agency-enhancing use of

AI tools for learning. Therefore, research on agency must explore its interaction with traditional assessments. There may also be students who do not have the skills or will allow handing over control to an AI developer or service. In these cases, AI can enhance learning without boosting agency, which can enhance motivation or a feeling of belongingness in the classroom.

5.1. Strategies for Integration

If AI tools can successfully be integrated into the classroom, students can benefit from personalized instructions, immediate feedback, and even assistance in soothing test-taking anxieties. A computer capable of generating humorous dialogue or drawing pictures does not seem like it should be able to create essays, but there are numerous practical classroom applications for text-based AI. Ideas such as having students create different texts on a single subject for different audiences could lead to lively discussions. Or students could write an essay, have the AI rewrite it, and discuss the differences in the two versions. They could even use AI to generate a "bad" essay to learn about essay structure. For non-native language learners, students could research a subject and ask the AI to generate text as if they were a certain age or native speaker. Students could then edit it before using it as a basis for their work. These exercises and others like them can help students learn about writing while also teaching them to be more discerning consumers of AI products.

Using AI as a classroom tool can help both students and teachers. Teachers can plan lessons where students work through subject material independently and autonomously but using AI as a support mechanism. AI can be asked specific questions, take quizzes, or even summarize textbook material in an easy-to-read format. Students could then work on skills, such as critical thinking, while teachers give personalized attention to those students needing extra help, using the AI to help answer other students' questions. The students can benefit from its quick and easily available answers as long as the education system provides adequate guidance and training on its limitations.

5.2. Teacher Training and Support

Limiting policies, mere mention of technology, and naïve or overly simplistic learning and teaching models are not likely to be useful ideas for integrating technology in the classroom. Teachers have to be invested to help students with technology purposefully and supported with training and resources in doing so. All teachers are somewhat reluctant to adopt new things in the classroom at the best of times. Wider use of AI tools and the inevitable shift of student work away from traditional assessment channels immutably shift classroom teaching goals and strategies. AI will not undo sound pedagogy and a growth-oriented curriculum, but these will likely be harder for teachers to build without adequate appropriate training to prepare them. Teachers have their own cognitive biases against technology use, such as Technology Adoption Life Cycle and the Gartner Hype Cycle. And AI tools are generally harder to use and introduce into classroom learning structures than previous web technologies, because they shift how we think about intelligence, skill acquisition, and assessment.

Meaningful training takes time; professional development is notoriously fragile. The tried and tested path is through workshops and courses. Just-in-time learning, communities of practice, and mentoring are also possible, although being busy prevents this more implicit and self-directed route. Currently available courses are looking at some nice effects of AI and examples of successful use blending it into the classroom or educational research, and positive effects with other technologies; thoughtful, focused, specific integration planning stays on the curriculum. Awareness-raising training is presently replacing serious thoughtful consideration: for example, recognizing AI-authored text or deepfakes. Teachers have enough challenges in their careers, whether in health or emotional aspects, without being either pointed at new risks or forced to alter established successful teaching methods for less communicative, collaborative, empathetic, resilient, and morally aligned methods.

6. Ethical Considerations in AI Education

While AI technologies have significant potential to improve educational outcomes, there is a growing need to address the ethical implications associated with their use in education. Most commonly in the media, privacy and consent issues are raised, as data on students' performance and activity are collected to provide insights or drive the adaptive engine. Equally concerning, however, is the potential for bias in the AI algorithms, which could result in students from certain demographic groups receiving less support or not being put on pathways leading to appropriate courses or programs. Similarly, students with learning challenges may require specialized algorithms to support their needs.

While educators typically have some influence as to the user data collected by the AI and the access it permits to learner interactions and data, little control exists over either training or testing of the algorithm itself. This not only limits the educator’s ability to identify underlying unfairness within the biased algorithm but also raises issues of consent when it comes to the AI using the educator's and student's data on demography, language, and regionally specific spelling and grammar constructs to improve the algorithm's predictive power. Even if consent to the AI program was obtained, release boxes require the provision of accurate demographic data, and learning with an AI program might need to be measured against a baseline inappropriately defined by the testing, groups, or control samples utilized by the developers. Once the AI program becomes pervasive, it becomes difficult to explain the inherent 'unfairness' in the algorithm to potential critics.

6.1. Privacy Concerns

Generative AI tools are becoming valuable assets in knowledge transfer and creation. However, their usage is not without risks. Many of these tools work as "black boxes," where users input a prompt and receive a response, but these services are proprietary, often use data scraped from the open web, and generally have ambiguous, incomplete policies concerning data collection, sharing, and monetization. This raises concerns about student privacy and possibly disallows academia from benefitting from the vast technological advancements that are being made outside its typically imposing walls. A large proportion of generative AI services are trained on data scraped from the open web. For these services, data used in training is not available to peruse, copy, or request deletion of. Therefore, they can potentially also use proprietary data that might be published online, violating copyright. When using generative AI services, students might be exposing their proprietary work to data models, especially if there are few safeguards available in the services being used.

Many universities have released procedures about what data can be used and what cannot when using generative AI services. Some have outright banned the technology from use. Others have also published extensive lists of services that can and cannot be used to process sensitive private data and have made efforts to build in-house generative AI tools for research and education -- a highly revelatory approach considering the early stage of these models and the years of research and development investment the in-house solutions would require. Some services have adopted a temporary ban on processing sensitive medical data but are notoriously ambiguous about the storage of data shared while using the service. What constitutes sensitive data, which genres do not always overlap in the context of data from the education domain, is frequently hard to navigate and are often surrounded by loopholes when restrictions are put in place.

6.2. Bias in AI Algorithms

The artificial intelligence community has generally acknowledged three different types of bias in AI systems: data bias, algorithm bias, and usage bias. Hardly any AI has been deployed without data bias nor has any recent technological advancement been claimed by the AI laboratory that was free from algorithm bias. Part of the trouble is that most of the data that are collected and subsequently used for training and testing AI in a wide range of domains are unobtrusively gathered outside researchers' and engineers' control. This includes social media data that users did not label as important when they clicked "I Accept" on the user agreement, and natural language corpora that nascent humans have unwittingly contributed to as they painfully learned how to speak. However, data bias is, stoically, only the first source of disappointment and frustration for the AI community. All models, algorithms, or rules are built using simplifying assumptions. The goal of these simplifications is to manage computational complexity. One common assumption is that the data are independent and identically distributed and are not biased with respect to decision thresholds that are of importance for performance. However, real-world data are rarely free of bias, and loss-costly, low-accuracy decisions are rarely sufficient for solving real-world problems.

Usage bias is the third source of bias within AI prediction, classification, and assessment systems. Usage bias may arise because normally higher quality test data have been used to validate performance or because users use the software differently than the designers intended. It is also possible that algorithm or usage bias are added on top of data bias, which leads to an accumulation of negative side effects of the AI system that is paired with unrealistic designer expectations. Occupying the largest value of both the standard error and influence functions, identification with the AI system and prediction unwillingness are the two most striking indicators of algorithm bias. Identification is defined as the degree to which a user thinks that he/she is of the group that an AI has been designed to favour when assigning tasks among different applicants. If a user identifies with the AI too strongly and thinks that his/her social group has also benefited from the AI, he/she becomes less willing to act against the AI results.

7. Future Trends in AI and Education

As AI continues to grow in capabilities, the implications for education and what education should look like will require broad discussions between educators, technologists, policymakers, clinicians, and other stakeholders. This chapter predicts what the education of the near future may look like.

7.1. Emerging Technologies Over the next ten years, we can expect broadening implementation of technology-enhanced learning systems with sophisticated features for recording, tracking, analysing, and informing learners and instructors about learning on an individualized basis. Relatedly, advancements in technologies surrounding expert systems, machine vision, and affect recognition will facilitate implementation of hybrid learning models that leverage both human and machine intelligence. Virtual learning environments that deliver content, assess learning, and provide feedback using a combination of software and human resources will begin to emerge. However, these developments will not impact education equally. Communities and systems that have available resources to tap into infrastructure and funding to support integration of these new developments into existing educational structures will be ahead of the technology adoption curve.

Perhaps the most certain prediction is that the use of AI in education will be pervasive. Chatbots will feature prominently in university student support services. AI will inform admissions processes and financial aid applications. Predictive analytics will provide institutions with information to develop recruitment strategies, assess freshman fit, and predict student retention based on information supplied, previous success, and cohort demographics. Primary and secondary school management and support operations will be automated to save resources at all levels, with little emotional engagement during the admissions and support cycles. Virtual learning environments will have virtual assistants built-in, serving as global multi-language automated student support representatives, available 24 hours a day to respond to inquiries for programs across the entire spectrum of educational experiences.

7.1. Emerging Technologies

The advancement of technology has brought with it a series of invisible yet life-altering changes. And education is not exempt from these changes, which require schools and universities to learn new codes and constantly adopt new modes of behaviours that will lead to adapt their structures and their logistics. Scanning the horizon, we will focus on the trends that seem to us the most significant and which will tend to develop and occupy a more central place in the coming years. These trends may be linked to disruptive technologies that constitute new modes of sharing, collaborating, and creating contexts, favourable on the one hand to pluripotential and experiential learning and, on the other hand, to individualization and personalization of training. This could allow us to overcome significant difficulties that traditional practices encounter such as the low level of motivation of students, attrition during the learning process, the non-recognition of informal, non-formalized, and validated learning.

The desire to guarantee the academic and professional success of students requires an increased accompaniment from the beginning to the end of the learning process. The use of social network and mobile communication technologies gives this accompaniment a considerable boost thanks to the immediate channels of interaction they allow, while AI now allows predictions regarding the behaviour of future students. These new systems will work in addition to existing devices that rely on the coaching work of human experts. The algorithms detecting dropout risk by analysing in real-time the patterns of engagement or non-engagement of learners provided by mobile communication need to be combined with other predictive methods linking initial profiles of learners to their academic and professional outcomes. This question of incorporating AI into predictive coaching methods is still in its infancy, and its development will increasingly become prevalent in terms of attractiveness for both learners and trainers.

7.2. Predictions for the Next Decade

The influence and import of AI will only become more pronounced over the next decade. By 2030 we will have a much more tangible understanding of how AI can augment teaching and learning. Until recently, we could not really know how to apply these models, particularly in the context of classroom teaching and formal learning. Now we can see specific applications that can be of great benefit to students, teachers and administrators. A key should be the incorporation of our knowledge of how learning works; the models do not yet contain that knowledge.

There is a dual issue here. A growing set of empirical work is showing how the use of specific types of feedback, whether from tutors, mentors and now AI, is crucial for deep learning. Such feedback might code rubrics for content area evaluation, together with expectations around self- and peer evaluation using the rubrics. The rubrics might also have links to examples of various rubrics in use, thereby answering the question "What are the characteristics of good archaeology?" In a sense AI can do for this type of educational support what search engines did for surface text-location; it will aggregate and enable both finding and using of expertise. Globally, this could enable deep learning opportunities in areas that are not privileged, both by providing very good mentors/training AI and also by making the process less costly, in time, for user-peers. The future development of good feedback systems will be vital for these impacts.

8. Case Studies of Successful AI Implementations

This section describes actual educational institutions that are in the process of or have been successful at implementing AI in some form of education. This discussion could be extremely useful for many institutions that are struggling with figuring out how to proceed. Knowing what others have done and how they achieved their successes would provide confidence in taking such steps; not taking those steps at this point may well result in institutional obsolescence. It is worth noting that, thus far, the information on AI implementation in education is sparse and primarily anecdotal, at least for K-12 education. However, for what is known, what can be learned from these experiences will also be discussed.

In the world of K-12 education, the field experiences from several actual deployments of AI in educational institutions tell a promising story. One such experience is with a school district in Ohio. The district has utilized an AI-based, personalized learning system for core students since 2017, growing its use within the district from 300 students to approximately 3,000. Their use of AI in education is used to promote individualized and tailored education to meet the students' needs. While other technology-based personalized learning approaches existed prior to engaging with AI, notably, how and why they proceeded with an AI-based strategy was revealing. The superintendent of the district understood the potential of students working at their own pace within large student populations. His research into AI led him to decide that AI was the tool to do that. He aggressively pursued the implementation both in the classroom and in students' homes to jumpstart deficits accelerated by extended online learning requirements during the pandemic. While it is necessarily early to demonstrate full effects, he has been pleased so far. "We have not hit all of our academic goals," he stated, "but we are on the right track."

8.1. K-12 Education

This chapter examines two case studies that highlight successful AI implementation, one in K-12 education and one in higher education. The K-12 study focuses on an initiative built around the five AI literacy concepts in the guidelines for AI literacy. It highlights a partnership between curriculum developers, researchers, and state education agencies in the United States. The emphasis of this case is on K-12 curriculum development. The HE case explores an initiative at a prominent institution focused on responsible AI for social empowerment and education. This initiative has two main foci: the creation of an interdisciplinary undergraduate curriculum in AI ethics, bias, and equity, and the development of trusted partnerships between student teams and faculty advisors with stakeholders outside the institution for the purpose of cocreating AI for the public good.

K-12 prepares future generations to thrive in a society and economy in which AI will increasingly impact everyday life and work. While K-12 has a natural responsibility for ensuring that no citizen is left behind, that every citizen understands these systems just enough to make informed decisions about their personal, social, or civic lives that are affected by or embedded in them, there is an urgent need for K-12 to prepare all students not only to understand and interpret AI, but to design and create AI systems as a part of growing up in a digital, technological world. For some students, this will be a supplement to the learning that they do in school; for others, it will be foundational to their future work. The purpose of this chapter is to demonstrate how today's K-12 can and should prepare its students for this future.

8.2. Higher Education

In this section, we describe several examples of higher education-related AI implementations. Higher education has not experienced as rapid a transformation related to AI use as K-12 education, though since professional education both reflects and influences social progress, that is beginning to change, with some college and university courses using AI as part of the course. For example, a course applied natural language processing and machine learning models such as sentiment analysis and auto-translation to real-world situations. The final speaker was one of the researchers who developed a language representation model. Participation was but one example of how college courses can expand the specialized expertise and availability of experts in this area. When preparing to teach a course on "AI and Creativity", a professor requested students prepare creative projects through various means, prompting them to integrate the technology into their practice, because disallowing AI use would create assignment outcomes that were not reflective of what AI could do.

A variety of uses of AI in higher education have been explored and often less enthusiastically implemented by faculty. Grading, in addition to being the bane of faculty members' academic existence, is potentially one of the largest areas for which AI can help. However, hiring teaching assistants to complete or assist with grading has been around for a long time and has only limited faculty buy-in. On the other hand, good results have been generated by using automated essay scoring for practice exams in a university-level computer science course, as a source of automated feedback for the grading of second-language-study short-answer writing assignments, and in assisting university teachers of English as a foreign language with students' writing.

9. Feedback Mechanisms in AI Learning Systems

AI learning systems are designed to process large amounts of data and turn it into valuable knowledge that can help students make better decisions and learn more effectively. These systems seek to support the student through feedback processes that ensure a level of connectedness between the AI learning model and the individual student. Feedback is often in response to a student input. When an automated system detects certain actions, feedback can be immediate. However, some feedback is asynchronous and may or may not be a direct response to an action. The feedback systems can be classified into two main categories: real-time feedback or delayed feedback. Some types of automated, preprogrammed feedback can lack adaptability and require customization of the feedback inputs. These types may be less satisfying but often represent the majority of feedback comments provided in graded evaluations of writing assignments. On the other hand, online discussions, such as peer review of student work, allow for input that can be responsive to the individual work being reviewed, and may help students achieve better understanding due to comments from multiple peers.

Different paradigms for real-time feedback exist. Some feedback occurs through student contact with the AI shaping the learning process. For example, some tutoring or exploration activities have feedback baked into the design of task, process and system. AI tutors based on intelligent natural language processing provide sustained conversations between AI and learner over time focused on the learned topics and potentially enabling deeper reflection than is possible for most topics in most derived non-dialogue interactions, at the cost of lower time efficiency for the interaction than the samples and models of using learnt knowledge in derivational interactions. However, real-time feedback is not easy to create. Important functions of a tutor are monitoring of the student performance database and checking for significant interesting cognitive reflection events. Automated systems can be used to provide power decompositions of keywords that are important for learning actions and student movement between previously gathered activity data clusters.

9.1. Real-time Feedback

One property that differs AI learning systems from traditional learning systems is the frequency which feedback is received on the learning process. Feedback of different types is received at different points in the learning process — from the design of the learning task to the completion of the task to an evaluation of what has been learned. The difference can be likened to the difference between oral interviews and typed exchanges. Learning in these two modalities is similar at times, but the differences in the frequency and depth of exchange create unique properties in the two modalities. In addition to the traditional feedback systems used in learning designed in AI systems, two enhancements are possible with AI systems, that of real-time feedback and that of peer feedback enhancements.

Most of the current computer-based instruction utilizes traditional instructional feedback methods that consist of a pre-formulated, expert provided solution path and expertise evaluation for students on the particular learning task. In contrast, humans in the proverbial one-room schoolhouse can observe several students while they work, offering correction to students who struggled with individual elements of the task. This level of real-time feedback requires more cognitive effort on the part of the expert than traditional feedback systems, and it becomes logistically impractical when the group of learners becomes large. However, this type of feedback is certainly what separates expert guided one-on-one tutoring from independent cognitive task analysis performed alone by students. The cognitive load of the tutor is decreased, and the potential benefit of the other feedback source is increased with the addition of multiple students working in real-time on a learning task with an AI system.

9.2. Peer Feedback Enhancements

Environments in which students can produce load of original and creative content such as videos and articles, teachers can no longer be solely responsible to evaluate students' productions. In fact, students are educationally motivated to receive feedback from peers if it is not just a decorative stamp of approval. The problem is that peer feedback can be incoherent, superficial, incorrect and even biased, due to the variety of training and expertise differences, offering little real support to the student. Moreover, most elements to provide a good quality peer review, such as use of checklists, rubrics, exemplars, practice of peer reviews, or allocating time to provide feedback are often neglected. Technology can help overcome some of the most common challenges in peer feedback, providing not only an enhancement of review quality, but making feedback more supportive, scaffolding and stimulating, filling the gap from the missing knowledge by other peers.

While peer feedback occurs when students respond to peers' work, primary expert assessment consists of the act of judging the quality of students' statements or productions. None of these assessors have the expertise or practical experience of the author of the work who writes the feedback, such as peers or the student who produces the work. For example, a paper can be of particular interest or importance for someone, but not for others; therefore, the value of the work may be very different for the student who creates it and for peers; they both have expertise of different kind, and they can both be important.

10. Collaboration Between AI and Educators

A collaboration between AI tools and technology-assisted learning needs the educators to integrate them, but this role is not explicitly described, nor does it guarantee that it will happen. Educators are responsible for shaping students' experiences and acting with a sense of agency to create experiences and spaces in which students can engage with the revolutionary possibilities of generative AI while maintaining an awareness of its limitations. University students are developmentally ready to explore ideas, take intellectual risks, and challenge assumptions both in themselves and in others. Educators have the responsibility to guide them through and to set the proper conditions so they might do this. How generative AI shifts the landscape of education is unclear, but an educator's relationships with their students will shape the shape that landscape takes.

By our definition, AI literacy embodies the two ways of knowing: AI understanding and instructional design knowledge. Generative AI can become a part of the digital tools in our classrooms, embedded within the existing practices within our discipline or those unique to the course being taught, but only if educators are themselves familiar with and use these tools. Because all of us regularly ask AI content questions, for example, we naturally integrate it within our communication and FAQ strategies as part of campus life. When students ask for movement help or video edits, we naturally have conversations about our choices of the instant AI tools – on which others contribute scenes and sequences. The reciprocal and collaborative relationships educators create with their students remain primary; they are the foundation upon which students' explorations and experiences occur, including those with generative AI.

10.1. Roles of Educators in AI Integration

With generative artificial intelligence tools being rapidly developed and increasingly integrated across education sectors, it is critical to examine and define how educators are involved in educational AI development and integration — not simply as consumers of enterprise solutions but as critical stakeholders. Educators are key in harnessing the creative potential such tools may enable, and educators' implications is especially necessary to consider given that current educational policies and service infrastructures are still largely influenced by the needs and motivations of governing institutions. Engaging educators in questions about how AI systems can enhance and augment innovative teaching and learning activities — and what kinds of new teaching and student engagement practices may be needed to put these opportunities into practice — is key to maximizing AI tools' positive impact and to guiding research and innovation efforts in AI. Education research also requires interdisciplinary collaboration between AI tool developers and education experts. To realize the most authentic and effective applications of AI in k20 and higher education, both educators and computer sciences must work together. Educators must leverage their knowledge of learning processes and pedagogy, and computer scientists must inform teachers of the technical capabilities of AI systems. Furthermore, we believe that the authentic implications of AI for teaching lie at the intersection of instruction and data.

The recent release and mass consumption of products illustrates how generative AI can automate tasks and serve as an intelligent collaborator across domains. At the forefront of this shift in creative production, critical examination of impacts on authorship, technical knowledge, and intellectual property violation and co-optation have revitalized discourse in design and media studies. Indeed, many educators may use generative AI in teaching creative projects, serving as an additional collaborator who provides parameters and direction for ideation. Given the speed at which generative AI is evolving, we framed our conversation for this chapter with an emphasis on collaboration — helping educators think about how to integrate generative AI into current teaching practices — so that they can gradually adapt to working with such tools. We cover our initial conversation on AI's implications for education research, immediate uses in teaching creative projects as well as longer-term paths for collaboration, and questions educators should ask themselves to consider where they want to go.

10.2. Building Trust in AI Tools

There has been a rapid development and interesting integration of AI technologies that impacts the education systems worldwide. Technologies like Machine Learning, Natural Language Processing, or Computer Vision have been main research targets of various scientific communities, including Education. In this chapter, we describe some key roles that educators have in the integration of AI into educational contexts. We also propose a set of guidelines that we hope may offer educators some practical advice for their work.

A primary option for teachers or educators is to design educational tasks that incorporate suitable AI tools and systems and hence take advantage of their affordances to offer students extra value. However, teachers have this same job in technology-enhanced learning by selecting non-AI educational technology.

Without the technologies becoming mainstream, educators may need some guidance about the pros and cons of introducing AI into learning tasks. Moreover, AI technologies come with new challenges of limited abilities that must always be considered and have a low-track trust issue, which represents a very common and constricting factor in integrating AI. For the students to trust these tools, they need to be exposed to them, but it must be in a safe context in which AI tools support their learning without being forced into the central role, nor students being obliged to use them.

Guiding learners into the responsible use of AI tools is, then, essential in the transfer of AI technology into learning scenarios. Here educators may take advantage of the role of co-learners, mentors, or facilitators of discussions, appropriate when learners are already aware of the strengths and weaknesses of AI tools being used in the task. It should be noted that students may have been the first to be introduced to the responsible use of technology. Throughout the last year, educational institutions have undergone a breakthrough of the integration of Learning Technologies in the classroom. They have been forced to experience the pedagogical and organizational integration of these digital tools for communication, research, and creation, which had previously been relegated to a subordinate role.

11. Cost Implications of AI in Education

With all this talk about incorporating AI into education, the first question that comes to mind is "At what cost?". Money does not grow on trees and for many schools and universities around the world, making the initial investment towards acquiring and maintaining AI systems is not a possibility now. Moreover, if education is meant to be accessible for all, then these costs should not fall solely on students or educational institutions. Instead, governments should offer larger subsidies. If we assume that humans will still play a role in education though, it is also important to consider the role of educators in this international discussion. The technology export and education export markets have great potential, so a use of proceeds model is key. Companies should commit to give back a portion of their revenues to fund AI research projects in education. There should be funding flows from big tech companies to fund the development of open-source AI tools with a focus on education. At the same time, governments must avoid using public funds to replace human educators with AI tools as a cost-saving measure since many technologies are supposed to be supplements, rather than complete replacements to the educators.

On the other hand, while these initial investment costs may appear difficult or impossible to manage for some actors, it must be kept in mind that there might be considerable savings in the long run. Additionally, using new technologies to help create lifelong learning systems may even translate into more revenue for a country as well. These tools can help remediate the schooling gap between high and low socio-economic status households within a country, which can help narrow the global innovation gap and spur future technological development. Through an international development lens, countries that offer their citizens quality access to education with the support of AI tools will increase their level of human capital and therefore enhance their comparative advantages in this globalized world.

11.1. Initial Investment vs Long-term Savings

Cost is a main concern of all teachers' and educators' concerns dealing with the introduction of AI in any daily activity. Anywhere a project is launched, the financial aspect is analysed. In education any innovation that is supposed to ameliorate students' learning experience as well as automatic correction of repetitive tasks for lecturers and teachers, can take a issuing launch. The economic side comes about because the investment that needs to be done in terms of financials, teachers training, infrastructure repair, as well as resources provisioning and auditing.

Undoubtedly education can benefit greatly, at least in the long term, from adopting this new technology. In the future we may even not have to rely on investing in economies of scale needed during the last centuries to enhance class sizes' heterogeneity and teachers’ shortages. The AI technology can provide complimentary and explicit advisory and feedback to students while undertaking repetitive or authentication-proving tests during the process of degree validation. We must remind that the education system is an experiment in itself and it is a powerful credential designed to provide value to the teachers and the national or international society. In this light there is a huge demand and need for this experiment to function properly. Therefore, nowadays, we cannot expect a zero investment in any change at that level. Indeed, times have changed and go through a tiny mild turbulence cycle from financial point of view. In the light of heretical views emerging, especially in the new technology, it would be more appropriate to think about downgrading the initial costs of funding the student’s education systems at least until graduation.

11.2. Funding Opportunities for Schools

AI in education is a growing area of interest for districts aiming to improve student outcomes and administrative efficiency. Gaining access to these tools requires funding. In the U.S., funding to support K–12 public education primarily comes from three sources: state appropriations, local property taxes, and federal grants. Budgeting timelines and practices vary by state, district, and priorities of current school leadership. With the influences of COVID-19 lingering for many K–12 systems, districts face unexpected budget restraints. It is worth considering how federal COVID relief funds and state pre-K–12 appropriations can be used to pay for AI tools and services.

Funding was earmarked for schools by states as part of the federal COVID-19 Economic Stimulus bill passed in March 2020. Nearly $30 billion was allocated to the Elementary and Secondary School Emergency Relief Fund to help educational institutions respond to the impact of COVID-19. Among its many other provisions, the law allows these funds to be used to pay for various activities and lists several strategies that could be funded, including Providing advanced coursework, dual enrolment programs, career and technical education programs or programs in other areas that the school or local educational agency has identified as being funds to pay for various activities. AI tools can help schools implement a brief list of allowable expenditures.

12. Global Perspectives on AI in Education

There are a growing number of AI-based educational tools being developed and or deployed across different educational levels and across different regions of the world. There are, however, very few comprehensive mappings available that showcase the breadth of this nascent AI in Education landscape. Fewer still attempt to tackle the unique social and cultural contexts that inform how AI takes shape in those different regions. For example, while the concept of AI and AI-texting technologies is being heavily discussed in Western economies, in many Southeast Asian countries, ongoing efforts to improve national education systems are still driving the public discourse. The global pandemic accelerated the use of AIEd tools across all educational levels, particularly K-12 public and private schools. Further, governments in several Asian countries have already invested heavily to spur innovation in the EdTech area, and in some cases, they are now seeking to build hard and software infrastructure fundamentals necessary to establish EdTech unicorns to help boost the economy in the post-pandemic.

We argue that education is one of the many areas in our society that reflects cultural and historical expectations within a specific context. As a result, AI in Education is also definitely a cross-cultural endeavour. Cultural diversity in applying a single technology influences the design and implementation of that technology in those specific local contexts. There are several cross-country differences that we have made also based on our own experiences and prior research. These include: a) the public funding: private vs public funded educational systems; b) the school policies: centralized vs decentralized control; c) the habits: Synchronous vs Asynchronous or diverse learning habits; d) the culture: collectivistic vs individualistic culture; e) the language: the availability of dominant language learning tool; f) the ethics: Privacy; g) the Partnerships; and h) the depth: surface vs deep approach.

12.1. Case Studies from Different Countries

AI has been around for a while and is generating tools that are now part of the curriculum for computer science professionals and digital learning designers. Whether those tools are used for educational purposes, for content production, or as a new field of work is up to the educational institutions to discuss and decide. The opportunity of teaching how to use these tools with a critical mind, understanding their ethical implications, or that they will create a new field of freelance jobs and companies for digital content creation is also an opportunity. Starting from the experience of advanced economies makes equity an even bigger issue to tackle and, of course, the debate should be an open one. Interest in the implementation of artificial intelligence into educational processes and structures is becoming more common at the national and global scale. The push is mainly stimulated by the plans designed to further and innovate student learning experience, teacher training, and institutional management. In the wide array of both social and political needs to be addressed, different countries around the world have developed concrete strategies and projects from which others can learn. Within this chapter we attempt to present several country studies, mapping present implementations and encouraging a discussion about how best practice shown in one country can be adopted by a different one, which political goals would need to be rethought, and which institutional players would need to be involved for the migrant digital project to bear fruit. As these examples show, given the globalization we live in today, new and better ways of serving our students across the world are becoming increasingly vital. However, the temptation of jumping on the new technological promise bandwagon for socially and educationally specific problems, or the top-down adoption of techno-solutionism by governments born from countries with fragile democracy, requires caution. Tailoring the new promises to the needs and structural difficulties of a country is paramount in producing sounder policies as well as in their automatic digital transposition in national or institutional level projects.

12.2. Cultural Considerations

Keywords: AI, education, perspective, matter, question

In focusing on the interaction between generative and supportive AI and the subsequent effect on the educational experience of learners, it is easy to overlook that a culturally agnostic view can also lead to misses bordering on catastrophe. Attempts at creating all-encompassing AI experiences have veered sharply off course in genuinely magisterial ways when sufficient concern for local culture and practices has been observed. For example, court-mandated spying on digital notebooks taken into schools has concluded with digital surveillance of minors as a direct result of asking the question, "How does an education technology AI product designed for the U.S. specifically operate within a country in which certain acts of war are illegal?"

At its essence, the issue is not merely about age-appropriate behaviour in pedagogical support by AI products or services – the issue runs much deeper and concerns the very identity of school systems and their educational experience which have grown out of the cultural specificities of formation within a nation’s society. For example, in countries where children are seen as miniature adults, the educational experience generally involves a painful but necessary process of earning and keeping respect through various acts of behaviour-modifying disgrace by teachers over years. The endpoint of this cultural-based educational process is the formation of fully responsible and adult citizens of a nation-state. In the West, children are typically regarded as in need of special care, with the responsibility of protecting children being placed primarily on parents. The obligation of a teacher is not to inflict harm on the developing child, but to nurture with a sense of mutual responsibility, leading each child to be concerned for growth and development within the community of class and school. Therefore, it is not unusual for punishments and public shaming of learners as a group by a teacher who has lost control of a group to attract severe legal repercussions.

13. Conclusion

The educational frontier is becoming a more challenging and contested space, and academia could be heading in the wrong direction, guided by systems which offer mystical answers to questions we should not be asking in the first place.

The trend toward e-tech delivery via commercial providers is intensifying, and institutions whose primary countryside has become increasingly stripped of support activities are seeking cash to fill gaps in their budgets, proposing to commercialize student data and partner up with increasingly rapacious technology providers. Corporate development is hungry for data, and policies encouraging the commercial use of student information.

This report does not claim to predict future scenarios. Rather, it is an attempt to reflect and synthesize the range of positions that have so far emerged in scholarly and non-academic commentary about the role of AI in education. Our central concern is not prediction but reflection. The essays collected here focus primarily on what AI can do to or for students and the consequences of these for the future of education. Predictions about the effects of ever-more-humanlike machines giving information or tutorial support to students pepper the prediction-driven commentaries on programs.

Less space has yet been dedicated to thinking about the appropriate educational context within which to make predictions about student-agent interactions. If we have tended to regard information and feedback as the dominant forms of educational input, it may be time to remember that education also comes through experience and interaction within. The essays collected here address questions about the future of the role of the educator and the experience of the student as they become staged within the metaverse as much as about the technology itself.

References:

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *Ieee Access*, *8*, 75264-75278.

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European journal of education*, *57*(4), 542-570.

Jeon, J., & Lee, S. (2023). Large language models in education: A focus on the complementary relationship between human teachers and ChatGPT. *Education and Information Technologies*, *28*(12), 15873-15892.

Kim, J., Lee, H., & Cho, Y. H. (2022). Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. *Education and information technologies*, *27*(5), 6069-6104.

Luckin, R., & Holmes, W. (2016). Intelligence unleashed: An argument for AI in education.

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., ... & Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. *Complexity*, *2021*(1), 8812542.

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Computers and education: Artificial intelligence*, *2,* 100025.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 6: Artificial Intelligence in Retail: Enhancing Customer Experience and Operational Efficiency

1. Introduction to AI in Retail

The last decades have seen a significant increase in digital technologies and the available data. With the proliferation of the Internet and the mobile developments in commerce, today there are billions of consumers that produce unsolicited data. Using this data can represent a big advantage, and more than before, companies should be prepared to follow the consumers and users during their journey and through the various channels. The retail industry manages many transactions; this becomes especially true for omnichannel strategies. The amount of data generated is hard to imagine from a conventional business perspective, and this requires Big Data tools to be able to treat the data volume and give it a sense. Of course, the importance of data in today's economy is not only to support the company in making its transactions quicker and to provide a better experience for its customers. The use of Machine Learning and AI-based solutions has already transformed and improved many operations in various business areas. There is today a vast literature on how to implement AI-based solutions in different areas, also selecting specific typologies.

The retail industry is not an exception, and it already relies on the numerous developments in consumer experience management and the retail operational sides (Haleem et al., 2022; Har et al., 2022; Mak et al., 2024). But like in every sector, the implementation of such projects is not without criticism. The bad experience of some companies that faced very costly failures should be mentioned. What's new is that there is a significant amount of new AI-based services that can help retailers in these processes. And what is even more interesting is that cloud platforms are integrating such tools into their services, hiding the complexity and making the technology processes even less cost-intensive. This allows also small and medium retailers to take advantage of the developments AI solutions can bring into these processes. Data privacy and protection are however some critical points, and the latest rules introduced by the EU dictate strict regulations that a retailer has to comply with if they want to use consumer data in their processes.

2. Understanding Recommendation Engines

To enhance user experience and increase sales, many ecommerce and online business sites use AI-based recommendation engines (Ooi et al., 2025; Oosthuizen et al., 2021; Weber & Schütte, 2019). The recommendation engines use machine learning algorithms to study past behaviors of users who visit the site and then recommend products or search suggestions that the customer is likely to engage with. These products may or may not be related to the previous search, and the earlier patterns are also tracked using data collection tools. A recommendation engine understands the customers' preferences with the help of deep learning, increasing the chance of customer engagement. Most of the ecommerce companies borrow recommendation engines and personalize them according to their requirements, creating a unique customer experience.

With the help of recommendation engines, you can do much more than just guide users to their goal. With additional UX capabilities like personalization and recommendation features added on top of a traditional search engine, you can now enhance user and customer experience by modeling who your user is and offering helpful suggestions that point to resources. Remember a time when you went into a store just to browse around because you weren't actually looking for anything specific, but knew that if you found the right thing, you might just buy it. Implementing a recommendation engine is going to be similar to that experience, only done through technology instead of an associate seeing you walk through the door. Also, you can analyze your user interactions, engagement, and satisfaction with the added bonus that you know who the user is, which is something you can't get from traditional search engines.

2.1. How Recommendation Engines Work

Recommendation algorithms are broadly classified into two categories: Content-Based Filtering and Collaborative Filtering or a hybrid model that attempts to combine the strengths of these approaches. Recommendation engines typically use one or a combination of the following approaches: Using ratings, classification, and clustering of products, attributes of users, and user activities to recommend products to a user. Generally, the more data available about the user, the better the recommendations. Recommendation engines are usually placed on the e-Commerce website at critical points in the user's shopping journey. Recommendations can appear on the search results page, on the category pages, and even on the product pages. Interestingly, it was found that placing the recommendations directly below the search box of the e-Commerce site especially helped improve conversion rate.

The aim of a recommendation engine is to help users discover products that they intend to buy, and at the same time, enhance the purchase decisions by incorporating persuasive advertising techniques. For this purpose, recommendation engines gather product preference data based on the ratings provided by users to different sets of products. Typically, users provide ratings for several watch lists. The items in the watch list represent the preference of the user for a particular item. This allows the recommendation engine to predict the ratings for other items that have not yet been rated or belong to the latent space. A user talks about the item in the latent space when the latent space has not yet been connected to the user. Connecting the latent space means recommending the user an item that has a long history but hasn't been connected to the user yet and is likely to be connected after some time.

2.2. Types of Recommendation Algorithms

Recommendation engines have become a popular research topic because of the rapid development of the Internet, the ever-growing number of online services, and the tremendous potential for personalized consumption enabled by information technology. And these algorithms can be divided into content-based filtering, collaborative filtering, and hybrid filtering algorithms. All of these recommendation approaches and techniques allow various types of filtering processes, such as the implicit or explicit utilization of user profiles, the content of products, and support from other user feedback and opinions, usually stored in the rating matrix.

Content-based recommendation systems utilize the description of an item and a user's profile to suggest new items, while collaborative filtering methods utilize a user-item rating matrix to suggest new items. The third approach, hybrid recommendation systems, combines both content-based and collaborative filtering methods to suggest new items to users. The advantage of content-based systems is that they can suggest items that have not been popular yet. In contrast, the collaborative filtering system suggests popular items based on the correlations between user ratings for the items within a community or between item ratings in a time-frame. However, collaborative filtering systems suffer from the so-called "cold-start" problem, where they cannot suggest items for users who have no history. Hybrid recommender systems have been designed to utilize multiple techniques. These systems can achieve better practical performance than single methods in many cases. In recent years, more and more hybrid systems have been developed.

The recommendation process consists of several phases, including the acquisition of explicit and implicit information for users and items, the selection of an appropriate technique to build recommendation models to filter and rank candidate items, and the evaluation of the proposed systems to assure the quality and accuracy of recommendations.

2.3. Impact on Customer Engagement

Shoppers shopping on the internet are often overwhelmed by the choice available to them. Some studies predict that over 90% of potential earnings for an e-commerce company are wasted when their recommendation system doesn't find the products the potential user needs and proposes other, less interesting products. This fact highlights the importance of recommendation engines in increasing sales figures and user experience for online companies. But recommendation engines are not only limited to the e-commerce industry. Recommendations can also be very useful in e-learning platforms, news aggregators, social networks, and online streaming services. Personalization is becoming an essential part of reaching and retaining today's consumers. If brands don't create a unique and relevant experience for consumers, they are unlikely to gain their loyalty. A study showed that 64 percent of consumers think that online retailers have lost touch with their customers and that no longer take into consideration their consumer journey. But the fact is that increasingly massive data, combined with new technologies of Artificial Intelligence, Big Data and collaborative economy provide companies with instruments to create customized value propositions to a customer segment. AI technology can analyze product characteristics and shopper behavioral data on every individual product and process this information to offer consumers unique experiences for each visit on the channel.

AI learns about consumers by analyzing behavioral data, to better define segments and dynamic personas, for immediate and proactive customization of offers and services, and is being integrated into the recommendation engines. While traditional recommender systems used a one-size-fits-all approach to recommend a single product at the account level, AI technology analyses real-time shopper behavior to deliver hyper-personalized recommendations for each consumer, segment, or dynamic persona. AI-powered recommendation engines can transform the challenges retailers face regarding overwhelming choice and zero moment of truth into market advantages.

3. Leveraging Customer Insights

The retailers must keep pace with the rapid evolution of consumer expectations, motivations, and methods. Fortunately, department, grocery, and other retail executives need to enable enhanced customer experiences and higher operational efficiency by focusing on leveraging targeted customer insights across the customer lifecycle, creating personalized marketing experiences and proactive, context-based customer service. By analyzing vast amounts of customer data generated throughout the customer lifecycle, organizations can anticipate customer behaviors and preferences and determine how best to nurture the relationship.

Knowing how customers think and behave has always been valuable information in the retail business. The creation of personalized customer experiences—attracting consumers more effectively, keeping them loyal longer, and improving profitability—is the prime directive in retail today. Retailers can address this challenge by leveraging customer data more efficiently. However, creating customer insight databases filled with raw data and then leveraging that information using analytics to bolster personalized customer interactions and experiences is a big step forward. Based on their needs and preferences, data-driven differentiated and personalized offerings can be sent to consumers via their preferred touch points, including web, phone, or social channels.

Decision science is the judgment-based application of mathematics: the use of statistics, mathematics, forecasting, and advanced analytics as supportive guidance for the business. Although retail marketing has traditionally been based on opinion, instinct, observation, and experience, today it can be driven by data, resulting in improved targeting of marketing activity and better thought-out choices of product selection and positioning contributing to increased company profitability.

3.1. Data Collection Techniques

In order to leverage customer insights into features, designs, and services that customers expect, retailers should effectively collect and analyze customer data. There are several different techniques or approaches available to retailers for collecting customer data. Retailers have traditionally relied on surveys and questionnaires to collect customer data. Although these methods have served their purpose well, there are a number of limitations. First, conducting surveys and questionnaires costs time and money and often the sample size may be small and the results biased. Second, customers often do not reveal their true preferences when answering questions. Third, it is relatively expensive to collect survey data at large scale. Finally, surveys and questionnaires generally provide providers with realized preferences and not stated preferences.

Due to the wide proliferation of e-commerce over the past 30 years, retailers can now go beyond traditional surveys and leverage clickstream data, also known as digital breadcrumbs. Clickstream data refer to unsolicited, passive, transactional data that provide information on the series of clicks or pages viewed by customers during their website visits. These data are a window into the real-world behavior of consumers and can supplement survey data collected during website visits. The advantages of clickstream data collection technologies relative to survey methods are clear. First, clickstream data is easily obtainable, requiring little time and money. Second, these data are unsolicited and reflect true preferences as opposed to stated preferences. Third, they can be collected at extremely large scales and at a relatively low cost. Finally, clickstream data provide data not just on realized consumer preferences but also paths taken by consumers not yielding purchases or the choice sets considered.

3.2. Analyzing Customer Behavior

To address the growing demand for personalization, retail businesses today have access to an unprecedented amount of data. Artificial intelligence has made it possible to access, organize, and analyze this data with great speed, generating insights into customer behavior that make it possible to customize the shopping experience. Through large amounts of data represented in different formats and cumulative experiences, AI helps retailers understand what customers want and provide them with precisely what they want, when they want it. Retailers can do this thanks to better tools for analyzing purchasing habits, improved customization, targeted marketing, and the management of customer relationships.

AI analyzes historical data and combines this with insights about the current state of consumers in a relevant context. Using machine learning algorithms, retailers can analyze their customers' behavior, using it to make predictions that allow for future actions. With AI, a retailer can deploy such analytics to generate a better understanding of which factors are most core to customers' decisions to act. And it can make segmentation much simpler. These technology-guided insights help create models of customer journeys, allowing retailers to provide relevant support at each stage of their consumers' journeys.

Factors such as seasonal variations, new product releases, and time of day are all significant catalysts of customer behavior. With AI-powered algorithms, retailers can analyze their data to determine which factors have the highest impact on the shopper journey. Doing so allows retailers to send messages at the right time and design specific pathways that lead customers through the online experience at the right pace. Those pathways can be based on segments of consumers with shared behavioral trends and can be modified by movements in factors that influence intent, throughout the year.

3.3. Personalization Strategies

Personalization ranges from product recommendations to website design, all aimed at enhancing customer experience. Personalized product recommendations are utilized by many retailers to suggest products that consumers might like. Several AI-powered services provide this functionality, learning from a shopper's past activities, analyzing purchase data from similar shoppers, and taking product attributes into account. They suggest items that other similar customers bought in one visit, correlate the trends from that visit with the shopper’s past shopping behaviors, and from this trend, predict which product categories the shopper might be interested in browsing during their next visit. Using this approach, companies have been able to increase click-through rates significantly.

Many e-commerce platforms offer personalized emails to their customers. When customers sign up for a mail subscription, retailers capture their demographic data and historical information, including wish list(s), shopping cart, purchases, browsing clicks, and engagement with previous emails. Most retailers will revamp their website's look and feel, and the recommended products will change continuously through the shopping session. It is very common for a shopper to receive personalized emails with product recommendations that are available at enticing discounted rates or that are tailored for a specific occasion based on the shopper's past purchases.

Additionally, providing customers with access to their own shopping data, such as a list of ongoing products or services associated with their activities or indicative data, is another effective way to enhance the shopping experience. An AI-powered platform for virtual styling creates hyper-relevant personalized content for every user at scale. Marketplaces can use this information to revamp product descriptions or to show how long users need to wait to have their products delivered. Promoting social interactions among consumers on a retailer's website through review systems and community forums can create an emotional connection, facilitating the personalization process and providing consumers with relevant product information.

4. AI in Inventory Management

Inventory management is one of the oldest applications of AI in retail. More recently, its subfield, known as supply chain management, has seen a resurgence in interest – thanks in part to the pandemic, which caused many retailers to rethink their supply chains. In general, companies have AI-based demand forecasting at the core, which helps companies know how many products they need to stock, where they need to stock them, and when. Companies center their products around demand forecasting. In other words, instead of reacting to demand once it's occurred, companies are trying to understand what will spur demand ahead of time. AI-based companies then add extra services on top of that core.

Fortunately, for retailers, the potential benefits of improving forecasting accuracy are huge. Compound annual growth rates in the high teens projected for the market for revenue management and price optimization solutions reflect a recognition of their importance, and for clients industry over reliance on historical data has hampered forecasting efforts. For example, grocery chains have historically focused on seasonality when forecasting demand. Delays in shipments, however, meant those chains had also started bringing in seasonal items in March and only reduced stock at the end of December. As the pandemic demonstrated, however, social media can also spur spikes in demand for desired products, meaning that the results of the most recent cycle might not be the most salient.

Retailers have historically dealt with inevitable forecasting errors in a reactive manner. Supply chain resiliency has refocused interest in AI-assisted forecasting, as macro-level steps can be taken to buffer against problems. These typically include holding more inventory to fulfill demand, faced particularly serious because of stockouts during the pandemic, embedding more flexibility in the supply chain to allow for external partners to expand production, or creating a centralized "control tower" that enables data sourcing and analytics for factories. Advanced planning and scheduling approaches including short-term distribution and fulfillment, as well as replenishment planning, have also seen increased investment.

4.1. Forecasting Demand with AI

Using AI in retail is key to unlocking value throughout the organization. AI can enhance customer experience, increase product margin, improve technology and website efficiency, expand revenue opportunities, simplify fraud and order issue management, create greater trust and transparency, and improve performance management and workforce production. The initial stage for retailers when using AI is to discover, then define, the business problems to be ideally solved through AI, based on a clear and thorough understanding of the power of all the developing techniques of AI. Then, the data required by those techniques need to be resident in the company with the requisite accuracy, depth, and breadth. Then, this data needs to be distilled and run through the appropriate AI algorithms and finally assessed for quality, leverage, and usefulness to the business.

An important first use of machine learning is in demand forecasting. While many companies employ historical sales data to forecast near-term demand, greater business efficiency and market share could result when forecasts are based on additional factors that determine customer demand at the SKU/store/location level. Accurate demand forecasting is a vital process for retailers. These forecasts help retailers make intelligent decisions about how much and what products to carry for the every changing needs of their customers. Forecasting methods routinely used by retailers are often based exclusively on known patterns in historical demand. However, only using historical data often results in inaccuracies, and the inability to know how sales are going to change with shifts in trends due to economic impacts or mix-shifts in the products being bought.

4.2. Automating Inventory Processes

Inventory management involves tracking and accounting for merchandise in a retail business and can be a major overhead cost. Retailers have used innovative technology to help manage their inventories for years: an early pioneering use of technology was the use of barcode-supported electronic Point-Of-Sale systems linked to computerized backend systems that automatically updated inventories after each sale transaction. In the last few years, there has been a boom in the use of Artificial Intelligence and Machine Learning algorithms to automate more sophisticated inventory decisions and processes. Examples include using AI/ML-based algorithms to enable visibility of inventory across points in a supply chain network, up-to-the-minute inventory levels across all channels and sites, and updating inventory data in real-time for view by all internal and external partners.

Another area of rapid growth in AI-based inventory automation is the automation of warehouse and storage management processes. Labor is often the highest cost component of these processes, and major retail corporations have invested heavily in automating these processes using AI-driven robots – for example, robots that scan shelves to detect out-of-stock situations or misplaced products in stores or identify stock levels and manage stock reconciling in warehouses and distribution centers. Other real-world examples of inventory process automation using AI involve the generation of real-time data-driven recommendations for cycle-counting and reconciliation considerations across items and locations, fulfillment of customer orders through transfers between stores, and inventory planning in terms of optimization of base or safety stock targets to achieve service levels at the lowest possible cost.

4.3. Reducing Stockouts and Overstocks

Stockouts inevitably mean lost sales, customer disappointment, and diminishing brand equity. And while reducing stockouts is a high priority for the majority of retailers, it is not the only issue they face. Overstocking can have a chilling effect on a company's financial health, especially in an era of changing consumer preferences, rising inflation, and environmental awareness, and it can erode profits, consume working capital, and spoil merchandise. More retailers are facing the dilemma of reduced sales margins on e-commerce products being met with hefty liquidation markdowns on excess inventory. These broad factors make it imperative that AI plays a key role in addressing the challenges of stockouts and overstocks.

AI can reduce stockouts and overstocks by assisting stores in using their omnichannel capabilities to meet demand without overstretching their financial resources or affecting their in-store customers. One of the main goals of an omnichannel supply chain is to enable the store to act as both a ship-from location as well as a physical location from which customers can purchase. With its on-the-ground presence, a store is in the best possible position to handle spontaneous demand — last-minute purchases when shoppers are likely to bundle items from multiple categories before going home to prepare for a celebration. However, without a precise balance between need and capability, an omnichannel supply chain may create stockouts on e-commerce purchases while wasting a store's space and financial resources in the fulfillment process, thus leading to greater excess inventory.

5. Case Studies of AI Implementation in Retail

To further illustrate the current state of AI in retail, we will discuss a variety of companies, large and small, that have implemented AI to support a retailer function or to support an operational area. We will discuss the function or operational area that the company chose to support, briefly discuss what the AI supported, data requirements, the algorithms used, selection criteria if any, and the observed benefits.

5.1. Success Stories from Leading Retailers

A North American grocery retailer implemented AI and ML consulting capabilities to improve produce shelf product rank, anticipate demand shifts, and generate better inventory forecasts. The company ultimately implemented a prebuilt ML solution, which allowed the company to rapidly solve business problems leveraging transaction data and applied multiple ML algorithms to the data using a single solution. The implemented AI capabilities have produced dramatic results across retail. For example, forecasting accuracy in food services has improved significantly. The AI investments also estimated to support a substantial bottom line impact in customer and associate experiences.

Another retailer has invested in AI supply chain and customer assistance applications. For example, the company has experimented with drone deliveries, robots that assist in store operations, and remote maintenance capabilities. It also has used AI to improve supply chain efficiencies in the wake of increased online orders. The AI efforts were augmented by a robotics effort less than two years ago. In addition, the company's CEO stated that the company had over two dozen robotics projects in development and aims to employ AI across a range of functions, including checkout-free shopping and order fulfillment. The AI products used in these efforts utilize numerous ML models across business and product launches. Recent AI implementation efforts and ML solutions have resulted in enhanced customer in-store experiences as well as providing increased employee support for in-store associates.

5.1. Success Stories from Leading Retailers

Walmart has leveraged AI to improve in-stock levels, saving over $400 billion in grocery spends and $600 billion in other key areas. AI systems analyze customer insights and market trends, develop AI-based forecasting models, and optimize inventory at a sub-county level. Other initiatives like scan-and-go mobile apps, AI-enabled stores, cashier-less stores, and virtual fitting rooms helped elevate customer experience. Macy’s also capitalized on AI for enhancing experience and efficiency by testing virtual shopping assistants, AI-based smart predictive solutions for inventory and price optimization, and virtual fitting rooms. They understood that AI-based chatbots could enhance customer experience, convert window shopping into purchases, and make the retail experience personalized.

Nordstrom has been testing AI assistants to help customers find the right sizes. The AI assistant would pull data regarding how many orders have been made, what sizes are being bought, what looks best on what figure, and so on. It will alert customers whenever an item in a desired color and size becomes available. The fashion brand Ralph Lauren recently claimed it opened a digital store that uses AI algorithms to analyze every item of clothing to make it easier for customers to find similar pieces. eBay has been using AI to help customers find the best items based on their preferences, using AI algorithms that understand the body structure and recommend the item to suit the person best. Beauty brands like Estée Lauder and L’Oreal have been investing heavily in AR and AI solutions to customize the beauty shopping experience. They offer virtual makeup apps that let beauty lovers try new products and shades on their handheld devices. L’Oreal developed an AR tool that allows customers to test out various shades. Estée Lauder uses Face Filters to allow customers to feel beautiful in minutes via an immersive experience.

5.2. Lessons Learned from Failed Implementations

AI is at a turning point in which many organizations are increasing investments in AI but at the same time the results are mixed. More than 50 percent of the surveyed companies reported little to no impact or value from AI and ML, and 5 percent said that they had encountered significant issues with the implementation. These realities have led some AI experts to advocate to embrace caution, at least in the short term.

In AI for retail, there are a number of examples where retailers have experienced false starts, despite eager interest. A good amount of these false starts have led to the label of “AI winter” in retail. Many reports had predicted that organizations would inundate themselves with data from the Internet of Things, use it to predict future trends and preferences using machine learning, and create a conceptual “retail ecosystem.” These ecosystems would include manufacturers, service providers, retailers, customers, and even competitors, and would allow retailers to deliver unprecedented personalized omni-channel experiences. In practice, research and interviews show that the results have been much more mixed, with many companies delaying or tempering their initial AI plans. They are moving more slowly than their peer companies in other industries, both in deploying AI and in seeing returns.

Implementing AI requires patience and strategy to actually deliver results and not all companies or use cases are suited for AI in the first place. The case studies in this chapter provide insights into the opportunities in AI, but also the cautionary tales of starting down the wrong path. These lessons learned from failed implementations are certainly not exhaustive, but highlight some elements of caution that retailers should keep in mind when considering AI investments.

6. Challenges in Implementing AI Solutions

AI Solutions in Retail: Challenges

Over the last few years, AI has proven its ability to serve as an amplifier of existing capabilities, improving operational processes at every level, from logistics and the supply chain to customer support, sales forecasting, staff management, and product recommendations. This potential does translate into new applications of AI in retailing. Experiments are being led, and efficient AI solutions are becoming the focus of increasing interest. Yet several issues remain to be addressed.

Even though plenty of data already exists, there are obstacles that retailers need to address first. Although these obstacles appear both at a technical and managerial level, we will focus our discussion mainly on their organizational implications, as AI implementation flourishes in organizations that embrace data-driven decision-making. We will discuss the following three issues herein: concerns about data privacy, the integration of AI solutions into existing processes, procedures, and management systems, as well as the question of change management.

Data Privacy Concerns

Because AI applications are able to analyze large amounts of data in order to identify consumption patterns of individual buyers, customers may be concerned about how their personal data is managed and stored. This could negatively affect consumers' willingness to share their personal information in the first place. At the same time, sound data management practices cannot exist without significant investments. However, companies are reluctant to invest and thus gain customers' trust, especially among smaller and medium-sized retailers who are ultimately more dependent on customer trust because customers have a larger choice of where to buy. Yet, failure is not an option. Retailers need to recall that dollar volumes of success depend on customer willingness to share personal data. Retailers need to make customers aware of the benefits they can derive in utilizing personal data. However, this is easier said than done since convincing customers is a matter of trust and may require increased communication before results become visible; thus, it takes considerable time and effort.

6.1. Data Privacy Concerns

Even when AI-enhanced solutions provide measurable benefits, their actual widespread adoption in retail applications is still hindered by multiple apprehension factors related to regulation, costs, and management. The application of AI in the retail sector promises a significant transformation of the shopping experience for customers. However, this technology draws attention because the power of AI lies in its data collection capabilities, including customer data inputs, utilizing important details, such as location, age, and gender to have the ability to understand user behavior, thereby being able to generate personalized experiences.

The enforcement of structured Data Privacy regulations is extremely focused on informing customers about information being collected. In simple terms, data risks are associated with the use of third-party services. AI can be utilized by customers themselves to fulfill requirement protections and genuinely provide increased security to the clients. Enabling AI processes, companies will be able to execute essential processes and predict unexpected consequences if any deviation occurs in their processes, thereby diminishing the risk in an unconventional manner. Even though regulatory measures are being initiated, the creation of boundaries is still impending concerning international data processing with third-party solutions, organizations participating in AI implementation need clarification on the way to stay in compliance with its usage and share regulations.

In all appearances, Data Privacy will be a barrier in AI privacy for organizations that use technology for the clients. On the other hand, it brings forth Cybersecurity, considering its usage would imply for commercial organizations with any deviation from clients identity data, colliding with important unseen effects. Thus, by being always in transaction with clients, organizations must seek for more personalized security or AI utilization in order to minimize and avoid these barriers as much as possible.

6.2. Integration with Existing Systems

AI systems designed with an ecosystem-integration strategy layer on top of existing systems and should work in concert with third-party solutions that serve our customers and retail partners. It is possible that systems already exist and function, and patchwork solutions appear to be the quick fix. However, if they are not designed as an ecosystem, they eventually become fragile – it’s like hiding your mistakes; it sooner or later catches up with you.

It is critical to create a seamless foundation by integrating all third-party systems with purpose-built APIs and establish a dependable and stable communication system. It must integrate across various operations such as third-party call centers, product inventors, smart carts, internal company messenger systems for employee communication, company self-census apps for customer awareness, decision-making company intranet, shipping and logistics systems, gathered data stored in the company’s cloud over the years, digital coupons, consumer customer relationship management system, and internal enterprise resource management workflows that face partners at multiple levels.

The ethos must be clear communication, voluminous use, and being helpful to all partners. Most of us don’t think twice about asking someone to help us find things while shopping, whether it be a sales representative or someone who looks like they work there. Why haven’t organizations devised methods for their customers to ask for assistance without having to search for a human being? A wonder of artificial intelligence would be that there is simply no need for an individual assistant. Your smart shopping cart and the members of the ecosystem who stay connected to it can guide you and help others as well. If you want any additional help, it connects you to an existing human assistant who is nearby and available.

6.3. Managing Change in Retail Organizations

Change is never easy, and especially in large organizations where inertia is a significant factor, an environment in which everyone behaves according to standard organizational operating practices. Technology adoption is something managers usually feel should be simple and straightforward, that people will embrace these new machines, tools, or processes and relish their change of routine. Yet, research has long established that resistance to change is almost widespread and has created models, guidelines, and toolsets aimed at helping managers in sales, manufacturing, logistics, and the like when new technology has been introduced into their department. For complexity and cost reasons, and unlike IT solutions, which are rarely subjected to this process, it is still common practice to roll out new technology and systems without advanced planning and without considering how the new systems should fit intuitively into employee work routines.

Retail organizations are perhaps more prone to technology rollouts without considering behavioral states. Store Associates hardly have any voice in decision-making and often feel that brand headquarters are far removed from the realities of working in a store. The associates are told to embrace artificial intelligence solutions as recommended merchandise topics from other parts of the world, proposed footfall forecasts, and guidelines for clearance of unwanted inventory. But discoveries of the digital revolution are themselves often unhappy when higher level artificial intelligence and machine learning systems fail to make their jobs easier, or even worse, make certain job functions obsolete and therefore not as readily promoted, indicate instead greater employee tracking and oversight. After investing millions of dollars in sensing, monitoring, and evaluation tools to increase their job efficiency, store personnel in return begin to feel threatened by their usage. They feel less motivated to service customers, and return visitation declines as long-terms sales also go down, despite deep learning mastering recommendation predictions at unprecedented accuracy levels.

7. Future Trends in AI and Retail

Technological advancements are constantly reshaping many aspects of our lives and as a result are also changing how retailers interact with consumers. Future AI innovations will be needed to respond to those challenges. In this section, we will reflect on some emerging technologies, shifts in consumers' expectations, and the role of AI in making retail more sustainable.

7.1 Emerging Technologies

Generative AI has already created many use cases in industries ranging from oil exploration to customer service. In the future, we expect to see a larger number of advertising use cases. This includes creating images that transform the advertisement from a static message to a personalized interactive journey while also optimizing the creation process. For instance, using dynamic optimization, the most relevant answers can be suggested to the customer while at the same time, the interactive nature of the advertisement increases engagement. While many of such use cases could also be applied to retail, the potential impacts on economics are less clear. We also anticipate seeing more human-centric optimization, in particular around the creative processes. The opportunities for retailers in these areas is two-fold: Either to create compelling use cases to convince customers to shift a portion of their spending towards them or to use the novel technologies to reduce costs significantly.

7.2 Shifts in Consumer Expectations

While technology is developing rapidly, the long-term implication will depend on how consumer preferences shift with it. First, we should again discuss the concerns around data privacy. Having gotten used to relying on a small number of costs-free services, consumers may once again turn more critical to companies gathering large amounts of data around them. Companies ignoring their customers' expectations around data privacy might see pushing back against personalized advertising.

7.3 The Role of AI in Sustainable Retail

Retail is in a unique and pivotal position to drive sustainable consumer behaviors, as it forms the bridge between production and consumption. Sustainability considerations influence the choices along the entire value chain from sourcing to logistics to consumers. Moreover, retailers can impose rules about sustainable sourcing on suppliers and address consumers' concerns at the point of consumption. In particular, the sustainability of certain high-impact categories such as plastic and packaging, food product, or textiles is determined by the consumer choices and needs constant addressing.

7.1. Emerging Technologies

In modern commerce, Artificial Intelligence (AI) technology is more powerful than others at larger scales. Retailers are looking for ways to continuously influence the mass consumer base throughout the buying lifecycle. This part of the business has changed forever, and major sections in-store have been refashioned to offer the customers the "experience" rather than pure product selection. Customers are looking for more in the aisles: more fun, interaction and bonding. Surprise and delight have emerged as critical components of shopping. In order to do that, retailers are employing a surprising amount of technology compared to what had existed even a few years ago. With the rapid application of robotics, the information from images, and smart RFID tags, shopper engagement is taken to a new level.

For example, high-dollar women's shoes are sold with RFID tags hidden in a smart way – between the leather layers – so that they cannot be seen. The imaging technology being employed in checkout-free physical stores is allowing brick and mortar to enter a new age as well where shopper behavior can be analyzed and repressed if necessary. AI is being applied to face and speech recognition solutions in order to assist in selecting and processing visitors that enter physical spaces. Some venues are actually employing emotion analysis solutions so that customer experiences can be pulled using software to evaluate key online and video facial inputs. Predictive shopping is being turned useful through digital technology-based recommendation systems that anticipate shopper needs.

7.2. Shifts in Consumer Expectations

After two years of pandemic-driven digital acceleration and deck-chaotic occurrences from politics to climate, consumer and employee customers seem to have all lost trust in the very retail and restaurant brands that built broad-positive equity for mission clarity and a purposeful center. Life is less predictable, people are more stressed, personal aspirations have shifted— to respect and support for self, family, and community—and work-life balance is more important than ever before. So, hold onto analytics— for hyper-local insights, AI and ML for the tactical optimization of business rules, demand sensing for smart price, promotion, and assortment strategies and portfolio choices, and cloud-based digitalization for the integration, agility, and resource efficiency of omnichannel execution. Demand signal understanding, prioritization, and fluid fulfillment execution have become increasingly critical to consumer and employee confidence, business reputation, and mission-driven brand loyalty. While the tools and technology capabilities are now available for meeting and exceeding current and future demand for personalization and mindfulness, executional persistence is important. AI and machine learning are key technologies in managing this increasingly data- and insight-driven demand. However strategy should not only focus on programmatic solutions for gestural and decorative AI. For consumers, authenticity or being real is critically necessary, but not sufficient. Consumers still need trusted sense-making at the core of their purchasing decisions. They frequently expect 'better' over pursuit of optimization, as well sustainability, and community. They also expect retailers and restaurants to go deeper and wider—over offer behavior-oriented solutions—beyond product- or service-oriented functionalities. It is about why and how something can be of value to them, not necessarily which product or service does deliver that value. Therefore, a new marketing mindset should be in place to serve purpose and profit profitably—while deploying the leverage of resource efficiency of AI and machine learning technology innovations.

7.3. The Role of AI in Sustainable Retail

The retail landscape is changing, unique materials are more difficult to discover, supply chains are disrupted, and consumer expectations for sustainable practices are higher than ever. Today, customers are turning to alternatives who are pioneering technologies in order to become more sustainable. Social and environmental factors drive consumer spending, whether it's for banned plastics, local deliveries, or vegan leather. On the other hand, new boundaries, regulations, taxes, and rising costs make it difficult for retailers to begin their transformation to sustainability, and every small retailer knows that jumping to a fully sustainable, eco-friendly business with all of their existing customers will filter supply and demand.

Most of these limitations are structured around the collection and analysis of data, as well as connecting omni-channel experiences to customers. Artificial intelligence provides the tools to create an intelligent data foundation that is resistant to the barriers limiting retailers. It gathers consumer insights, data management, and analytics and forecasting to help manage expectations with omni-channel, personalized communications. AI also answers the ever-growing concern for product certifications and verification by helping to create a better and optimized supply chain.

The AI-enabled supply chain analyzes past product journeys while also monitoring the impact on sustainability and emissions to offer feedback for product creation and streamline optimization. It consolidates suppliers and works through them to choose the most eco-friendly production house while educating customers on the environmental impact behind every product option. Finally, within the store, computer vision makes sure products are arranged properly and allows retailers to trace the inventory flow in the format requested by consumers.

8. Conclusion

Chapter summary: In this chapter, we looked at the three basic AI techniques, namely machine learning, natural language, and computer vision, and we explored their applications in retail in detail. As a guideline, we divided those applications according to the customer touchpoints in the retail customer journey. We also looked at areas inside the retail store operation where we could apply AI. We provided a framework when choosing an AI application for business needs. Finally, we summarized the main drivers, type of data needed, AI approach as well as challenges for the respective applications.

In our digital economy, driven by the rapid introduction of new technologies, we see an increasing number of companies that are pursuing a customer-centric strategy. Their goal is to create higher customer satisfaction as well as increase employee productivity, thus increasing the company's profitability in growing customer markets or defending it in mature market scenarios. With increasing detail in competitive analysis by consumers, this strategy can create a point of differentiation that can have a significant impact on the company's bottom line. However, companies can only create a competitive advantage if the improvement in customer experience is above and beyond what competing companies can offer.

Increasingly, we see that managing customer expectations in the retail area can be enhanced by applying artificial intelligence. With the pace of technology development in this area, AI techniques are available as managed services and can be integrated into existing retail applications through APIs. In many cases, data is available from both online touchpoints as well as in-store touchpoints. In addition user-generated content is increasing rapidly through reviews and ratings, helping improve the training of AI algorithms to drive better predictive decision support.

References:

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119-132.

Har, L. L., Rashid, U. K., Te Chuan, L., Sen, S. C., & Xia, L. Y. (2022). Revolution of retail industry: from perspective of retail 1.0 to 4.0. *Procedia Computer Science*, *200*, 1615-1625.

Mak, K. K., Wong, Y. H., & Pichika, M. R. (2024). Artificial intelligence in drug discovery and development. *Drug discovery and evaluation: safety and pharmacokinetic assays*, 1461-1498.

Ooi, K. B., Tan, G. W. H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., ... & Wong, L. W. (2025). The potential of generative artificial intelligence across disciplines: Perspectives and future directions. *Journal of Computer Information Systems*, *65*(1), 76-107.

Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2021). Artificial intelligence in retail: The AI-enabled value chain. Australasian Marketing Journal, 29(3), 264-273.

Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. *Digital Policy, Regulation and Governance*, *21*(3), 264-279.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 7: Artificial Intelligence in Manufacturing: Predictive maintenance, quality control, automation

1. Introduction to AI in Manufacturing

Artificial Intelligence (AI) has seen a renaissance in recent decades (Ali et al., 2023; Amankwah-Amoah et al., 2024; Bullers et al., 1980). The booming performance of Machine Learning, mostly due to an increased availability of data and computational power, has led to astonishing capabilities of software applications in certain tasks traditionally considered requiring human intelligence. AI is probably best known for its applications in image recognition, automatic translations, and natural language processing systems. However, AI goes far beyond these applications.

AI is impacting many industries. Medicine, insurance, transport, entertainment, services, and also manufacturing are reaping the benefits of deep learning and AI approaches to solving problems that were rather impossible to solve a decade ago (Dwivedi et al., 2023; Haleem et al., 2022; Kim et al., 2022). These impacts are unfolding in multiple ways. AI is transforming the nature and quality of services and overseen processes in social and human-centric services industries. AI applications in services are reshaping tasks, expertise, and content not only for service procurement – transport, food delivery, housing, entertainment, etc. They are also impacting key services associated with other economic activities, as security, consultancy, and financing.

In manufacturing, AI is being used to boost what has become a standard in the industry, namely, using large amounts of data collected continuously to monitor and fine-tune processes, both discrete and continuous one (Liu et al., 2022; Nti et al., 2022; Nwabekee et al., 2024; Wach et al., 2023). The commonly known ability for machines to "talk" about their current operation has been considered a landmark for Industry 4.0 and the so-called Internet of Things. More recently, both large incumbents and many innovative startups have been offering data analytics solutions based on machine learning to monitor production processes, aiming at solving complex Multivariate Time Series problems.

2. Understanding Predictive Maintenance

2.1. Definition and Importance Predictive maintenance (PdM) is a data-driven approach that minimizes unneeded maintenance and increases equipment longevity by predicting the optimal time to perform maintenance. Predictive maintenance is expected to reduce the cost of predominantly reactive maintenance approaches, reduce equipment downtime by moving towards proactive rather than purely reactive maintenance, and alleviate the risks of accidents or environmental damage relating to equipment maintenance. Predictive maintenance techniques have existed, in various forms, for decades. Currently, more sophisticated PdM techniques are enabled through the advances in sensing and communication technologies that drive the Industry 4.0 agenda. Businesses are now able to benefit from rich, reliable datasets on machinery use and performance. Traditionally, maintenance activities have focused on hardware performance improvement, operational task development, preventive maintenance via control several maintenance scripts or heuristic approaches that schedule maintenance tasks based on likely needs or manufacturer specifications. Moving to a PdM approach is an attractive industry initiative as it moves to a condition- or performance-based maintenance strategy. However, the predictive aim of PdM relies upon the ability of the user to define models for normal operating conditions and for failure themselves for different operational circumstances. The move to PdM should therefore be a collaborative research effort between researchers, vendors and consultants, and users, as businesses seek to develop cost-effective solutions that also deliver the expected improved customer service levels. 2.2. Technologies Used The techniques and technologies that can be used and implemented for PdM fall into a number of areas, including: data collection and advanced analytics; digital twin, modeling and simulation; cloud-based PdM solutions; IoT-based sensor fusion; advanced coupling with maintenance approaches such as dynamic scheduling and workforce management; specialist asset solutions, such as batteries, robotics, pumps, track-and-trace design and technology; specialist predictive maintenance service providers; and supply chain integration.

2.1. Definition and Importance

Industries have even been able to generate tremendous cost reductions through improvements in availability while keeping in check costs related to maintenance and real-time support. Predictive maintenance is a maintenance strategy used in many industries because it maximizes the added value to customers and minimizes the lifestyle cost. Namely predictive maintenance tools may provide you and your customers with flexible solutions to reach these predictable, measurable objectives. The availability and reliability of production systems are increasingly important for companies exposed to the competition. Any failure of a component not only results directly in the cost of maintenance and repair but also, and having a greater impact, incurs the costs related to lost production, idle resources, and the negative effects on customer relations. PM strategies base primarily on essentially monitoring constituent elements of the system according to their real-time behaviors in order to accurately predict if, when, where, and how the malfunctioning would happen. These predictions would afterward artificially activate a maintenance action on the machine at such a convenient time, and the strategy is called Predictive Maintenance. The main advantage of PM consists of being able to plan the maintenance action due to the prediction, a string of reductions in the aforementioned drawbacks related to unplanned actions.

2.2. Technologies Used

There are many technologies and industrial tools useful for building predictive maintenance solutions. Below we list just a few:

- Cloud platform – Cloud platforms provide infrastructure and services for running predictive maintenance applications and storage. Data can stream securely from the factory to the cloud platform, where a team of engineers build the logics that analyzes incoming data for events, alerts and risk profiles.

- Sensors and data injection tools – These are any industrial sensors and hardware you need to monitor equipment condition, uptime and failure. They can consist of vibration sensors, temperature sensors, cameras, RFID tags, accelerometers, etc. Industrial IoT tools, gateways and data injection systems allow you to push data from factory equipment to the cloud securely.

- Data science and analytics – Data scientists utilize statistical models, AI algorithms and software tools to build the machine learning models that predict equipment failure from incoming data. Data scientists can also build decision trees, correlation algorithms and alert generating logics to notify staff of an imminent failure.

- State estimation and Kalman filtering – These predictive maintenance tools produce real-time estimates on the operation of industrial equipment by filtering out sensor noise and removing downtime from the signal. This state estimate can be used to monitor equipment in real-time and check whether it is operating under healthy or unhealthy conditions.

- Predictive health meters – Predictive health meters leverage machine learning algorithms to benchmark the real-time health of a system against a baseline health. Such health dashboards can help you visualize and explain failures, using trending analysis, while pinpointing the location of equipment problems along with cause.

2.3. Case Studies

In this section, we present several examples of successful predictive maintenance implementations. The results showed that manufacturing companies can save time and money in their predictive maintenance plans.

During a one-day workshop, experts received germ cell ideas to develop further into Business Cases. Engineers validated the Business Cases by showing their feasibility with historical data available. The Business Development department decided to start developing the Cases extensively. The next step is to develop technical architectures and commercial models to deliver Predictive Analytics solutions for operations.

A company predicts the remaining useful life of its 3D printer parts using machine learning algorithms. Customers use the Multi Jet Fusion 3D printer solution to manufacture prototypes, models, or production parts. Companies have adopted this technology. With its Digital Manufacturing Network, the company provides its clients with a complete solution focusing on technology, expertise, services, and materials needed for 3D production. The company uses its Predictive Analytics solution to detect production failures and take proper actions before real production stops. These models allow the company to increase its production line availability and at the same time prevent the release of defective production parts.

For critical ATMs parts with high-value production, a company extends the tray changing of its ATM to improve its life-cycle without any downgraded performance or risk of ATM failure. For that, the company applies an advanced decision-making model that, combined with the company's operational experience, is capable of providing an answer to the question "When to change the ATMs trays?" Specifically, a specific Predictive Maintenance component is used to predict and analyze the risk of ATMs availability failure, combining 100% structured and 100% unstructured data.

3. Implementing Predictive Maintenance Strategies

Proactive maintenance strategies can significantly reduce unplanned downtime and servitization costs in manufacturing. However, most organizations still use a reactive or time-based maintenance strategy. Predictive maintenance strategies utilize real-time data as input to machine learning algorithms to model the state of equipment and periodically inform planning and maintenance activities. This section discusses aspects of implementing predictive maintenance strategies, such as data collection and machine learning algorithms. We also highlight some of the major challenges in implementing predictive maintenance strategies and the potential solutions.

Data Collection Techniques. Data from machines can be collected either through built-in sensors — e.g., temperature, vibration, electrical, immersion, bearing, and ultrasound sensors — or by adding retrofitted sensors. The built-in sensors are usually more reliable and robust. They may not always be available for specific equipment or sensor types or installed in earlier models of the machinery. In such cases, adding retrofitted sensors for predictive maintenance monitoring is a common practice. Another strategy is to use an industrial internet of things platform. For equipment with built-in sensors, such platforms simplify real-time data collection from several machines. Such platforms are also available for equipment without built-in sensors. With such platforms, various sensors can be added around equipment in less than a day. Valve, temperature, vibration, and ultrasonic sensors can lead to easier automatic management of routine asset-management programs enabling predictive maintenance when integrated with the platforms for different types of assets. Predictive maintenance use cases include detecting whether equipment is running in a normal state or is about to have an anomaly, predicting equipment failure time, or informing machine operators of equipment issues and their urgency to address them.

3.1. Data Collection Techniques

Section 3.1. Data Collection Techniques.

Harnessing data through Internet of Things (IoT) sensors is essential if the manufacturing industry wants to transition from reactive to predictive maintenance among its industrial machines. Industry leaders must adopt a data-driven enterprise approach, using predictive maintenance backed by analytics to improve their bottom lines. Their challenges are to first, gather the right data, and secondly, sift through large datasets to derive actionable insights.

What Type of Data Do You Need? To conduct failure analysis for predictive maintenance, manufacturers need data about the equipment. That data can include several factors like performance and utilization measurements, regime changes, and maintenance schedule history among other things. Here are a few examples: • Performance and Utilization Measurements – By continuously monitoring spare part deterioration, with sensors on additional elements of resistive loads such as motors, bearings, and gears, manufacturers can reduce unplanned costs by shutting down production and resources only as necessary to replace damaged parts, thus optimizing equipment lifespan. Sensors can also be used to check voltage and current as well as simply identifying explosions, arcing and air leaks. • Regime Changes – Data should also include regime changes, such as changes to load cycle frequencies when equipment performance negatively deviates from improved benchmarks due to altered schedules or disturbances in plant processes. • Maintenance Schedule History – To achieve a successful integration of predictive maintenance within the enterprise, manufacturers need historical data on sorts of machine maintenance schedules, lessons learned, maintenance shutdown periods, and significant events.

Collecting the data is only half the battle. The next step is to analyze the collected data to build models that predict failures and thus generate actionable suggestions. You can obtain failure models in two ways: Data-based methods and physics-based methods.

3.2. Machine Learning Algorithms

Supervised, unsupervised, or semi-supervised models can all be used to handle PD problems depending on the nature of the labeled data and the monitoring scenario. This section discusses widely used algorithms. First, we present the supervised methodologies that are mainly used in the case of existing labeled data. Then, we present and discuss some techniques that are commonly used in the case of domain-related unlabeled data according to a data-synthesis technique. Then we present some algorithms in the general case of a variety of unlabeled data. We will focus primarily on the technique most commonly used to solve PD tasks: condition monitoring based on supervised methodologies. In this context, supervised machine learning is commonly used for PD problems. It consists of using labeled samples of fault-free and fault-class data to train the model. Some supervised classical machine learning techniques are commonly used in the context of PD. Support Vector Machines are commonly used for pattern recognition. The main novelty of SVMs comes from the use of kernel functions to transform data points into a higher-dimension space to render the vectorial distribution more easily linearly separable. Using this technique, the SVM searches for the hyperplane, which is as far as possible from the two-dimensional classes representing the faults.

Random Forest is also widely used for fault detection, especially in structural systems. RF is a bagging-based method that combines the result of several decision trees calculated on different subsets of the training data using different features. The final RF decision is the majority voting of the decision of the different decision trees. These classical supervised techniques are efficient, particularly when there are enough labeled classes in the training set and when the underlying problem is simple.

3.3. Challenges and Solutions

Predictive maintenance is integral to Industry 4.0. However, it is still at an early stage and there are many issues that have to be addressed before it can reach its potential. In this section, we present some of the main challenges and their proposed solutions. Overall Cost: Implementing smart predictive maintenance technologies may imply high costs upfront that small and medium companies will not be able to afford. A gradual implementation of low-cost solutions can diminish these costs and allow these companies to be part of the new paradigm. For example, cloud-based infrastructures make it possible to implement IoT sensors, capable of periodic condition monitoring, at a low cost. Centralizing the data produced by these sensors and performing analyses at remote servers should be seen as the first step. As more investments are made, in-house solutions can be adopted. Limited Data Labeling: For supervised learning algorithms, label subject matter expertise is needed to label data. This may be difficult for failure data, particularly for rare events. Many intelligent data labeling systems are being developed, with users having to label only a small number of training samples to help automation build the rest of the labels. Nevertheless, these still assume the labels are available, which may not always be the case. Knowledge Sharing: Manufacturers rely on their suppliers for access to their data, particularly if they are heavy-users. Nonetheless, suppliers are often unwilling to share data. The use of transfer learning can mitigate this issue by allowing manufacturers to use models that trained on other similar data sets.

4. Quality Control through AI

Quality control has been one of the most common applications of AI lately. AI can readily analyze quality, recognizing defective products and processes from large amounts of data or images through pattern learning. PCA and neural networks have been especially effective in these applications. QAC techniques such as "Counting Problems," "Neural Network Control," and "Embedding Control" apply AI-based smart quarter strategies. The quality of features should also be controlled, which can be performed by the SPC method with pattern recognition techniques. Any product or part can be equipped with special sensors for product recognition and necessary feature measurement. After collecting enough product measurement data, SPC can be applied. The common distinct feature phase, associated with any fault or problem, is found and used as a defect for hardware control. The products detected after the common feature moments are controlled by the corresponding hardware component. After detecting the out-of-control moment based on the time basis, the source of causing the time signal can be recognized and classified as "Fault Signal" or "Problem Signal." Any feature, either present or missing, can contact products with allowed value boundaries, either face-to-face or stepwise.

As with many AI applications, most of the initial excitement in QAC came from the speed and efficiency of neural networks. But the balance weight and loudness check problems have so far been about the only real successes. Other pattern learning techniques may hold more promise. Still, no answer yet. "Early conclusion," they say. "More basic exploration, scrutiny, and modification of neural networks are required before practical applications of neural networks become widely realized." Long-range control and distributed control functions have high potential for neural networks as pattern classifiers. Yet, substantial advantages are still unproven – not only for neural networks but also for other types of pattern classifiers. It was also pointed out that multi-layer, back-propagation neural networks classify the operating condition of the process contemporaneously by conforming nearest the training sets due to incremental, learning rates.

4.1. AI Techniques for Quality Assurance

To assure the product or process quality on the assembly lines, several computer vision techniques based on AI are implemented to study the defects. The AI techniques based on learning could derive patterns of any defect or failure from a few training samples. During die faults testing of MEMS array, a neural network was trained using only six defective samples from the entire wafer and detected unknown defects for image processing. A similar approach is also adopted in detecting certain defects seen in actual life after patterning of transistors on silicon. A deep learning-based approach could recognize half-screen black defect of a display having very few realized samples.

Visible light Communication in smartphone display for remote unlock could be attacked by unauthorized reflection of similar structure displays. A neural network is trained using four reflection samples, and other reflection samples are tested. A trained convolutional neural network could detect arbitrary degradation of OLED screen efficiently. These are some of the successful implementations based on few-shots learning to determine a certain defect from the lot. However, the availability of such few-shot learning-high-quality damaged product data from the manufacturing process is essential. Data augmentation techniques that produce more samples for detecting unknown examples by digital boosting the original images. A meta-learning based approach could be trained with multiple classification tasks set and able to classify entirely unseen tasks. Due to the complexity to detect certain complaints with consumer electronics and quality control concerns, CNN is mostly utilized and few-shots learning where the number of defective samples available during training with neural networks.

While inspecting the product with as many defects, a neural network could be trained at many levels.

4.2. Real-time Monitoring Systems

Any conversation about quality control will include benefits from enhanced monitoring of the work. While earlier monitoring was limited to laboratory analysis of random samples, real-time monitoring will reduce costs, improve quality, and shorten product delivery times. The introduction of AI-based monitoring has enabled the actual implementation of these physical and economic improvements. It should, therefore, not surprise us that the maximum use of AI implementation in quality control is to increase reliability through enhanced process monitoring. Real-time monitoring involves the comparison of actual to planned operations. Any deviations from the plan having a potentially long-lasting effect are reported to the relevant manager for immediate correction. An overlooked deviation, such as a variation beyond the limits of normal operation that occurs during the production of high-ticket items could have disastrous consequences. A neural network based on presentation graphics workplace data can alert us on far more operations than the plant manager could consider at any point in time, enabling far greater overall effectiveness in seeking deviations. The need for reliability and business objectives should convince us that routine process monitoring by analyses are now of almost only historical importance. The limitations of current capabilities should lead us to a blend of monitoring, neural networks, and business objectives. Manufacturing, like other capital-intensive industries, has been shifted by capitalism toward the development of abbreviated, erratic monitoring. Although these periods provide many opportunities for AI quality monitoring, both during initial development and during post-introduction, the potential rewards of this strategy present serious problems. The introduction of faster turnovers in development and full-scale production would likely confirm the pessimism of the search for reliability. If we refuse to optimize our processes, we will have no “free” errors available, and we will not be able to rely on the fortuitous occurrence of “free” downturns for the stability of our neural networks.

4.3. Impact on Product Quality

A possible key selling point of any manufacturing application of AI is that it has the potential to improve product quality. In doing so, it addresses the original purpose of quality assurance and the TQM concept that first called for the prevention of defects instead of detection and rework. Indeed, Shift monitoring offers a clear picture of the production quality and a reverse montage allows detecting symptoms of different problems in the depth of the montage. Detection of specific symptoms could be further automated, triggering alerts to assemblers in case of doubt. Moreover, these symptoms support the advanced interpretation of recurrent issues and favorable periodical analyses of shifts and specific symptoms.

On the other hand, AI Diagnostics supports solving issues that the Shift monitoring cannot solve. Unlike the Shift monitoring, it gives access to the history of different modules. The assembly process history has indeed the capacity to reveal long-term defects, for instance, related to a subsequent unfit montage as well as frequent repeated issues. Diagnostics results on specific subassemblies could be further compared and merged in order to detect recurrent symptoms or evolutive faults. Moreover, the system has the capacity to automatically explain some abnormalities to the operators, addressing the famous analysis. Like Shift monitoring, the key advantage of these tools is that they provide clear indicators and a good source for guiding engineers and operator actions to improve assembly quality. However, it will be essential to associate the system with easy to understand results in order to convince users.

5. Automation in Manufacturing

Robotic automation plays a significant role in several phases of the manufacturing process, including assembly, welding, painting, logistics, sterilization, inspection, or even in tasks that are considered exploratory research, for instance, the micron and nanoscale manipulations. Robotic systems are implemented mainly because they increase productivity and quality, reduce time to market, allow the repeatability of tasks, reduce operational costs, and increase the safety and ergonomics of workstations. The integration of robots with AI and Machine Learning enhances the production system with perception capabilities as well as decision-making in real-time, allowing for smart and flexible robotic scenarios. AI in robotics allows speed and flexibility in the decision and execution of multiple activities, including face detection or pattern recognition using visual or audio data at very high speed, robot path planning and motion control, human-robot interaction, search in dynamic environments, as well as search or rescue missions in dangerous or unsafe places where humans are not able to intervene. Automation in manufacturing is heading toward cobotic systems, that is, the integrated operation of production robots and humans. New designs of lightweight robots with compliant actuators at an acceptable cost together with haptic sensors allow safe physical human-robot collaboration in manufacturing applications. We expect that the future of the employment landscape will be favorable to the coexistence of robots with humans, keeping the firmness of humans on important aspects such as the setting of goals, decision making, conceptual creativity, personal relationships, and emotional and human factors.

5.1. Robotics and AI Integration

Supervised, semi-supervised and unsupervised learning paradigms, together with reinforcement learning, can greatly ennoble the abilities and skills of robots, allowing them to deal with workings where they were unable to reach operational stability, or where they failed in the past. Skilled robots using more advanced learning algorithms can implement working conditions with lower cycle time and increased accuracy, being also capable to work safely in collaboration with human counterparts or co-workers. The advancement of robots is exposed by different parallels. The marketing and the productive integration of cheaper robots while greater investment for demanding production modules of automation proceed at steady pace. The latter are exploited for high productive plants as factories of automotive sectors; whereas the lower cost robots are offered for processing sectors and industries, such as electronics and appliances, where the production rates are relatively lower. Demand for automation would continue increasing annually. Success cases of those early users set roots for stronger demand from sectors such as automotive. The large mix production of automobiles both in terms of design and specifications is met with efficiency by demand simulation systems in connection with robots, improving production time and costs as well as quality and variety of product. Realizing this, robot builders have developed and created sophisticated programming that permit, for example, from vision, to recognize product inside a pile of others in disarray formation and get it out, depositing somewhere else with precision and care. Some robot builders have additionally searched for productive integration, associating guiding and programming with situations and products that will guarantee a strong demand, such as automotive or computers, for example. Their answer to assist electronic industries is a combination of basic and clever robots destined with AI.

5.2. Benefits of Automation

Automation plays a vital role in optimizing and advancing manufacturing. The application of automation in manufacturing has many benefits, but the most significant ones are closely connected to its results in terms of reliability, quality, and pace. Reliability results in the best practices being executed consistently and efficiently with no mistakes. Quality means lower thresholds for producing out-of-spec goods. And production pace means more goods in a specified unit of time. These benefits of automation show themselves primarily in areas of enacting simple and repetitive tasks as well as more demanding assembly activities. Areas of automation help to achieve a world where high quality and reliable and cost-efficient production is possible. This is obtained by enabling and empowering manufacturers and workers to be experts in demanding cognitive work, allowing them to utilize the best practices the company has gleamed over the years.

Automation of repetitive tasks allows the operator to focus on parts of production that need specialized skills, but even that limited focus increase experience is put to better use. Automating production simplifies the process; it breaks it down into smaller logical tasks simpler for automation to enact. This provides a reduction in training for new employees on complicated production processes. Companies can better use new employees to enact particular steps in production quickly all while learning on the job. Once the tasks are automated, the need for skilled experience reduces to those looking after the machines and equipment. Manufacturer companies can better take advantage of the reduced hassle of low-skill demand; in particular, high demand periods need not be concerning.

5.3. Future Trends in Automation

New technology in automation is progressing hard, driven by emergent relationships with connectivity, enterprise software, and manufacturing business process reshaping. The future vision for automation is flexibility and agility to match the new advanced manufacturing model, collaborating humans with machines in a flexible way. Recent breakthroughs in AI can change how people perceive reliability, performance, and capability problems. Robotics are increasing the promise of greater vision, more dexterous grippers, and more intelligent integrated systems with increased important software content.

Future automation designs will have implications for a business processes area in manufacturing. Demand volatility, product diversity, short life-cycles, and customer proximity drive the way products are made and the nature of relationships with product developers and customers. Change cycles in products are shorter, and customer information requirements are more intense. Increasingly development organizations with the best information linkups with manufacturing and with internal flexibility will be the long-term winners. Information technology can greatly enhance product development time, product life, and product differentiation. Rapidly identifying information in the marketplace and integrated internally is becoming a paramount need for advanced manufacturers.

The design of the physical manufacture of products must change to handle the new time and product environments while being sensitive to customer requirements. New elements of manufacture, such as automation, must be integrated with the use of people and natural resources to create a responsive overall system. The economic integration of a continually changing set of suppliers and sub-manufacturers is emerging as a critical design component for many advanced manufacturing businesses as well. Enabling rapid and market-responsive new changes with integrated computing and automation that is engineered into new factories is a compelling long-term vision as well as a long-term imperative.

6. AI and Supply Chain Optimization

Traditional supply chains require significant human resources for optimal configuration and ongoing supervision and maintenance. With the ever-increasing complexity of supply chains coming as a result of globalization and digitally enabled e-commerce expansion, leading companies have become extremely reliant on supply chain optimization technology. Recent advances in Artificial Intelligence technologies will enhance already synergetic supply chain relationships further, optimizing the entire web of supply chain actors for maximum efficiency, cost savings, resilience, responsiveness, ethical, and environmentally responsible behavior.

AI-driven demand forecasting elevates human judgment work, becoming an in-house science. AI technologies, especially Machine Learning and Deep Learning, enhance forecasting precision as they combine diverse data inputs. Besides, neural networks can learn complex patterns in the time series data. These advanced methods are especially effective when hard-to-know human behavior or sudden changes in the market conditions are not predominant and should be recognized month-over-month. Fine-tuning period is essential as the neural architecture needs to learn the idiosyncratic patterns and adapt quickly.

Manufacturers can use AI to enhance demand forecasting and address demand variability proactively, enabling automatic replenishment based on forecasted demand and flexible capacities. Addressing demand variability proactively, OEMs can auto-generate Purchase Orders to their Tier 1 suppliers based on demand forecasts. With assistance from suppliers in terms of reliable lead-time estimates and capabilities, suppliers, distributors, and OEMs can maintain inventory efficiently along the supply chain to reduce excess inventory and out-of-stock situations that hurt sales.

6.1. Demand Forecasting

After back-end operations, the next question that arises is about Supply Chain Management. Supply Chain Management, abbreviated as SCM, is the professional or commercial activity associated with the planning, development, and execution of all procurement, manufacturing, and logistics activities on a broad level. Today's customer possesses multi-faceted needs that change frequently. Demands can be fickle in nature, following unique shapes. However, the supply chain must be strong and maintain a baseline process. Demand forecasting entails using techniques and systems to predict customers' future demand. It serves as a basic input to SC planning.

Several organizations formulate demand predictions based on faulty processes that utilize outdated statistical tools. Their approaches are sporadic, disparate, error-prone, and ineffective. The pitfalls are apparent. Demand forecasting excels in the vital demand planning step of aligning supply with demand. It also facilitates fundamental decisions involving production and capacity planning, inventory carrying costs, purchasing and replenishment planning, product life-cycle support, and resource allocation. Demand predictions also form the basis for a plethora of vital business functions, including physical distribution management, sales and operations planning, inventory control, and financial budgeting.

Traditional forecasting methods are mainly based on the means of historical data. Company experts rely on heuristics. More recently, company sales information using more advanced data-mining techniques is pumped into a statistical forecasting model. Historical data predictions are generated. Regardless of the method implemented, the need is to generate multiple forecasts for each product at various levels of aggregation, which can include SKU, product family, geographic region, and distribution center. Aggregating demand is key because the degree of variability often decreases as a result.

6.2. Inventory Management

AI technologies reduce lead times and help improve suppliers' performance, resulting in better estimates of inventories. More accurate estimates of inventories by item are key to enabling planners for making the right decisions regarding purchase orders in the period ahead. A major challenge in planning the materials resources needed for production in a make-to-order environment is accurately estimating the inventory levels of raw materials requested on pending customer orders. Many companies simply adjust forecasted demand downwards according to a fixed rule of thumb, such as a percentage of the order quantity, with no allowance for seasonal or promotional patterns. This is too simplistic, as order the level is at times of the essence. However, to incorporate known order policies with seasonal or promotional demand patterns is much more complex and not practical for many companies.

The traditional economic order quantity model ignores ordering costs as an objective and instead attempts to minimize the total cost of holding unsold inventories. Using advanced predictive analytics technologies with artificial intelligence, a cloud-based inventory optimization application can provide sales, inventory and operations planning managers the capability to analyze and predict product demand patterns while taking into account internal promotional plans and known seasonal demand fluctuations. These capabilities then enable them to streamline the entire process and enhance productivity by enabling data-driven, insight-based decision-making. They align demand and supply by determining the right inventory level of every item in every location to ensure that demand flows smoothly while reducing supply chain costs.

6.3. Logistics and Distribution

Logistics is a major part of a company or corporation's supply chain management. Logistics is a sector that has unique problems, is large in scale, has a specific volatile structure, and deals with time and space, all of which are quite unique to logistics. Additionally, logistics specifically affects a company's performance in terms of costs and services. Supply chain and logistics activities encompass the planning and execution of the transport and storage of goods, services, and related information between the point of origin and the point of consumption, with the aim of supplying customers with the desired level of service at the lowest possible cost. The improvement of performance in logistics and distribution is essential to gain competitive advantage. Transportation is one of the most important links in the supply chain process. The increasing volume of goods and their worth as well as the growing sophistication of customers have resulted in the need for an efficient and effective transportation system. Today’s environment is ever-changing and more dynamic than ever. With rapid globalization of commercial transportation, business is being conducted around the world, so companies must increasingly rely on global providers to handle their freight. Furthermore, globalization has resulted in the need for shorter leadtimes, lower costs, and flexible service. The importance of transportation policy should not be understated. Indeed, the entire supply chain process is impacted by transportation management. Transportation costs can substantially affect logistics costs. The distribution management process handles the flow of handling, storing, and transporting value-added services into and out of the company's distribution centers and retail locations.

7. Ethical Considerations in AI Implementation

While the digital revolution will open vast developments in many companies and industries due to increased efficiency and productivity, the danger of job displacements looms over the future of workers in the manufacturing field. Not just on the factory floor, but also in all activities that make the factory exist, from putting together the supply chain to keeping the factory running with maintenance and logistics. The integration of AI into the manufacturing industry as we know it opens up new advanced features but may lead to reducing manpower in multiple tasks. Besides using AI for production tasks such as welding, polishing or assembling, there will also be new usage of AI for controlling quality, transporting goods, monitoring data or workforce rounding. These applications of AI may lead to job displacements in quality control, logistics and maintenance, by restricting their existent tasks, or even removing them completely. The required qualifications for the workforce will also change from physical effort or low-tech qualifications to ensuring that AI behaves and performs as expected during quality and data monitoring. The use of AI also raises other ethical questions for data privacy policies. Systems may be seeing, listening or gathering data at any moment. There is a need to be aware of the massive amount of data being used for storing, processing and outputting. The manufacturing/production processes of a company may involve the general understanding of consumer behavior or how these processes impact society, including vulnerabilities or discrimination. Using data to train AI systems may lead to biases powering AI development. Specific measures and delineating privacy conditions to be agreed before using the data is central to building a solid business case about the use of AI for a company.

7.1. Job Displacement Concerns

The most significant ethical concern surrounding the rise of AI is job displacement among the low-skilled workforce. A transformative actualization of the fear over job displacement from the Fourth Industrial Revolution – and, particularly, the actualization of the concerns articulated during the first Industrial Revolution over machines destroying livelihood – requires not just optimism among government officials that historical cities can transition to centers of innovation without losing or displacing skilled workers. The difference, today, is that the story about the displacement of workers from the current economic model by machines can be written today just as it was during the Luddites, without resorting to skilled workers.

In this digital age, any kind of worker is subject to a loss of livelihood simply for a bad quarter in the labor market – or, for that matter, a persistent misjudgment on the part of corporate leaders over what kind of specialty is required to get them back in the red zone. Looking back over the nineteenth century, moral concerns over machines disrupting livelihood have often been dismissed as those of a little thought elite who resent that they are emotionally incapable of taking part in reforms such as universal basic income. However, while some have already moved on to a world in which photovoltaics are embraced along while incentives are removed from coal plants, the story of vulnerable workers who are incensed by others' talks over the past century of more evolved and 'better' jobs need not distract from the empathy required of a just wealth redistribution. The votes of sitting workers suffering from job displacement concerns may be just as apparent as the stars in the billion-solar-systems view of the developed psyche.

7.2. Data Privacy Issues

The second ethical consideration of importance is data privacy. AI techniques rely on large quality data, which in the case of manufacturing may include proprietary product designs and consumers' personal and financial data and, even copyright material that belongs to the data provider. In some cases, confidential company data must be shared with the data collector that can report business performance and strategy secrets to other businesses or be used by the collector to create competing products. Exchanges of data ownership and transfer of rights are not routinely done while signing a contract. Consequently, data privacy, ownership rights, and contractual liability need to be appropriately addressed while enabling the AI infrastructure especially in a multi-party data economy and diverse legal environment during its implementation. A report on addressable data rights has been created to address privacy issues. An addressable data rights structure defines the ownership and rights of the data user and creator. The proposed data rights structure consists of legal, economical, and technical capabilities to control and share data more freely and securely for mutual interest. Legal capability defines the legal framework of property rights over data through laws of different forms and scope including contracts, data designations, property, copyright, and protections. The economic capability enables the inclusion of agreement and compensation for data use. Data ownership can be monetized through licensing and truncation rules that incorporate a precondition aimed at securing consent from the data creator before setting the transaction rules.

8. Case Studies of Successful AI Implementation

AI-powered technologies already exist and are being successfully applied in manufacturing plants around the world. Major companies including Tesla, Bosch, and Siemens are examples of innovative enterprises deploying pioneering AI applications. Despite the well-tested history of their manufacturers, they all integrated state-of-the-art AI features to enable disruptive functionalities of their applications. Smaller enterprises, such as Sight Machine and Instrumental, are releasing ground-breaking products developed based on nascent AI technologies, exploring the potential described in this chapter.

Industry Leaders Tesla is famous for its development of electric cars, which are based on pioneering technologies, such as lithium-ion batteries. Nonetheless, Tesla's desire to outperform competitors specifically in the automobile manufacturing field led to the integration of advanced robotics in its production system. In particular, Tesla deployed a huge number of standard industrial robots, which allow for very high automation of the assembly line. However, the choice of being a pioneer in the production of electric vehicles on a large scale, and the stringent product performance specifications prompted the company to innovate also in the area of manufacturing systems. Continuous product innovation led Tesla to implement a vertically integrated model, controlling most of the components of electric vehicles. While this approach could lead to scale diseconomies, for Tesla it allowed obtaining a better level of quality.

Quality control is a key function of the manufacturing process. Bosch is heavily investing in the use of vision-based artificial intelligence and deep learning to enable the automation of visual quality control in production. The company reinforces the importance of quality for industrial applications claiming: "Only industry solutions, which are proven to be safe and reliable in the long term deliver the level of quality that plants require these days." The company claims to offer solutions that surpass humans for specific applications, new products, and markets. It offers "smart cameras" to be integrated into production lines boosting speed, robustness, automation, and cost reduction. The camera is capable of performing high-accuracy defects detection on a wide range of possible defects and on multiple different products or variants, even in challenging industrial environments.

8.1. Industry Leaders

As a central focus of the industry, manufacturers are using AI to transform their operations, from the shop floor to the supply chain, and from analytics to automation. The business case is clear: similarly sized manufacturers using AI see, on average, a +16% revenue boost and a -17% cost reduction compared to their peers who do not yet have AI in place. AI enables manufacturers to improve efficiencies, reduce downtime, improve yields, add predictive capabilities, and reduce overhead–all attributes that help improve margins that often run lower than the rest of the economy.

A survey on the Effects of Artificial Intelligence Adoption by Manufacturers found that 93% of manufacturers have invested in AI for increasing productivity and profitability. The AI use cases in the survey included Supply Chain and Procurement; Design and Engineering; Manufacturing Operations; After-Sales Service; Maintenance, Repair and Overhaul; Quality Management; Sales and Marketing; New Business Models and Service Offerings; and Product Development and Innovation.

In addition, a strong majority of large manufacturers have deployed AI-enabled applications in consensus areas like Demand Forecasting; Predictive Maintenance; Supply Chain Analytics; Production Planning; Computer Vision for Quality Inspections; Natural Language Processing for Demand Analysis; Machine Learning for Yield Optimization; and Data Mining for Process Optimization. Industry leaders are now busy bringing the rest of their operations online and building models for AI-enabled production.

8.2. Innovative Startups

Contents:

8.2. Innovative Startups

In the dynamic landscape of manufacturing, several promising startups have emerged, dramatically reshaping production processes and product offerings with technology-driven solutions. These ventures bring vibrant innovation into the sector and offer so much creative energy potential for rapid growth and transformation. This section covers several startups that are making a difference across the manufacturing and AI space. The startups discussed here are mostly USA-based, although others are discussed as may be relevant to the subject matter we intend to convey. Readers familiar with startup ecosystems may find these interesting not just from a manufacturing perspective, but also from advising capabilities in other industry verticals.

FlexLogIX provides the only open-architecture, faceplate-compatible alternative to traditional PLCs and PACs. FlexLogIX is small, flexible, expandable, affordable, and fully integrated. A new FlexLogIX product can be used with the solution-prototyping Kits to quickly put together new solutions that are smaller, more flexible, expandable, and easier to modify. So, every development and deployment is unique to manufacturer.

Sentact provides mobile device and AI solutions for manufacturers who want to optimize operations, achieve new levels of efficiency, and improve their bottom lines. Their product-hosting solution integrates flood sensors, wearables, phones, and tablets for instantaneous communications. AI algorithms analyze data to troubleshoot electric systems, prevent flooding, and avoid thermal runoff. This cloud solution is perfect for buildings, infrastructure, and processes that can be damaged by leaks and flooding.

A great example of AI for improving supply chains is Brightly. Brightly is a global leader in asset management and environmental sustainability software that helps create a world where every space is nurtured and protected for generations to come. Their solutions are built for asset-intensive organizations with complex operations that require modern solutions to automate and optimize their processes. Organizations choose Brightly to centralize asset data, mitigate risk, and drive efficiency in the management and maintenance of their physical assets.

9. Future of AI in Manufacturing

9.1. Emerging Technologies

It is the goal of the Outline of Artificial Intelligence in Manufacturing detailed in the previous chapters to provide the reader with an understanding of why and how Artificial Intelligence (AI) can be used for problems in manufacturing. In addition, it is also important that the reader understands how rapidly AI in manufacturing and how many things are changing. It is within this context that the future of AI in manufacturing is discussed. This chapter gives some of the predicted directions as well as a brief list of what is in the future of AI for manufacturing.

The dramatic growth of AI in Manufacturing is supported by heuristics-based intelligent agents, knowledge graphs and deep semantic answering, improved reasoning capabilities of Vision AI and AI in Natural Language, Hyper-Automation and Virtualization of AI, generative AI and ML, real-world applications, shifting understanding of agencies and addresses, 3D printing with AI, cloud-based smart devices and systems, AI in precision delivery and advanced manufacturing, quantum information technology and quantum-enabled AI systems, etc. New approaches enable the next stage industrial revolutions and model allowed for simulating physics with deep learning.

9.2. Predicted Industry Changes

Software as a service (SaaS) in AI, the outsourcing of AI, and new thinking and platforms for research and development. New forms of devices: Tablet, direct mapping devices, and AI chips. Demystifying the meanings of creativity, cognition, consciousness, and the human mind. Cyber-physical-world networks. Training of technologies and systems: Cyber agents for agents. New mechanisms for trust, privacy, and security in AI, knowledge, information, cybersecurity, and AI-enabled devices and systems. Shorter time to deployment and lifetime for science and technology at research and industry levels. Visual constructs for AI devices. Higher School of AI. Crowdsourcing of AI and crowdsourcing the creation of the new generations. The continued wave of technological change over the decades to come. A digital world with the interaction of the physical design and the cyber model. A digital economy that depends on the new digital devices and systems with more of the new changes than in any expected change mystics. These changes and conditions will characterize the Twenty-five to fifty years.

9.1. Emerging Technologies

The manufacturing landscape is set to undergo significant changes as a result of new technologies such as generative AI, foundation models, and other advanced tools. Manufacturers will adopt a variety of tools to augment their workforce, from image generation tools that support design engineers to code generation tools that help software development teams. Deeper, multimodal AI will become increasingly available, particularly with new neuro-symbolic approaches. These next-gen AI tools promise to significantly increase worker productivity, particularly for the knowledge workers who are essential to maintaining and developing complex manufacturing operations. These tools also hold significant promise for helping manufacturers manage for greater efficiency through recommending actions based on past outcomes and specifying first-order principles and performing impact analyses across complex digital twins of manufacturers' operations. As a result of these advances, the use of AI to optimize and control complex, nuanced, and interdependent work streams will become possible. Companies will begin to routinely build generative models of their operations in order to anticipate failures of machinery and subassemblies in large and complex factory operations where partial differential equations are of limited use. Manufacturing operations will be able to automatically optimize supply chain configurations based on deep learning generative models that predict fluctuations in demand as well as low-probability, high-impact events such as natural disasters or geopolitical supply chain shocks. Using computer vision as the nerve systems for manufacturing operations, enterprises will use advanced and far-reaching sensor networks enabled by low-cost sensing combined with AI-powered predictive analytics. Already, companies in disparate industries are working to replace their legacy sensor systems with highly sensitive, deep-learning powered, imagers.

9.2. Predicted Industry Changes

In summary, Liaison offers the most comprehensive AI software solution for manufacturing in emerging areas like Industry 4.0 and smart factories. With Liaison's machine learning, manufacturers can increase efficiency, decrease costs, and offer higher quality products allowing factories to become "lights out" factory in the near term. This section contains future trends that should be on every manufacturers' radar and include but are not limited to: • Increased proliferation of automation everywhere • Increasing utilization of AI and ML • Increased investment in cybersecurity solutions • Augmented and virtual reality will become common-place in all manufacturing deployments. Whether it's testing robots, or training employees, AR and VR will assist in all aspects of hiring and training employees. • Non-robotic automation technologies such as Li-FI, Intuition Robotics, smart chairs and smart kiosks will enable more employees to be more productive. • Continued consolidation in the manufacturing software industry. • Hardware will become more inexpensive and AI more straightforward to deploy. Edge configuration, powered by machine vision, will require AI insights to be available closer to the machine. This combination will enable plant-level insights, answers, and actions more quickly than ever before. • Industry 4.0 strategies supported with the right software solutions will enable the data driven factories of the future – optimizing manufacturing execution, maintenance, product development, and the value stream – while providing the right visibility and speed for your entire supply chain. • Personalized manufacturing, where mass customization meets consumer demands for unique products, and lead times are reduced to a level that will be competitive with mass delivery. AI software driven personalized manufacturing offers the opportunity for manufacturers ready to embrace this challenge, to capitalize on a dramatic shift in our economy.

10. Conclusion

While this chapter focused on AI achieving efficiency goals such as reducing production costs, maximizing through-put, or minimizing change-over times, there are equally, if not more important issues of quality that AI has a lot to offer. In fact, given the focus on quality defects determining product quality thresholds and their consequential financial and reputational effects on organizations, it is perhaps the use of AI in controlling quality that should receive first priority. For example, AI could be used in both presence sensing and quantification of physical attributes of materials, products and processes as a basis for control – and sometimes even closure – of quality defect types that are attributable to managed factors during the manufacturing process.

Control of the attributes by AI would provide a basis for immediate feedback to the manufacturing process, with the information either being acted upon by operators or automated control actions being undertaken by AI technology enabled systems. Where these defect types relate to product attributes, it is necessary to focus on the end product as the managed entities influencing the defect type. The information resulting from AI is then used for assessing and preventing the defect type on the product throughout the manufacturing process. There would also need to be similar warning and default automated alert systems in place that are similarly enabled by AI. AI can also be applied to product testing and assurance to support manufacturers to meet the continuously increasing product quality demands.

References:

Ali, O., Abdelbaki, W., Shrestha, A., Elbasi, E., Alryalat, M. A. A., & Dwivedi, Y. K. (2023). A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. *Journal of Innovation & Knowledge*, *8*(1), 100333.

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, *79*, 102759.

Bullers, W. I., Nof, S. Y., & Whinston, A. B. (1980). Artificial intelligence in manufacturing planning and control. *AIIE transactions*, *12*(4), 351-363.

Dwivedi, Y. K., Sharma, A., Rana, N. P., Giannakis, M., Goel, P., & Dutot, V. (2023). Evolution of artificial intelligence research in Technological Forecasting and Social

Change: Research topics, trends, and future directions. *Technological Forecasting and Social Change*, *192*, 122579.

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119-132.

Kim, S. W., Kong, J. H., Lee, S. W., & Lee, S. (2022). Recent advances of artificial intelligence in manufacturing industrial sectors: A review. *International Journal of Precision Engineering and Manufacturing*, 1-19.

Liu, K., Wei, Z., Zhang, C., Shang, Y., Teodorescu, R., & Han, Q. L. (2022). Towards long lifetime battery: AI-based manufacturing and management. *IEEE/CAA Journal of Automatica Sinica*, *9*(7), 1139-1165.

Nti, I. K., Adekoya, A. F., Weyori, B. A., & Nyarko-Boateng, O. (2022). Applications of artificial intelligence in engineering and manufacturing: a systematic review. *Journal of Intelligent Manufacturing*, *33*(6), 1581-1601.

Nwabekee, U. S., Abdul-Azeez, O. Y., Agu, E. E., & Ignatius, T. (2024). Digital transformation in marketing strategies: The role of data analytics and CRM tools. *International Journal of Frontline Research in Science and Technology*, *3*(2), 055-072.

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., ... & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(2), 7-30.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 8: Artificial Intelligence in Logistics and Shipping: Route Optimization, Autonomous Transport

1. Introduction to AI in Logistics

With the increased demand for faster and inexpensive transportation, it's crucial for logistics companies to use these resources efficiently and effectively. This is achievable with the introduction of AI methods. AI methods by themselves cannot solve all problems or optimize all processes (Agrawal et al., 2024; Bhargava et al., 2022; Jahani et al., 2023). However, logistics is a domain that generates a lot of data, and AI provides the tools to analyze these data and optimize the decision processes. Logistics has a long tradition; in supply chain design optimization, inventory level optimization, fleet management, warehouse process design, etc. There are rules or specific methods to apply for each of these processes, but the availability of large internal and external data with no or little extra cost provides new opportunities to improve these processes. What AI methods can offer are mainly combinations of the rules and methods that already exist, or can enhance them with the use of AI and data (Kazancoglu et al., 2023; Soori et al., 2023; Tsolakis et al., 2022). In this sense, AI methods are nothing more than data and computer power-enhanced optimization tools.

Logistics is an area rich in data. All interactions of suppliers, customers, distributors, transporters, stores, etc., leave huge volumes of digital trails. These data were traditionally underused in decision-making processes. Decision methods had access to predefined pools of solutions, developed after years of experience from operators, analysts, and experts in the area. Today, AI methods are helping in tailoring these solutions and, in some cases, going beyond predefined limits using the computing power available today. With the new era of big data and with the methods developed in AI, normal parametric restrictions are being lifted. AI methods are helping or replacing humans in designing new solutions, with obvious improvements in logistics metrics.

2. The Role of AI in Supply Chain Management

Artificial intelligence has had a profound impact on the logistics and shipping business in recent years, and it has become a critical tool in supply chain optimization. AI-based tools and techniques can be used to develop models of supply chains that have large amounts of historically difficult to reconcile transaction data. These models can be used constructively to assist in planning supply chain scenarios and operations or used operatively for command and control of existing supply chain dynamics. In this way, AI is being used for short-term decision-making, such as creating daily loading plans for delivery and taking into account such factors as docking space availability constraints, cargo mix, contention from other shippers, and physical and time requirements for loading cargo. Long-term decision support or decision automation would analyze expected trends in dynamic patterns of demands, customer profiles, and the behaviors of competitors, suppliers, and shippers.

AI is being used at different stages of supply chain optimization to achieve higher objectives. The traditional approach to supply chain modeling and operations has relied on optimization methods based on linear and non-linear programming heuristics. Linear programming has traditionally been the preferred optimization method to minimize transportation costs. These optimization methodologies have enormous advantages for planned supply chain operations over the traditional ad hoc approaches, but the static nature of existing optimization abilities has hampered their value to rapidly expiring short-term decision-making. The essence of the industry problem to be solved is the rapid expiring nature of short-term data on supply chain flows, coupled with the volatility of data trends.

3. AI Technologies Transforming Logistics

Logistics and shipping management have always been a challenge due to the amount of data required to optimize and manage all the components and nodes in the delivery and transport systems. There are multiple locations – suppliers, manufacturers, destroyers – sending products to various locations – distribution, wholesalers, retailers – with a constant flow of data such as delays, requests, inventory levels, and so forth. Additionally, transportation can take place via various modes including air, road, sea, and railway. Each mode requires a specific strategy that can take weeks to finalize and optimize. Traditional systems that require huge amounts of manpower along with multiple algorithms to optimize actions for all the business processes are prone to lag, delays, and poor data utilization and analysis.

AI in its various forms impacts every single activity related to logistics and ships (Woschank et al., 2020; Zhang et al., 2023). Starting with machine learning, many companies are using algorithms to match people who need to send products with trucks who have the space or capacity to take on those products for delivery long before the delivery request is made. This helps address last minute requests and reduce costs. Various firms are taking data from traffic, weather, and logistics to predict sailing transit times across different routes. By relying on real-time data, organizations are using ML algorithms to forecast short-term and long-term cargo volumes for logistics services and create precise capacity plans.

Additionally, Robotics and automation are playing a key role in operations, directly impacting efficiency and cost, with enhanced collaborative robots, sensor-based technologies, drones, and vehicles that carry out the functions without human intervention. Today, predictive analytics is being used at the macro-level to look at various data influences such as economy, growth forecasts, trade policy changes, and exchange rates to determine the logistics route effectiveness across long-haul shipping, rail, port services, and air services. It monitors and enhances logistics performance.

3.1. Machine Learning Applications

Logistics has undergone remarkable digital transformation since the Fourth Industrial Revolution, aimed at becoming hyper-connected, autonomous, and data-driven. Emerging technologies such as big data, AI, the internet of things, robotics, blockchain, and 3D printing support logistics transformation. In logistics, AI is applied to process and analyze extensive data to automate operations, predict customer demand, and optimize decision-making. However, only a few large logistics firms have effectively harnessed AI's potential. Additionally, the dearth of in-house expertise, insufficient quality data, and high implementation costs pose challenges to the profitable use of AI in logistics.

With extensive, high-quality data, logistics firms can train machine learning models to predict customer demand, optimize process design and performance, automate processes, and develop autonomous vehicles. Through machine learning, autonomous driving algorithms can predict driving conditions for vehicles based on historical data about weather patterns, accidents, and regional traffic norms. Additionally, machine learning algorithms can reduce energy consumption by self-learning to determine the routes and speeds of delivery vehicles that minimize energy use, develop tools for drivers operating delivery vehicles or manage the parking spots of delivery trucks during congested daytime hours. Furthermore, through machine learning, logistics firms can predict package delivery times and estimate the level of demand at specific places and times by using a combination of historical GPS data on drivers and trucks.

Additionally, machine learning can help detect risks of cybersecurity breaches that can disrupt logistics operations or lead to theft of personal customer data. Through machine learning, logistics firms can track transaction data across their supply chains and logistics networks and identify abnormal behaviors that pose risks of cybersecurity breaches. Blockchain allows users to maintain a shared tamper-proof digital ledger of transactions. In logistics operations, it enables tracking the digital transfer of assets, be they physical goods, financial assets, or data stored in IT systems.

3.2. Robotics and Automation

The often-quoted terms robots and robotics can refer to anything from a simple assembly machine to a complex system capable of behavior once thought limited to mankind. Within the domain of robotics, there are many differing types of machines capable of performing a range of various tasks – some versatile and some very specialized. An autonomous robot is capable of performing tasks independent from human control, but robots are often operated by humans as a form of tele-manipulation. These are commonly referred to as tele-robots. Full automation of warehouses, production, and distribution processes has been the ultimate goal for decades. But though parts of the logistics system have been automated almost to perfection, several bottleneck operations still require highly flexible manual intervention. Complete systems consisting of several robotics components that need to be programmed for a new task for each product variant have for a long time been a costly but feasible alternative to high-volume production without automatic feeding of the last stages of the process. These systems are often limited to highly standardized family products. Today's significant expansion of e-commerce has widened the gap between traditional logistics companies, skilled in mass logistics for supermarket chains, and new competitors with full logistics capabilities supporting order picking of a wide variety of products and product components in small quantities over the full day. The use of collaborative robots, forklifts delegated to a warehouse with mixed-pallet load but without strictly sequenced order fulfillment, order picking of small parts in parts warehouses, and of warehouse-respectful delivery to the customer by means of drones is today labeled as the Internet of Things. This means that the ongoing transformation of logistics and supply chain management has been paved by a commercial explosion of smaller-scale machines, including, by example, parcel delivery robots, handheld wireless scanners, static and dynamic cargo short-term storage systems, automated guided vehicle systems, and order-picking robots in productivity range.

3.3. Predictive Analytics

Predictive analytics refers to techniques that construct a model which can predict future outcomes using a variety of statistical, modeling, machine learning, and data mining techniques. The prediction for the future is conditioned on a statistical model that is developed using training data. Predictive analytics differs from other types of analytics in the type of prediction being made and its heavy reliance on development of ad hoc models. The future outcomes can be predicted as a specific number or a range of values. Using prediction models developed using predictive analytics requires attention to the coincidence of the target outcome being used to develop the model and the predicted outcome being made.

The difference between prediction and other types of statistical analysis is primarily one of emphasis, predictive analysis, as the term suggests emphasizes prediction, whether using point estimates or probability intervals for the predicted outcome. Given the heavy use of examples of predictive analytics in marketing, it is helpful to have some general information about prediction models. One simple expression of a predictive model is: $Y = f(X) + e$. Where Y is the predicted value, $f(X)$ is the predictive function that provides the mapping from the predictors X to the predicted value Y, and e is an error term reflecting the uncertainty of prediction. Predictive analytics uses these statistical techniques to accurately predict the future by finding predictive relationships in the data.

4. Benefits of AI in Shipping

Shipping plays a critical role in global trade and is a key driver of economic growth for the world. As product life cycles continue to evolve, competition increases, and customer demands expand, the international shipping industry is being forced to adapt and innovate faster than ever before. The technology that has helped to shape this transformation is artificial intelligence (AI), which is not only helping global shipping companies identify new business opportunities, but is also allowing organizations to gain a competitive advantage. AI enables shipping companies to take into account many factors which affect demand, such as weather and shipping routes, distances for temperature-controlled cargo, and container availability. AI is continuing to gain momentum in the shipping sector, but what exactly are the benefits of using AI for shipping and logistics?

4.1. Cost Reduction

The use of AI in the shipping industry allows organizations to reduce costs by automating processes, improving predictive functions, and enabling real-time decision making. Optimized loading and unloading of cargo and other factors help to increase fleet utilization, while machine learning algorithms are improving demand forecasting accuracy, allowing cargo to be placed in the right container at the right time. AI is also being used to provide predictive maintenance services for shipping containers which monitor temperature levels and report anomalies, allowing shipping companies to address issues before they become expensive problems.

4.2. Improved Efficiency

While the main focus for many shipping organizations is cutting costs, the use of AI for these businesses is not just about lowering costs, it is also about gaining efficiency benefits elsewhere. AI is now used to predict the most efficient shipping routes and improve shipping schedules. AI systems can take into account earlier than human input how long a vessel will take to reach port and what time would be the best to leave. These systems take into account factors such as the size, weight, and contents of the shipping container. It helps when vessels are required to wait for other vessels before an operation can take place, such as another vessel discharging cargo. AI is also being used to improve actual loading and unloading times for vessels.

4.3. Enhanced Customer Experience

Today's consumers expect to be able to pinpoint the exact location of their order within a very small window. The adoption of AI within the shipping industry is making it easier to do this by helping organizations better predict arrival times. AI can be used to offer more accurate predictions of when cargo vessels and barges will arrive at their final destinations. Shipping companies are finding delays easier to predict with better access to real-time data.

4.1. Cost Reduction

AI technologies are widely used in various industries with the goal to enhance efficiency and productivity. However, the implementation of AI technologies requires significant economic investments, which raises the questions regarding the return on investment ratios of such systems. In the shipping industry, particularly regarding logistics processes, AI technologies can deliver high direct cost savings in a relatively short period of time. Furthermore, AI technologies can indirectly help logistics providers to further expand their services and operate with higher profit margins.

Many logistics business models are based on high volumes and very slim profit margins. Thus, due to the relatively limited nature of the site services, logistics providers are sensitive to indirect service cost increases like energy costs for transportation and fuel costs for management of the fleets. Implementing AI technologies could minimize delivery delays and improve the overall scheduling and planning, thus indirectly reducing costs for logistics service providers. AI technologies can also increase margins and profitability of logistics providers through the implementation of very complex pricing models, which allow breaking down transport costs per parcel or by volumetric units, for example.

AI technologies allow integrating diverse information streams like real time weather data, fuel and energy prices and travel times, thus enabling cost-optimized routing for each delivery. This optimized routing could reduce travel distances and overall travel costs and further contribute to the overall profitability of logistics providers. Thus, due to the need for long-term optimization, many of the AI-based logistics solutions tend to shorten ROI periods in large-scale and increasingly data-driven logistics companies.

4.2. Improved Efficiency

With the boom of e-commerce and growing customer expectations, supply chains ask for a greater efficiency than ever. Artificial Intelligence is getting smarter daily and is able to explore big amounts of data in a very short time, unveiling relevant information about markets, customers, patterns, and trends. Such information is likely to reduce the uncertainty that surrounds logistics management and help various decision-makers throughout the supply chain. A good utilization of such information is expected to lead to higher efficiency for companies. Additionally, a wide range of tasks regularly made in logistics and shipping may be conducted by more efficient AI systems, such as routing, forecasting, and scheduling.

Forecasting demands is crucial for a smooth logistics management. Companies whose management have a poor demand forecasting may find themselves suffering penalties due to late deliveries, incurring extra costs for emergency shipments, or holding high levels of safety inventory to avoid stockouts. Passive AI systems that employ data from location tracking, customers' profiles and purchase histories, and the analysis of seasons and trends, may be implemented to predict cargo shipment demands with more accuracy than today's systems. The transparency and reach of the Internet allow logistics companies to have a general picture of what cargo is on the road of a region at a given moment. Were such data aggregated and analyzed, it would probably create a great and updated demand forecasting tool not only for logistics companies but also for governments and city planners. Consequently, better forecasts would help decision-makers throughout the supply chain, from suppliers to customers.

Artificial Intelligence is also being used for automating tasks related to route forecasting. Picking – in the large and automated structure of ports, airports, and warehouses, as well as in foreign trade zones – is in charge of hundreds of expensive workers conditioned by the heat and the smell of items whose weight can reach tons. Experts predict that AI-assisted robots will be able to perform those tasks in about ten years. However, today companies are able to apply computer-based systems designed to evaluate the electromagnetical spectrum of the area around a scanned product in the search for its item code, using a very short time to apply the corrections called for on the address of that product, resulting in a reduction of incorporation costs and days between origination and receipt.

4.3. Enhanced Customer Experience

Customer experience is an often-overlooked aspect of shipping. The shipping industry is regarded as a cost center rather than a customer satisfaction driver. As the shipping industry grew, players attempted to leverage it as an upselling opportunity, persuading retailers to share in extra shipping expenses to get their products to customers faster by methods such as air transport. However, not investing into a better customer experience has made the industry vulnerable to disrupters. Today, many other marketplace players, such as these retailers, can offer consumers up-to-the-minute tracing information along with fast shipping. The growing threat of retail disruption has intensified the focus on enhanced customer experience, as demanded services have tended toward increased availability, reduced price sensitivity, and heightened expectations regarding the shipping experience, especially the delivery timing. Major shifts in e-commerce trading patterns have underscored early responses by retailers to thinning margins, notably the provision of free returns. This trend mirrors a parallel development in bricks-and-mortar retailing as companies attempt to leverage customer experience as a competitive differentiator across the multi-channel journey. In recent years, AI systems have been introduced to improve customer service and experience management. AI's various applications include product searches, queries, responses, and customer analytics behind a variety of devices, including chatbots, mobile apps, robots, social media, and voice- or text-based communication systems. Shipping is a major logistical function wherein AI can be intelligently applied to provide positive customer experiences and create a beneficial competitive advantage.

5. Challenges in Implementing AI Solutions

Artificial Intelligence is revolutionizing logistics and shipping. AI solutions can optimize various activities from container loading and unloading to reducing air and fuel consumption. However, there are a few hurdles that need to be tackled for AI systems to operate at their full potential.

5.1. Data Privacy Concerns Data is a critical part of logistics. With eCommerce growing explosively, logistics activities need to operate at large scales, handling millions of transactions on a daily basis. Confidentiality and privacy concerns arise while analyzing large amounts of data. The purchasing details of these transactions are different for each transaction, making it difficult to identify sensitive and confidential information. However, the data contains a wealth of information that can be useful in predicting demand for various consumer products. Every player in the supply chain should be willing to share their transaction details related to customers, advertising partners, and retailers. Additionally, companies need to reduce the risks associated with sharing information, such as modifying sensitive information.

5.2. Integration with Existing Systems The implementation of AI technologies in logistics should be carried out in phases. The logistics industry has been slow to adopt new technologies. The companies are still heavily reliant on legacy systems. While utilizing these technologies together would provide greater benefits, it is also a challenge due to the complexities involved in integrating legacy systems with AI solutions. Typically, logistics systems are made to handle exceptions. Thus, integration may require significant customization efforts which are time-consuming and expensive. Moreover, it is challenging for system integrators to ensure that AI solutions produce results that are optimal and expose exceptions in a standardized manner. In addition, as AI solutions are complex, specialists in data science and transport logistics are required for operation.

5.3. Skill Gaps in Workforce Technical personnel skilled in the adoption and implementation of AI systems are scarce. In recent years, there has been an explosion of demand for data analytics competencies. The hiring managers are forced to compete for a limited talent pool. Data scientists able to speak the language of the logistics industry are in even shorter supply. Many companies are forced to train existing employees in data science and data analysis. Current data scientists employed in the logistics industry need to spend years developing their operational skills. Moreover, the level of education is lower among many logistics employees. Typically, most employees have a high school level of education and have taken on the job and learned the required functions through experience.

5.1. Data Privacy Concerns

As more companies go for digitization, the data is already shared with third-party vendors giving them access to crucial functionality of a business but the data interchanged is usually considered secure. Privacy and security concerns during the application of various AI technologies make data sharing or exchanging challenging. Most of the AI applications executed in the logistics and shipping industries may require the sharing of sensitive data, often regulated by local and global laws. Companies might hesitate to share their data with Cloud-based AI service providers due to concerns such as loss of competitive advantage, liability in case of data breach, and risk associated with utilizing the data. To circumvent the risks, AI service providers offer solutions in a closed-loop and after acquiring specific Data Protection Measures. However, this may not be ideal for all use-cases as companies need to entrust the service provider who could be their competitor either in the present or the future. The concern stretches to augmenting the technology with Machine Learning approach which always requires sharing of a portion of sensitive data either with the AI provider or among the users. Policies can be enacted for data to remain securely in-house in these cases so that the concern can be relaxed.

Another considerable concern is regarding the possible bias in decision-making by AI algorithms. Enterprises often adopt the black-box approach for AI algorithm development, leading to organizations untrusting the outputs predicted by the models. So, when these adopted AI methods are used for critical logistics functions, validation and verification of decision-making become an arduous task. Some AI algorithms could be more self-explanatory and trend how the data is transforming compared to others. In such situations, companies could choose for utilization of AI models which are self-explanatory for the businesses to trust the outcome or provide more business-related data in training the models to get more trustable results.

5.2. Integration with Existing Systems

Due to the rapidly changing environment of AI development and implementation, integrating into existing processes or with existing IT systems is far from trivial. Companies attempting to adopt and utilize AI-powered solutions are often faced with questions of how their existing platforms will work with the new solutions, how existing processes will be altered, and how to leverage years of data gathering. Existing systems are often built around legacy warehouse management systems, transportation management systems and global trade management systems. While they present challenges, these legacy systems usually possess mission-critical features supported by many years of specifications and test results. Products selected to work with these same legacy systems will need to carefully build on, or work in parallel with, the legacy solutions and features.

Another integration factor is the amount of data currently stored in existing information systems. Older systems tended to be data thinned due to concerns over storage costs. Newer generations of afterthought implementations are much more information rich: perhaps requiring higher computing power capabilities, but also presenting many more potential integration opportunities. These have arisen not only from increased computing analytics power but also the development of AI techniques intended specifically to augment decision making processes and to discover the areas where and when predictions tend to falter. Investors looking to profit from successful AI solution implementations will need to carefully examine potential vendor solution strengths, weaknesses and integration costs to ensure that they can be acceptable partners.

5.3. Skill Gaps in Workforce

Worldwide, 80% of business leaders think that AI will automate enormous parts of daily tasks and automate a large number of work processes. AI will not replace workers in difficult tasks but replaces the easy tasks, changing the way people do their work now, making them do those tasks in a different way, but using a variety of AI-enabled tools. All in all, educating the workers to use AI tools will be very important, otherwise success with AI analytics will be missing, requiring change in traditional methods. Although many organizations have very little understanding of how these technologies work.

A strategy needs to be defined. Thinking about workforce skill gap, it needs to set AI expertise level to execute tasks, roles like architects, data engineers, and data governors are level 3 to do things like set up and govern how to use the AI tools, from infrastructures, budgets, and policies, also maintain and support data ingestion and data labeling. On the other side, we have automation experts, data analysts, and marketing experts where they are level 2, who will assist the experts in the data ingestion process; on the other hand, they will help them in the configuration for machine learning and provide services to discover how to use the technology implementing the tools the right way.

Also at level 1, we have the data associates role: data workers who will accomplish specific tasks on the high level, operational processes for model training and implementation, business solutions implementation, and workflow. In other words, measure once applied the model and repeat the process transferring the results to data business executives who will focus their activities in the business.

6. Case Studies of AI in Logistics

Several companies have invested in AI to provide more efficient logistics services. These companies have launched smart logistics solutions that leverage machine learning, big data analytics, and computer vision.

6.1. Use of AI

AI is key to logistics capabilities. For example, during the peak of Black Friday, over 15 million packages were shipped in a day. ML models analyze historical data alongside real-time data, such as bad weather or social media trends, to forecast demand. The data is processed and demand is forecasted at the level of individual postal routes, down to the hour.

Recently, a patent was filed for a new demand prediction system based on artificial intelligence that provides greater accuracy and will help improve logistics processes further, increasing speed while reducing costs. When it comes to same-day delivery, logistics operations are complex and need to be executed with efficiency. This is done using AI technologies such as machine learning, which pre-computes precise geolocation information for last-mile vehicles and uses computer vision to automate the loading and unloading operations of packages. Secondly, the MLOps and MCD pipelines help the model be updated quickly to utilize the latest data. Such ML systems ensure that packages are delivered to the right place in the shortest amount of time.

AI is also used in machines and robots to sort packages automatically with ML algorithms that select the correct package out of the hundreds of thousands available in a warehouse sorting center. The sorting process must be accurate and efficient because it directly impacts the time taken for the package to reach the customer, or the performance of the logistics external service provider, or both.

6.2. Smart Logistics

The Resilience 360 platform uses predictive analytics services powered by machine learning to support supply chain management by companies. These predictions are based on real data provided by sources of economic indicators; data on logistics flows; and social media data and news about political instability or violence. At the supply chain management level, Resilience 360 provides, for example, a risk score for doing business with a certain supplier. In particular, this risk score indicates, in relation to the chosen supplier, the likelihood that it will become insolvent or face potential damage to its business or reputation. The tool also goes further, predicting the impact of a change on logistics, including the risk of instability in transportation.

6.1. Amazon's Use of AI

As the leading e-commerce firm, Amazon is a clear trendsetter of using AI in logistics to make for speedier order throughputs. In total, the company currently operates 175 fulfillment centers, many of which have been outfitted with advanced robotics. Amazon adopted a wedge-shaped box to use robotics for automated assembly of “small order” baskets of grocery items in warehouses located next to its Whole Foods stores. The facility is able to assemble 800 orders per day, which are delivered to the bottlenecked stores, waiting for final deliveries. Amazon’s robotics, which has been interested in in-house developments, have also been used to speed up packing operations.

Last Mile delivery is also being enhanced with AI, including check-out services. Worldwide, the company has seamlessly included drones in last-mile deliveries, including an option for drone delivery for customers. Customers receive a notification by email or through the mobile app, and the drones can be used to take delivery at locations with little if any ground interference. The first hour of the delivery free service is heavily timed, and up to a 5-day lead time is required for completion. At the other end, transporters conclude any transactions through their mobile devices. The drop by drone takes only a few minutes, to be used for time-sensitive items. From tests of small parcel deliveries, the speed of delivery is twice that of robots. Drones are also being deployed for continuously moving items both to and from high-traffic launch points.

Reuse of used packing materials is another use of AI at Amazon. It conveniently “remembers” all prior orders of a product and can easily be instructed to complete a current order using the same box. Doing so is a good thing for the environment, as it spares wasteful box-making. Currently it is estimated that 600 million Amazon boxes are used each year. One of the biggest uses for packages is Amazon’s Prime Day, during which an estimated 250 million individual items are expected to be sold at greatly reduced prices.

6.2. DHL's Smart Logistics

The logistic market is today evolving quickly. New players are entering the market, and old players are expanding their activities and cubing profits. The air freight volume is forecast to increase, and supply chains are forecast to be more complex. With its latest investment in expanding ground operations capacity, DHL continues to be the backbone of U.S. air freight logistics, with cargo loads originating from its ground locations spilling over to its air transport network. Technology is driving the logistics segment forward, as it opens the door to streamline and innovate processes throughout the economic ecosystem. It is obvious logistics needs to itself, innovate, operate and push the envelope on technology, develop solutions continually and deploy technology ahead of edge cases, in advance of being competed against by new players leveraging new technology.

DHL turned logistics services into solutions based on AI by embedding cutting-edge AI and machine learning technology into its public solution platforms. It also continues to innovate add value to more traditional relationships, by developing customer-specific, bespoke, dedicated Artificial Intelligence, machine learning and operations tools, to answer specific questions for customers. For example, DHL now offers a dedicated Heavyweight Air Freight offering, to handle increasing volumes of heavy cargo, and a dedicated Pharma Life Sciences facility in Mainland China. Decision makers use insights to manage, optimize, and reduce logistics-related risk during the sourcing, manufacturing, transportation, oversight, and administration stages.

6.3. Maersk's Digital Transformation

Logistics is essential for global trade. As the demand for goods transportation grows, logistics and shipping companies are faced with the challenge of providing a timely and effective service to companies and consumers. Moreover, these companies must also reduce their environmental footprint and improve their efficiency. This has resulted in logistics and shipping companies picking interest in artificial intelligence technologies to help them face such challenges. The global leader in shipping and logistics has embraced the digital transformation that new technologies bring. Its approach uses AI to provide cost-efficient and sustainable logistics solutions, enabling its customers to leave the logistics part of their business in a safe environment. It has claimed that technology plays a key role in changing traditional logistics from a cost center into a real business differentiator, unlocking new levels of innovation, efficiency, and customer-centricity.

Though this technological use involves setting high targets, setting priorities, and taking bold choices, these investments offer the potential to secure market leadership by using a combination of amazing people and advanced technologies. The company is developing a new digitally enabled platform that combines its scale and infrastructure with advanced technology, like AI, to deliver a far better customer experience at the same or lower cost. This will allow the company to boost the productivity of its customer service organization, allowing the team to focus on supporting the company’s most valuable customers. Furthermore, the digitization of supply chain solutions will enable the company to support its customers using digital self-service options. It wants to create secure, automated, and efficient activities in which boring and repetitive human jobs are replaced by algorithms and robots, embedding state-of-the-art technology, including AI and automation.

7. Future Trends in AI and Logistics

Even though we are already seeing the great benefit of AI in logistics in terms of cost and efficiency, we can expect more significant improvements in the coming years. This is the result of the continuing advances in deep learning, sensor technology, data mining, computational tools, and cloud computing infrastructures, along with the responsibilities and increasing requirements from customers, from inside the company and also from the regulations covering logistics. This chapter will cover three of the major trends in AI use for logistics for the coming years.

7.1. Autonomous Vehicles

While fully autonomous vehicles may still be a few years away, the combination of semi-autonomous or self-driving vehicles and AI technology for logistics will improve product flow, reduce costs, and reduce accident rates. Driver-assisted trucks on the main routes will help reduce the burden of truck drivers in the US. Automated guided vehicles, especially in the large distribution centers for ecommerce companies, are already transforming the last step of logistics. These vehicles, when combined with other robotic technologies, such as collaborative robotics and advanced control techniques, will reduce both costs and error rates in these centers. Finally, the introduction of small delivery drone technologies in the coming years will enable near-instant delivery times for emergency and critical goods.

7.2. Blockchain Integration

Meanwhile, the full integration of fault-tolerant, secure ledger systems needed for the tracking of logistics events with AI technologies for prediction and analysis is coming. This will support deep integration for supply chain logistics, from order prediction through replenishment, along with customer demand forecasting. Both AI and Blockchain technologies are in their infancy today. As the two technologies are applied in industry, we will learn more about the best practices for their combination for improved business practices.

7.3. Sustainability and AI

Finally, the internal and external pressures toward sustainability and environmental responsibility are also coming to logistics. Through fewer empty runs of logistics lifters, especially trucks and vessels, optimal sequencing of logistics demand via technology, and smarter matching of customers with logistics suppliers, emission goals for international logistics will increasingly be met through tuned use of AI in logistics.

7.1. Autonomous Vehicles

While decades of delicate research that has gone into the development of cutting-edge AI algorithms have often seemed detached from reality or considered merely as the province of niche tech circles, the recent developments in the processing capabilities of commercial chips seen in edge devices and robotics have also allowed experts to rapidly and remarkably reduce the gap between these earlier prototypes and real-life systems that are now either already commercially available, or will soon be offered for commercial sale. These advances have indeed finally begun to offer commercial solutions integrating the AI algorithms with the required processing hardware for some levels of autonomy in vehicles and driver-assistant systems. Over such vehicles as passenger and commercial cars, scooters, trucks, busses and shuttles, drones, and even naval vessels. It is no surprise, therefore, that logistics is one of the sectors where the largest potential for the introduction of autonomous vehicles is being seen – and where much investment is taking place. Air commerce, rail transport, and land shipping are areas that have seen, are seeing, or will see the arrival of driverless or pilotless vehicles, perhaps going furthest and highest in the prediction of possible future capabilities developing at a lightning pace; but also strategic yet cost-sensitive operations that heavily lower the cost of freight transport, which would normally imply a high environmental cost. It is thus projected that by 2030, autonomous vehicles with at least partial autonomy driverless or pilotless capacity will be deployed for logistics operations in at least three visible key areas: air commerce, rail transport, and land shipping.

7.2. Blockchain Integration

Blockchain technology integration is another promising direction for the development of AI in logistics. In supply chain management and logistics, the parties participate in the chain, often interacting with each other at many levels. Therefore, there is a wide range of information needs between supply chain partners. This information must be shared, but there is a risk of breaching confidentiality, data protection and integrity. Solutions are usually centralized in order to solve these risks. However, a central organization holder is vulnerable to attacks and is responsible for the security of the entire system, which makes it difficult to manage LSPs. This stimulates the software developer’s efforts to find a model that can help in achieving the desired secure, efficient and dispersed system for LSPs. Some companies have found a solution in the integration of their system on blockchain technology.

Blockchain technology evokes high rates of innovation. Thus, logistics service providers can create cost-efficient, flexible solutions for many partners across the chain in a secure way, and on the other hand, partners can be relaxed about the confidentiality of information. Blockchain technology creates the possibility to act in transparency and security, allowing all partners along the logistics chain to track the process in real time, and creates the foundation for adding AI algorithms for decision-making processes. The integration of AI and blockchain technology can bring new benefits for the transformation of LSP businesses. Indeed, the advantages brought by AI and the potential of blockchain towards business function levels can improve LSPs. The combination of artificial intelligence and blockchain makes it possible for logistics service providers to offer more efficient, faster and cheaper transaction solutions. The proposed solution will foster the collaborative and decentralized decision support, which enhances the automation aspect provided by artificial intelligence.

7.3. Sustainability and AI

The adoption of AI technologies is significantly contributing to the goal of climate neutrality. Real-time visibility is at the heart of any transition to net-zero emissions. Detailed visibility is becoming critical in logistics, which is often a blind spot for companies when it comes to their greenhouse gas emissions. AI applications help optimize logistics routes, minimize environmental impacts, and reduce wait times and costs, improving last mile logistics sustainability. AI adoption is creating more productive supply chains, meaning we can produce more for a given amount of energy, and deliver for less energy. This is fundamental to reducing energy use and ensuring energy is not wasted. AI entails the risk of creating local emissions hotspots. For example, the route optimization algorithms can bring a lorry past the same spot in a city without considering whether there are high emissions neighbors.

The share of emissions attributed to moving goods has grown steadily over the past 30 years and shows few signs of being curbed, even as pressure increases to build more resilient supply chains after recent shocks. More digitalized logistics networks track products through supply chains. But much of the data generated by the warehouse trackers and fleet monitoring systems is also unused. Optimization uses machine learning to reduce energy used in operating a distribution center, or at least work it toward net-zero emissions, using fewer and fewer emissions-intense resources for its power. AI and other technologies enable this more energy-efficient use of these now smaller centers by constantly monitoring their operations. This allows companies to optimize to lower power use throughout the day, achieving a smoother demand profile rather than one that spikes at any one time.

8. Ethical Considerations in AI Deployment

Although AI is a powerful tool that can improve profitability and have a positive impact on reducing emissions and greenhouse gas emissions associated with supply chain operations, its potential negative impacts also must be examined. These potential negative impacts are often referred to as ethical considerations, because they relate to the potential negative impact of new technologies and special algorithms that are being widely used in different commercial and social aspects of life. The major ethical consideration associated with the widespread deployment of new predictive techniques, including AI algorithm, is the potential bias that may be associated with the algorithm that is implemented. AI algorithms learn “how to think” like a human by digesting huge amounts of data. If society has latent biases and racism or other restrictions against certain minority groups or other types of people, this bias will flow into the data used to train the AI algorithm, making the algorithm biased as it learned from biased data. If the AI algorithm is biased, its practical application will also be biased. In these cases, the AI modeling would have different predictive performance on various groups of people or businesses. Job displacement caused by robots, automation, and machine learning is a major fear of many workers as they see self-driving vehicles or robots whizzing around requiring no human intervention. However, AI technology is not a monolithic, push-button solution to make work tasks go away. Rather, AI technology needs to be applied for the appropriate optimization tasks while ensuring that workers are deployed to those tasks that best utilize their human gifts and skills.

8.1. Bias in AI Algorithms

8. Ethical Considerations in AI Deployment

Machine learning algorithms learn from training data. These training datasets are generally meant to be representative of the real world; however, this assumption does not always hold. Some training datasets may be biased due to sample selection processes or may under/over represent different groups present in a population or in a specific domain. An example of biased training datasets is a dataset originally used to train Convolutional Neural Networks for image classification. This dataset was found to not represent a set of culturally diverse images. This lack of diversity caused CNNs to perform better on certain faces compared to others, such that these CNNs were prone to making racial mistakes. This problem has also been documented in facial recognition algorithms. However, biased datasets can lead to undesirable consequences for many machine learning tasks, having fairness-related impact on people and groups.

Consequently, an emerging body of work has focused on the issue of bias in training datasets. Addressing bias requires an understanding of the cause of bias, the stakeholders affecting the data and potential uses of the data. Addressing bias also requires insight into the lifetime of bias, i.e. how bias could flow throughout the data pipeline from collection to application. Some of the ways data bias can be addressed includes relying on trusted design patterns, taking preventative measures, integrating diverse stakeholders and relying on algorithmic tools. Although many suggestions for addressing bias in training datasets exist, the reality is that bias is still prevalent in many applications.

8.2. Job Displacement Issues

Being on the executive side of a shipping or logistics operation can be a rewardingly challenging job with a huge emotional investment. A high conductor has a 24/365 involvement with the logistics and shipping practice, as the orchestra conductor is at the top of a massive operation that engages thousands of personnel directly and interacts with millions of employees of its customers. Also, the company is really involved in the economy and operations of whole regions and sometimes even countries. So, if you were the CEO of a very large company in this practice, would you take the differences in margins over the effect of a process automation or reengineering in human workforce? Or, would you opt for a bottom line generation voter? This is a huge talk question since it clearly tells us how much a leader and a politician can be a job maker and what this really means.

From a more technical point of view, it is widely known that AI and robotics are here to stay and replacing repetitively manual, simple, low adding value, in some cases risky and exposed to errors, jobs, to one extent for service related occupations, being drivers and couriers very exposed jobs, and for industry blue collar and also white chattered functions. This is trivially true if we focus on the very short term business line for large companies with enormous investment capacities. Of course anybody is in the position of forbidding a corporate to layoff employees in cases where it is possible to improve business performance. The question is whether society is prepared to give a profitable answer to take care of the people that will lose their jobs because there is no other alternative.

9. Regulatory Landscape for AI in Shipping

As we have already explored the fact of AI replacing people performing tasks within ships but also other processes like ship surveys and inspections among others, AI integration into general shipping affairs may seem unregulated and uncontrolled. But, how many of us have ever thought about the multi-decade design, development and deployment process of regulatory frameworks designed to govern the work of the most classical example of concentration of people and goods across the globe? Sea transport has been around longer than many think, however the first regulatory frameworks come from the 1950s mainly because of the Cold War. Artificial Intelligence is expected to revolutionize shipping in the coming decades provoking technological advances never seen before. What could possibly respond to such an evolution in matter of safety and security of persons and goods? The work of the regulatory bodies has just started.

There are two parallel paths of regulation. The first one pursues adaptation of existing sectorial regulations to new technologies and methods of operation capitalizing to control risks induced by ship boards. The second one aims at the creation of a more general legal framework for the responsible use of AI in shipping. This paper outlines some of these policies and strategies through examples of rules and regulations under development. A global regulatory framework for shipping, safety of life at sea, safety of the ship and to the marine environment, but there is no duty of collaboration between the members of the team playing that framework. Compliance is a strict liability. This leaves a great part of the work of establishing a “captain letter” for the corporation in charge of the ship. Maritime law was made for ships not autonomous systems.

9.1. International Regulations

The shipping industry is predominantly regulated by a specialized agency of the United Nations. Established in 1948 with a focus on creating a regulatory framework for shipping safety, environmental performance, and efficiency, this agency has adopted more than 50 treaties that address a variety of subjects. Most of these treaties are legally binding on their state parties. The more major treaties include: - Safety of Life at Sea (SOLAS) Convention - International Convention on Load Lines - International Convention for the Control and Management of Ships' Ballast Water and Sediments - International Convention on the Prevention of Pollution from Ships - International Convention on Civil Liability for Oil Pollution Damage - International Convention on Maritime Search and Rescue - International Convention on Standards of Training, Certification and

Watchkeeping for Seafarers - International Convention on Tonnage Measurement of Ships

This agency has a unique mandate for international shipping, and so to a diminishing extent is the only body that can regulate AI in shipping. But domestic ports of call and port states can impose rules regarding port safety and security, while coastal states can impose rules regarding the safety of the shipping that passes through or enters their zones of control. There is a focus on global port regulations, advocating that specific port regulations should require integration between marine, land and cargo transport.

9.2. Compliance Challenges

At the same time, businesses should consider more local opportunities to assess the risks rendered by AI systems, and particularly of those ones without an exceptional level of reliability. Regulatory instruments calling for the assessment of additional local environmental risks when approving new AI applications have been established. More countries are following with voluntary initiatives. These factors, combined with a gradual shift on the side of local authorities as to who takes the lead on cooperation or other distributional issues, will make jurisdictional concerns a very dynamic and evolving area of cooperation. The shipping and logistics industries have been busily developing guidelines and voluntarily commitments on how to design and deploy trustworthy AI systems. As these guidelines enable companies to respond to national laws, jurisdictional challenges may be overcome by AI providers developing their products in line with these principles.

The challenge is for these industry level guidelines to be implemented, to be capable of catching up with rapid technological developments, and at the same time to be able to comply with applicable principles of international economic policy and incentives. To achieve these relevant and lofty goals, a number of areas needs to be tackled. For example, to what level will companies be ready to self-assess more difficult risks or take on additional obligations and responsibilities, especially in the face of the inherent opacity of some AI applications and the extra-territorial reach tools? Other areas might be the value added and adverse consequences of the use of risk categorization in practice or the purpose limitations. All these fundamental challenges would benefit from substantial public-private dialogue.

10. Collaboration between AI and Human Workforce

Logistics and shipping account for more than 80% of global merchandise trade. The world of logistics and shipping is accelerated by the exigencies of global deliverance faced by players in the industry. Consequently, AI technology is seen as an enabler addressing cost optimization, increasing productivity, improving the quality of service, better utilization of human resources, lower carbon emissions and better inventory management. Many companies in the logistics and shipping are already employing AI technologies. There are fundamentally two classes of work focused in logistics and shipping, to state, physical movement of goods and information work. The horizon of AI in logistics and shipping expands from autonomous vehicles for the physical freight movement to smart robots operating in warehouses, to drones deployed for inventory management of warehouses, to quoting of prices for freight movement by analyzing news and events around the globe. AI identifies routes for shipments, analyzes meteorological data for the shipment route, augments efficiency in capacity utilization and freight forecasting, quotas cost for shipment, recommends mode of transport to be chosen based on cost impact and duration impact, alerts about disruptions due to weather and identifies digital trade lanes. AI leads to operational improvements in shipping, analyzing data. AI is on the forefront of the highly competitive and technology-matured maritime sector, by offering decision support algorithms for the maritime operations and discovering hidden causal structure. It engages in extensive cooperation with the human workforce, using the workforce for training and often continuous human intervention.

11. AI-Driven Decision Making in Logistics

AI can only do its magic when powered by high-quality data at its disposal, and logistics decision-making at all tiers is replete with big-think moves involving real-time access to, collection of, and response to information on thousands of variables. Supply chain flow management requires an eagle eye on changing conditions. AI assists ops teams by finding patterns in massive quantities of data in almost instant time. Anywhere from ten minutes to about one hour of lag time is considered acceptable for logistics marketers, as long as the load prediction for the last mile ends before they arrive at the hub or the delivery spot of the last customer. Many systems rely on a mixture of streaming data, perhaps collected from devices and servers deployed in the delivery environment, and batch updates in such measures as traffic flows on specified routes.

Real-time data collection makes just-in-time logistics a reality and brings the cycle time down to zero; and millions of consumer-company interactions can be intelligently harvested and put to productive use by neural network machines that have gone through supervised training. Only the fastest smart logistician can beat the learning ability of a good AI. An increasingly critical factor for logistics scheduling and route optimization is business continuity, which has different meanings for businesses in different industries; for takeaway food delivery, major hotels, essential services firms, restaurants, and hospitals, downtime has very small proportions and extremely limited hours during the night, while for offices, clinics, schools, and factories, downtime occurs after the last customer has been served for the day.

11.1. Real-time Data Utilization

Impact of AI-driven decision-making in logistics is profound. To begin with, an efficient bonus of Artificial Intelligence (AI)-driven logistics is the facilitative management of supply chains through business ecosystems, where third-party services are seamlessly integrated, accelerating the transition from supply chain management to supply chain ecosystem management. With deep learning techniques, sentiment analysis and image analytics-based real-time process damage monitoring can be achieved. AI-backed decision making can also eliminate a lot of costs involved in shipping products down to the customer, all while increasing the flexibility of how products are shipped. This has the extra advantage whereby logistic changes become extremely private, with close to exclusive visibility.

Companies can enable true partnerships with key third parties, dwelling into driver management and big data, proactively addressing risks together, managing and optimizing the entire process jointly. AI-assisted large language models can assist logistics managers through the entire shipping operation and document process. Satellite imagery analysis could help dynamically change prices on freight service during high traffic stress situations. High-performing predictive IQ-based logistics planning can decide the correct actions that logistics service providers should take. Higher IQ in demand forecasting can also impact the individual company success. Optimization of logistics networks should maximize service levels while minimizing costs. AI-based predictive analysis can also help negate the risk of clients underestimating what key organizations are actually involved in the product life cycle. Automation is key for all organizations to retain their competitive edge.

In logistics, AI-based systems can help foresee future uncertainties or extreme conditions in logistics planning and pre-build certain structures and capabilities needed during those times. These are like the trees built by nature that cannot change or sway during strong winds. For example, the sub data flows could be the LSPs involved in each step, the guide data could be the data associated with those LSPs, route data is last data information.

11.2. Scenario Planning

To effectively mitigate uncertainty, logistics service providers can employ predictive scenario planning and risk visualization based on AI analysis of digital twins from past behavior. The prediction of logistics demand at the SKUs or even the line-item levels through AI algorithms has the potential to greatly reduce the bullwhip effect. The long-standing bullwhip effect in supply chains refers to the distortion of demand information as it travels backward in the supply chain toward suppliers. Many AI projects today involve the comparison of different scenarios. Today's decision-makers may ask many "What-if" questions: "What if demand rises or falls," "what if one of our suppliers suddenly fails," or "what if there is a sudden change in the weather?" With AI-driven decision support tools, the impact of the possible outcomes of these "what-if" questions can be reviewed quickly.

However, answering these questions is not straightforward. Correct answers don't come easy. Most of the deep learning models available today provide no insights into their internal workings. Decision-makers may be unable to fully trust the outcome of the model and its ability to take into account all factors included in the decision-making process. This is the reason why deep learning has not really found its way into critical corporate decision processes. When trusted visualization models are available, companies can trust AI to help in answering these questions. With trusted scenario modeling, decision-makers can then supplement the process with their intuition regarding possible patterns of social behavior. It enables them to bring explainability to the prediction and visualization models. AI can then be relegated to a co-pilot, leaving human decision-makers in control of the teachable moment.

12. Impact of AI on Transportation Modes

The positive impact of AI on logistics is seen in all transport modes. Degree of automation of their operations is a determining factor in introducing AI innovations and machine learning in logistics for air, maritime, and land transport. The concept of “smart” solutions, autonomous cooperation of autonomous vehicles and unmanned aerial vehicles or flying drones, and their integration into AI supported infrastructure are at the focus of intelligent transport innovations. First successful implementations of such solutions can already be observed. They spread rapidly beyond pilot tests thanks to the decreasing cost of autonomous vehicles, mobile mapping, detection technologies, 3D sensing systems, multiple cameras, LiDAR, and GPS technologies. AI is constantly integrated into the tools for autonomous vehicles. This allows to combine advantages of automated driving for long distance transport, operation speed of passenger vehicles, and operational flexibility of delivery services with thanks to the usage of public roads and highways and advanced extended mobile applications.

Innovative companies deploy drones for air freight transport and for automation of transport operations at warehouses, airports, and ports. Additionally enhanced capabilities of aerial drones and recently developed cargo drones open up their usage also for delivery services and longer air freight routes. Large logistics companies are investing into less than truckload and same day same hour delivery services provided by drones to pioneer innovative solutions. First stages of drone ubiquity in tier 1 cities and urban hinterland can be identified for 2030 and 2035. As a temporary measure, drone-assist air transport is planned to bridge critical freight transport needs. State of the art of drone innovation implementation is reached in China leading AI usage by close to 50 percent in selected sectors, particularly in logistics.

Innovative onshore-to-onshore last mile solutions are being eagerly implemented into freight flows by multinational corporations. Their solutions aim at optimizing their intercontinental logistics networks. New maritime shipping routes are developed between Dubai and Romania and seeks to implement its intelligent port solution in Constanta Romania. Such solution would optimize ship loading ramapping loads. In this way, shipping containers would dominate the ramp and facilitate offloading by cranes. Investment into such algorithms would become another substantial contribution to the success of the Belt and Road initiative.

Despite being somewhat slower than their competitors, the European Union pilot implementation of an autonomous train system may considerably enhance the whole smart solution concept. The first commercial operation contracts are already signed. As part of their utilization in land transport, the knowledge readiness level of autonomous vehicles has already transitioned into establishing commercial pilot operations. The planned actual scale of operations aim to develop U.S. logistics networks.

12.1. Air Freight Innovations

Air cargo is revolutionizing the shipping sector as the need for speed in commerce escalates. Although it accounts for only a small percentage of total volume, air freight is the fastest growing and perhaps most lucrative portion of the industry thanks to increasing consumer demand for next-day and even same-day delivery. These pressures are enhancing the role of air cargo hubs within existing networks as well as leading to new routes and development of point-to-point services. To meet service expectations, air carriers are focusing on reducing costs through technological advances and better route optimization, integrating operations with key customers, and working to eradicate hidden costs and delays. Freight forwarders are finding new ways to meet global demand for speedy delivery. They are innovating within traditional business models and experimenting with new ideas. These efforts are changing the shape of the air cargo industry in fundamental ways, forcing traditional boundaries to shift. New entrants are facilitating destination-to-destination services without using traditional consolidators. Tech-enabled freight forwarders handle customs brokerage and last-leg delivery to shippers' doors without physical warehouses of their own or trucking fleets. Digital freight-forwarding players focus on customer-friendliness and tech platforms that unify data flows for all stakeholders and expedite decision-making. They are investing heavily in technology to enhance visibility, boost shipment value, and differentiate their service. Their platforms yield operating costs reductions. Blockchain, AI, and IoT are also torchbearers for freight technology advances. Smart contracts eliminate the need for third-party verification.

12.2. Maritime Shipping Advances

Just as overland shipping with trucks and with trains accounts for a relatively small share of freight and transport sector revenues and emissions, transportation by ships across the oceans accounts for a much smaller share of the two globally, but can be a potent force for local destruction of emissions. Maritime shipping is the most global of the freight modes, literally a means of transporting goods from port to port worldwide. Historically, this has involved sending vessels loaded with goods to their destinations, but afterwards returning to port – empty except for air. Has this not been wasteful? The increasing use of container ships and containers, within which the cargo is sealed for transit, has changed this situation by enabling shipping to take on return cargo that ties into the vessel's route. Why not a global network of shipping vessels, linked by satellite communications and computerized transportation systems so they know when and where to pick up and drop off cargo? Further increasing rapidity in seaborne transportation has been achieved through the use of very high speed container ships, specially constructed for faster transit over selected trade routes.

Ships now transport 90 percent of the world's goods, making shipping a promising domain for AI innovation. What progress have we made enabling AI to manage the world's shipping? New methodologies and algorithms are being developed to support the decision-making processes and planning problems of the maritime shipping industry. Models have been developed helping the shipping industry better anticipate accurate time of arrivals, considering a wide range of weather scenarios rather than a deterministic solution to the benefit of safety, costs, and reliability.

12.3. Land Transport Enhancements

In North America, railroads have introduced improvements and cutting-edge technologies that allow them to better compete in the transportation space. For example, a prominent North American intermodal rail service provider has collaborated with an artificial intelligence pioneer to create vehicle inventory software that utilizes AI for estimating the availability of containers and trailers, forecasting supply-demand imbalance in select markets, and ensuring the timely return of empty containers from inland areas. This helps the provider enhance its asset utilization. Furthermore, as consumer demand shifts toward higher-value goods, impactful shipping options are developing within the motor carrier segment with time-definite and same-day delivery being offered by some players. These services cater to the needs of shippers looking for solutions lower than airfreight costs and higher than traditional trucking solutions. From a geographical perspective, majority of close-to-door deliveries of freight throughout the United States and Mexico continue to be driven by the trucking industry. This segment also dominates Canada-to-U.S.-North East routes in logistics networks.

The aforementioned shifts with respect to railroads and motor carriers open new and unique niches within the intermodal segment. Offering specific freight service requirements, these niches may prove to be of interest to intermodal players providing door-to-door delivery. With supply chain managers increasingly focused on cost management, greater intermodal activity is expected from railroads. Long-term growth in intermodal traffic is being anticipated as additional rail partnerships with ocean carriers that prompt growth in maritime container import volumes from Asia continue to be developed. Another growth driver for North American intermodal railroads and logistics companies is recent developments pertaining to service expansion within China on the part of shipping lines experienced in the container services business. Partnerships between ocean and rail carriers augment capacity by fostering partnerships in rail operations.

13. Conclusion

As the use of AI in logistics and shipping continues to grow, an increasing number of organizations are expected to leverage AI technologies. The logistics and shipping sector has specific characteristics, as it centers around a physical product supply chain with clear capacity restrictions, high capital costs, and narrow profit margins. Players in this market are also highly sensitive to price changes and are responsible for major emissions to the environment. The market was estimated at a significant value in 2021 and is expected to increase over the coming years. Air freight is the fastest-growing of the major transport sectors based on demand, growing at a notable rate, and fastest-growing based on capacity. With an increasing focus on de-carbonizing global supply chains, logistics and shipping players are accelerating their investments in sustainability initiatives. The crisis has exacerbated the appreciation for agile supply chains with higher inventory levels, which has counter-impacted demand.

However, the sector faces numerous challenges, from structural shifts in demand propelling the urgent need for digitalization to the complexity of the volatile environment ahead, with geopolitical tensions, commodity volatility, inflation, new technologies, and climate change. Supply chains have been increasingly challenged to optimize processes further, by moving towards more transparent and efficient ones, gaining more control and visibility over the end-to-end journey of goods while protecting the environment and finding new ways to unlock value. AI emerges as a key enabler to successfully address these challenges and, when implemented in a purposeful way, can significantly contribute to boost the position of the logistics and shipping player into higher market positions, as it will create more profitable waves of product and consumer demand to be captured.

References:

Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, *3*, 54-70.

Woschank, M., Rauch, E., & Zsifkovits, H. (2020). A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics. *Sustainability*, *12*(9), 3760.

Bhargava, A., Bhargava, D., Kumar, P. N., Sajja, G. S., & Ray, S. (2022). Industrial IoT and AI implementation in vehicular logistics and supply chain management for vehicle mediated transportation systems. *International Journal of System Assurance Engineering and Management*, *13*(Suppl 1), 673-680.

Kazancoglu, I., Ozbiltekin-Pala, M., Mangla, S. K., Kumar, A., & Kazancoglu, Y. (2023). Using emerging technologies to improve the sustainability and resilience of supply chains in a fuzzy environment in the context of COVID-19. *Annals of Operations Research*, *322*(1), 217-240.

Agrawal, S., Agrawal, R., Kumar, A., Luthra, S., & Garza-Reyes, J. A. (2024). Can industry 5.0 technologies overcome supply chain disruptions?—a perspective study on pandemics, war, and climate change issues. *Operations Management Research*, *17*(2), 453-468.

Tsolakis, N., Zissis, D., Papaefthimiou, S., & Korfiatis, N. (2022). Towards AI driven environmental sustainability: an application of automated logistics in container port terminals. *International Journal of Production Research*, *60*(14), 4508-4528.

Jahani, H., Jain, R., & Ivanov, D. (2023). Data science and big data analytics: a systematic review of methodologies used in the supply chain and logistics research. *Annals of Operations Research*, 1-58.

Zhang, J., Yang, X., Wang, W., Guan, J., Ding, L., & Lee, V. C. (2023). Automated guided vehicles and autonomous mobile robots for recognition and tracking in civil engineering. *Automation in Construction*, *146*, 104699.

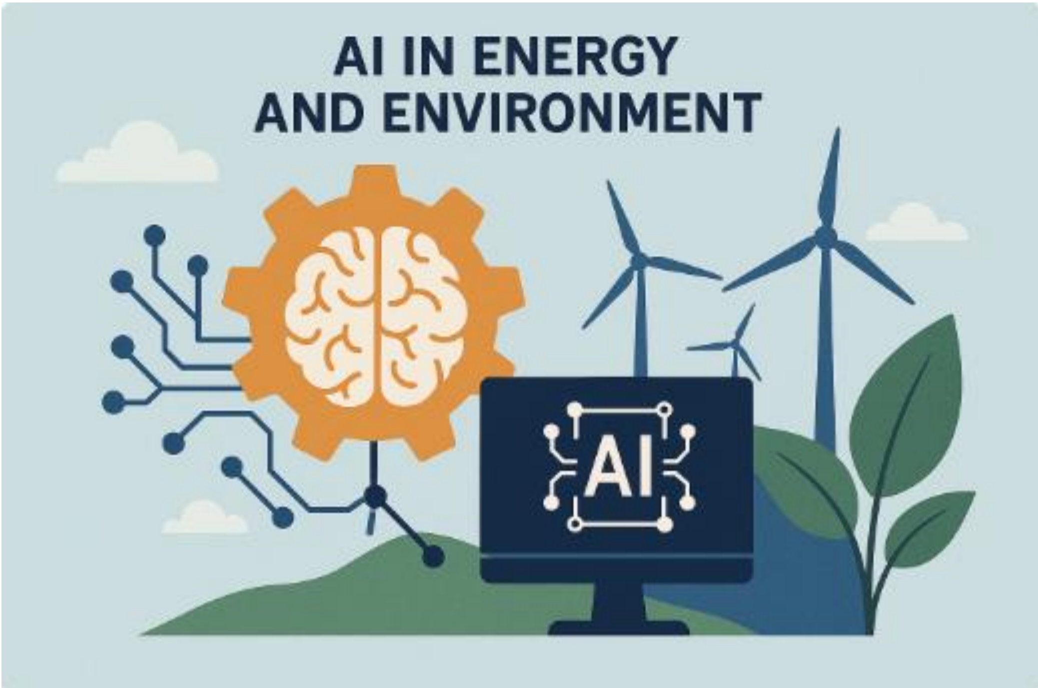
Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 9: Artificial Intelligence in Energy and Environment: Smart grids, energy forecasting, climate modelling

1. Introduction to AI in Energy and Environment

Artificial Intelligence (AI) has surged to the forefront of various scientific and technological innovations (Abdalla et al., 2021; Ahmad et al., 2022; Baduge et al., 2022). Besides accelerating basic research, fundamental scientific breakthroughs, and technological innovation, AI lies at the core of many interdisciplinary applications. These research challenges take place at the intersection of AI and other sciences and technologies, where AI has been seamlessly integrated. Within this framework, some application domains are mature, while many others are still relatively nascent. AI applications broadly occur in robotics, computer vision, natural language processing, biomedical applications, financial systems, social systems, and energy and environment, among others (Booshehri et al., 2021; Liu et al., 2021; Mehmood et al., 2019; Wu et al., 2020).

In this chapter, we focus on one of the most critical and ancient application domains, energy and environment. AI in energy and environment can naturally be further delineated into two broad directions: one focuses on the development of AI methods and technologies; the other focuses on leveraging AI in energy and environment applications. This chapter will mostly concentrate on the second direction because our purpose is to present examples of AI applications in energy and environment domains. We will recall AI methods only when needed. Energy is the key component for the development of all industries. The imbalance between energy supply and demand has a negative impact on the economy. Thus, it is crucial to optimize energy systems, supply energy of high quality, and satisfy people’s demand. These demands for energy save no effort in the development of energy technology, especially the continuous development of AI and other technologies which accelerate scientific research, fundamental scientific breakthrough and technological innovation. The other side of the coin is the environmental issues caused by energy and service industry development. The core of solving the environmental problem is to reduce carbon emissions.



2. Understanding Smart Grids

2.1. Definition and Importance

A smart grid is an electricity supply network that uses digital communication technology to detect and react to local changes in usage. Also, it integrates the behavior and action of all connected users in its operations, from power plants to producers and consumers. The term "smart grid" is broad and refers to the application of digital technology and network communications to every part of the power system, enabling real-time data gathering and implementation of improvements throughout the electricity system. This provides a wide range of benefits, including greater energy efficiency, improved reliability, lower operating costs, easier integration of distributed power generation, and a faster transition to a low-carbon future.

The smart grid is also important for the larger environment. The smart grid will provide the communication and networking mechanism that implements improvements to the entire power structure, including distributed energy systems, demand response, microgrids, better efficiencies in industrial power usage, electric vehicle and transportation systems, and micro-storage systems. Global economic changes and the need for reduced emissions are providing all the impetus necessary to convert the current power grid into a smart grid.

2.2. Components of Smart Grids

Smart grid technology is the integration of renewable energy generation; smart meters; smart substations; smart inlet lines; smart transformers; supervisory control, data acquisition, and energy management systems; real-time monitoring; energy management systems supported by energy storage; demand response; electric vehicles; and cybersecurity. Smart grids are envisioned, designed, and developed to deliver integrated functions encompassing Sensing, Communication, Computing, Control, and Cybersecurity at all levels to the electric grid. To accomplish these goals, electric grids must be automated, optimized, maintained, and operated redefining conventional approaches. Communication, signal processing, and control technologies must be integrated to develop intelligent functions, capabilities, and systems for each smart grid device as well as for the grid as a whole.

2.1. Definition and Importance

What is a smart grid? A smart grid is an electrical grid that uses digital technology to monitor, predict and manage the transport of electricity to meet the varying electricity demands of end users. Basically a smart grid employs digital technology to make the electricity supply more reliable, resilient, efficient, sustainable and safe. In addition, a smart grid collects data in real-time to help in optimizing demand, generation and management of existing electricity system assets. It provides reliability on demand supply to electric utility.

The importance of smart grids stems from the increasing complexity of the electricity supply chain that can vary from a central generating resource to less controllable local distributed electricity resources. Changes in energy use patterns are posing a serious threat to the reliability of the electric system. The two primary drivers of the changes in energy use patterns are the economic and environmental catalysts that limit the demand as well as cost drivers that lead to a rampant increase in market prices. This has been made worse by climate change which is leading to a host of reliability concerns for grid operators. These changing reliability concerns as well as the emergence of new technology and regulatory frameworks that favor distributed energy resources heralds a new approach to electricity management by grid utilities.

2.2. Components of Smart Grids

Smart grid technology integrates numerous devices and systems to create a unified, interconnected domestic and industrial power system. A smart grid has the same basic components of a conventional grid, with the addition of devices and systems that give it enhanced capabilities and advanced functions. Progress in smart grid research and development activities has shown that the fundamental components of smart grids are two-way energy flow, smart sensors that play a vital role for grid insight, automation devices for grid control, digital communication technologies for relay of grid data, distributed intelligent controls, advanced decision support mounted on appropriate software, and the advanced fiber optic network that serves as a backbone for communication of all smart devices in the grid. Development activities on these fundamental smart grid components have progressed significantly in recent years. Encouraging additional development of key smart grid components can help accelerate the uptake and commercialization of smart grid technologies. As special purpose utilities, power distribution utilities have a limited business model to sustain and justify commercial use of intelligent grids, unless it helps accrue significant financial savings through improvement in network efficiencies.

The Smart Grid is a combination of technical and technological components of the electrical grid. It goes without saying that prior to describing its components we should imagine what a Smart Grid consists of in its whole. In a general view, the Smart Grid should be able to successfully execute four major domains of work: 1) Generation, 2) Transmission, 3) Distribution, and 4) Consumption. Using a more detailed description, Smart Grid consists of components for local generation of power, transmission and distribution networks, automation and control technologies, cybersecurity protocols, data management and communications, information and decision support, markets, demand and end-use technologies, and business. In short, the Smart Grid includes all modes of electric power generation, sustainable integrated new energy renewable resources systems, including wind power systems and applications, advanced energy storage systems and applications, household electricity storage, energy storage managing systems, hydrogen production and fuel cell applications, intelligent distribution and real-time controllable micro-grid systems, electrical vehicle development and power modified technical standards and systems, and everything that can improve energy utilization and minimize pollution.

2.3. Role of AI in Smart Grids

Artificial Intelligence (AI) is envisioned as a major driving force for digitization of the energy sector as an enabler of the wide vision of Energy 5.0, by creating a cyber-physical domain where AI controls the physical energy networks and systems through the vast amount of data collected through digitalized, interconnected, dynamic sensors. Smart grids increase efficiency and flexibility of energy transfer from supply to demand, from large-scale generation plants through transmission grids down to local distribution grids with rooftop solar PV, local storage and electric vehicle charging stations, and finally to consumers able to collectively exploit their demand-side flexibility in aggregators and virtual power plants; and the interconnection of multiple domains – electricity, heat, hydrogen, mobility – which can exchange energy in digitalized and flexible energy marketplaces, balancing supply and demand in each moment in different time frames, supporting the unilateral flow of energy with local intermediaries and electricity users, and prioritizing local energy flow and storage through local balancing markets.

The functioning of smart grids is ensured by the autonomous and secure control of vast networks of decentralized generators, storage systems, electric vehicles, loads; by a decentralized management of prosumer interaction and economic exchange, respecting local market clearing constraints; by ensuring flexibility for centralized generation and by the decentralized coordination of cross-network inter-exchanges, which ensure mutual balancing between networks operated by different TSOs. The achieved decentralization relies on a digital exchange of the traffic data between the local energy marketplaces of TSOs and DSOs, the data suggested by AI, through predictive big data algorithms, energy demand forecasting based on weather forecasts and their impact on production; and based machine learning algorithms for predictive fault diagnostics and preventive analysis of control cybersecurity, control and technology for data privacy protection.

2.4. Case Studies of Smart Grid Implementation

The successful operation of a smart grid requires the development and integration of several information and communications technologies, plus a commitment from governments, utility companies, and consumers. As illustrated by the following case studies, action at these three levels is necessary to implement a smart grid.

In August, 2015, the Turkish government announced its plan for renewing the energy transmission infrastructure, which already had run for 40 years without being replaced. Most of the work, to be done by the Turkish Electricity Transmission Company, mainly included the replacement of pylons, conductors, and substations, and the deployment of advanced communication systems, such as optical transmission lines and fiberoptic cables. The plan aims to optimize energy transportation with lower technical losses, better real-time management and monitoring, and to facilitate energy trading with neighboring countries. These actions will also protect the infrastructure from cyberattacks. Although the investment amounts to around 6 billion euros, the system was only recently updated with technological improvements in 2015.

In 2016, a company received funding to develop a cost-effective, smart grid-based electric vehicle charging station. To achieve its goal, the company replaced the charging station's low-cost, non-smart photovoltaic array and variable speed power electronic converters with smart technology. As a result, the company created a microgrid with PV and battery systems that optimally operates independently or connects to the smart grid during demand responses. The station could adjust directed and inventive loads, and charge vehicle batteries with grid and renewable generation power. It also conducted vehicle-to-grid interactions with vehicle charge times estimated for different times, with predefined charging electric and time power profiles to reduce grid peak loads.

3. Energy Forecasting Techniques

Energy forecasting is a central building block for smart energy systems design as it provides the inputs for many control and economical functions such as optimization and decision making. Energy forecasting is the process of predicting future energy needs, generation capacity and production as well as storage, balancing, and pricing. Flexible electricity consumption is pivotal for cost efficient operation of future power systems. Forecasting is regularly used in numerous sectors like forecasting energy production, forecasting energy load, and forecasting financial energy markets. A distinction is made between short-term and long-term forecasting horizons.

Traditional methods for energy forecasting are dependent on the expertise that can be provided in the forecasting model development phase. However, the increasing penetration of renewable energy sources, distributed systems, and flexible energy use requires the development of enhanced, data-driven forecasting techniques. Artificial intelligence-based methods are data-driven and more flexible, making them better suited for the increasing needs of actual forecasting accuracy. These methods cover Artificial Neural Networks, Machine Learning, and Deep Learning models. Such models are much easier to implement and are already available as state-of-the-art in other sectors. One of the main issues that data-driven models are still encountering is the forecasting using heterogeneous data sources assuring the necessary variety and representativeness of the data, enhancing uncertainty where needed, and modelling gaps in data in case of missing or unclear information. The challenge of inaccurate or volatile data in data-driven forecasting models can be partially prevented by employing shared data warehouse concepts and open data platforms.

3.1. Traditional vs. AI-based Forecasting

Forecasting models have existed for a long time and can enter into one of two broad categories. The first category contains traditional forecasting techniques that generally utilize statistical models. These methods use global statistical characteristics to derive functions that represent future values from past values of the forecast variable. In the second category, we find the newer class of AI-based techniques. This class uses different types of AI, including machine learning, to analyze past behaviors and learn the underlying processes that generate activity to extrapolate future values. More specifically, these methods utilize structured models, which model the various underlying temporal, spatial, and function approximation relationships explicitly, and non-structured models that focus on learning-to-forecast without explicitly specifying a priori the underlying temporal, spatial, and function relationships.

Time series forecasting is usually performed based on one of three assumptions. The first assumption is that future values of a variable are linear functions of past values. Based on this assumption, time series that act accordingly can be accurately modeled by one of the variants of the auto-regressive model, which is the basis of various statistical methods. However, there are many time series whose underlying processes are nonlinear. In these cases, one must resort to nonlinear techniques. A second assumption states that one can extrapolate the curve formed by a given series into the future. This assumption serves the basis for curve-fitting techniques, which can be extended into nonlinear regression. However, the accuracy of the forecasts produced by these techniques is strongly dependent on the choice of the curve and the goodness of the fit. A third assumption is that the future behavior of a time series can be predicted by a different time series. This is the basis of the transfer function. However, in many forecasting applications, the choice of the candidate variables must somehow be determined.

3.2. Machine Learning Models for Energy Forecasting

Forecasting the future energy consumption/supply pattern is crucial for ensuring energy management, distribution, and billing. Traditional models use physical laws to describe the complex dynamics of energy/electricity systems. Some of these traditional techniques include autoregressive moving average, autoregressive integrated moving average, and seasonal-autoregressive integrated moving average for univariate time-series forecasting, econometrics for deterministic modeling of time-varying energy/electricity demand for a given structure of the economy, and regression analysis. However, with power networks becoming more complex due to decentralization of electricity generation through the wide deployment of renewable energy sources, forecasting the behavior of energy/electricity systems is also becoming a daunting task. One of the main limitations of traditional models is that they are data-collection-centric, depending upon extensive historical data, which is not always available. Furthermore, complex and dynamic energy/electricity systems can create nonlinearities, coupled multi-frequency patterns, and other non-Gaussian noise structures in both deterministic and stochastic time series that are impossible to model with traditional forecasting methods' linearity. Deep learning techniques, including convolutional and recurrent neural networks, are among the AI/ML-based forecasting techniques whose efficiency, accuracy, and speed are among the best in a range of forecasting applications.

Instead of using physical laws for forecasting energy/electricity systems, the AI/ML methods use the available data itself for detection of the hidden relationships that exist among nonlinear features in the forecast period and prediction of future energy consumption/supply values. AI/ML-based models availability of data, and its ability to deal with model structures of varying complexity are some of the factors that account for the popularity of AI/ML-based forecasting techniques. The AI/ML models are semiautonomous and learn/create their structures from the available data without the need for a human expert to specify relations among input-output variables, unlike traditional forecasting models that are data-collection-centric, and dependent upon statistical tests to identify the specific variables to use in the model that dictates relationships among input-output variables.

3.3. Data Sources for Energy Forecasting

Energy demand and generation forecasting requires several types of input data such as power demand and generation, standard meteorological data, meteorological input data sources from weather models, and other auxiliary data. Time resolution of time series data associated with the most forecasting tasks is in the range of a few seconds to one hour. Therefore, power demand and generation data samples are used which are commensurate in their time resolution. Moreover, modeling high-dimensional time series data with diverse patterns across time may require a large amount of input data, better choices of model hyper-parameters, and careful design of training strategies. A large amount of data samples are easily available to train models for deep learning approaches. Data from the past few years are generally used for the respective forecasting tasks. However, task-specific and scenario-specific reasoning during forecasting need to be ensured while choosing the data for training. Data for state-of-the-art energy forecasting techniques are fairly easily available since they are listed at public repositories. Various standard data sets are discussed in this section.

Data for macroscopic long-term daily energy consumption forecasting are very easily available for every country. One country has adopted new data sets providing information on population forecasts, household energy consumption, and others. Good estimates of electricity export, import, demand, generation, and consumption data plus estimates of other energy sources for every country are available. Data on fossil and nuclear fuel reserves plus other energy supplies, consumption per capita, and global warming dimensions are easily available. Reports consisting of long-term energy consumption forecasts with specific recommendations for reducing negative impacts and mitigating global warming have been published.

3.4. Challenges in Energy Forecasting

While recent developments in AI technologies catch the attention of academia, industry, and policy makers, they do not solve all energy forecasting problems. Instead, AI and ML-based forecasting models face challenges such as data limitation, model interpretability, restricted planning horizon, domain changes, and ever-changing inputs. Many of these challenges are longstanding issues in energy forecasting and AI is not a cure-all solution. Like any technology, AI has limitations and energy forecasting practitioners must be aware of the conditions and circumstances under which they can use ML to improve forecasting. Complex energy systems are notoriously difficult to model and quantify; there are many sectors with insufficient data on stochastic, edge effects with little historic occurrence, and rare extreme events such as major energy crises or blackouts. For instance, electricity markets are constantly under scrutiny, balancing energy supply–demand and providing price signals for market participants. It is crucial to develop reliable electricity price forecasts that recognize random price spikes and market behavior pattern changes or irregularities. There are occasions, however, where data is lacking because of restricted access, history length, or formal reporting, and this may adversely affect AI methods that have heavy data requirements. AI explains decisions based on predictive input data. It does not however mean that the decision-making processes can be mechanically implemented without introducing bias in the initial data. By contrast, traditional methods have strong theoretical foundations coming from statistical econometrics, physics, applied mathematics, and stochastic modelling so forecasters can derive clear forecasting insights based on their modeling decisions and the people behind developing the model. ML methods on the other hand are opaque black boxes making forecasting interpretable outcomes difficult; simple algorithms with low bias and high variance are easier to use for forecasting because clearly mapping parameter selections to predictive outcomes is feasible.

4. Climate Modelling and AI

4.1. Introduction to Climate Models

Climate Change is the defining challenge of our time and we are at a defining moment in history. We have a brief and rapidly closing window of opportunity to deal with it. It is therefore crucial to make accurate predictions about how the climate might evolve. These predictions are made using Earth System Models, commonly referred to as climate models, which are the best tool that scientists have to forecast future climatic conditions, including events at great depths of the oceans, and all throughout and above the land and atmosphere, following climate dynamics over a century or longer. Furthermore, these models are the only tool that can provide estimates of how climatic conditions change in reaction to changing expectations, for example about fossil fuel use, about clearing the forests, or about geoengineering the climate. Climate models are large-systems of nonlinear differential equations, posed on long temporal and multi-dimensional spatial domains, with many uncertain parameters.

4.2. AI Techniques in Climate Modeling

Climate models were originally based on physical theories of how solar radiation warms the air, how the air warms the oceans and land, and how warmed air and oceans shift the clouds and rain. But some parts of the climate system are not well understood, notably the processes that determine clouds, precipitation, the physics of ice sheets and sea ice, the physics of the deep oceans, and various important biophysical processes. Such processes are represented in these models by computationally intensive parameterizations, approximations of poorly understood dynamics of very small-scale phenomena, such as turbulent motions that transport heat and moisture.

4.3. Predictive Analytics for Climate Change

Despite imperfect process formulations and inadequate spatial scales, these models can provide complex output, including a century or longer projections of future climate conditions over the Earth's surface, in its oceans and atmosphere, and at great depths. They have relatively highly uncertain spatial temporal projections, particularly at seasonal and sub-seasonal temporal scales. These models suffer from very large noise in their projections because they are not data-oriented models using optimal information, accumulated over millennia and long time periods, about the actual behavior of the climate system.

4.4. Impact Assessment of Climate Models

The long time, long distance projections are typically statistically downscaled. Geoclimate-related datasets from many sources are now available to climate modelers. Thus, geoclimate datasets are available for both training climate models and for applying other methods to generate downscaled forecasts from antecedent forecasts at higher temporal resolution. Climate modelers have both matched and meaningful alternative frameworks for leveraging vast historical climate data.

4.1. Introduction to Climate Models

Climatic modeling is traditionally viewed as a multiple step process. An environmental simulation model is a simplified expression relating some aspects of climate to a set of climatic input factors. The use of environmental models to predict climate change of various time spans has a significant historical foundation. However, limited understanding of the biogeochemical and physical processes that govern the Earth System limited their initial application to carbon cycle permafrost. Global coupled atmosphere-ocean climate models to climate change problems and transient simulations followed by calibrating against independent observations or empirical relationships generally produced little. Thus, much of the investment in model development went to long-term steady-state simulations of changes in surface temperature, sea level and at high latitudes, which were used primarily to develop statements regarding apparent pre-anthropogenic ranges of variability or noise.

Few models supported the transient climate and so had little impact on the debate when it was focused on the longer time scales. Most had been fitted to paleoproxy data and implicitly augmented by the proxy data to account for other climate influences, thus implicit in quasi-equilibrium were assumptions of stationary climatic variance about the mean and an ability of liable lay within the range of model error. Analysis subsequently established the likelihood of natural fluctuation on time scales longer than promoted pause and larger than model error. Until recently, we made them out to be insufficient for assessing longer time worldly changes, simply because the models could not simulate abundance or key isotope measurements made on clusters of individual foraminifera nor the key climate boundary/input variables that climate models required were not sufficiently known.

4.2. AI Techniques in Climate Modeling

In this section, we explore the intersection between AI and climate models, and how AI and ML techniques have been integrated into climate models development pipeline for different applications. Within these three thematic areas, we analyze publications in and related to energy production, extreme weather agent prediction and estimating weather impact on human health.

Many different deep learning techniques have revolutionized the fields of computer vision, speech processing, and natural language processing. More recently, these advances have been extended to the following areas in climate modeling: simulations and predictions from existing models, or from observations only; model components, such that their implementation in physical models have a form for long-term climate simulations; infrastructures, when climate and Earth system models use AI-based components but are not AI-based themselves; flexible data-driven model emulators operate at a similar scale as those being emulated; components which need to be used in long-term climate simulations, hence being used in a hybrid model combining a traditional simulator and an AI model.

In climate modeling, the two main families of AI-based techniques employed are statistical emulators of climate and Earth system models and the AI incorporation in these models. When these AI-based models are used to post-process Earth system model variables, they are referred to as AI downscaling. Three different activities can be performed with ML methods. First, they can be used to produce powers for renewable energy sources. Relevant research efforts are devoted to the forecast of solar energy and its magnitude. Recently, wind energy system demand forecast has extended to wind generation ultra-short-term forecasting.

4.3. Predictive Analytics for Climate Change

Climate change was first predicted in 1896 by the Swede Svante Arrhenius, who argued that anthropogenic emissions of CO2 would have a warming effect on the climate. Since then, our knowledge of the workings of the climate system has greatly expanded, as have our computing capacities. Because of this we are now able to simulate the response of the climate system to insolation changes, greenhouse gas emissions and feedbacks much more realistically than in Arrhenius' day. Climate models can be viewed as improved calculators based on Arrhenius' insight. One way they do this is by solving the physical equations describing the flow of heat and moisture in the atmosphere, or the movements of air and water in the ocean, including how they interact with each other and the land surface, incorporated increased atmospheric concentrations and forced by changes in insolation, volcanic eruptions and emissions. In the other, models describe the response of the climate system to insolation, natural aerosols, and land surface emissivity to reflectivity changes, volcanic eruptions; what is known as "climate sensitivity". Both types of models have undergone increasing sophistication over the years and the convergence of their predictions is one assurance of the robustness of the predictions.

If climate models are basically calculators that have built on Arrhenius' insight of the force on climate, what new talents does Artificial Intelligence bring to the task of climate modeling? For predictive analytics for climate change, AI brings several new talents. Smart algorithms able to mine massive datasets locate statistical relationships in the properties of climate variables and better estimate climate-sensitivity parameter values. Better paleoclimate reconstructions of climate states during periods with similar boundary conditions allow better training of the climate models. More skillful property predictions imply more accurate training of the climate models. AI optimized predictions of temperature, other climate variables, and their relationships augment the training datasets for the climate models by providing realistic additional counterfactual states.

4.4. Impact Assessment of Climate Models

The purpose of impact assessments is the identification, prediction, evaluation, and communication of the effects of decisions on both environmental change and human welfare. They involve dealing with a multitude of spatially distributed changes such as floods, droughts, crop yields, popular health problems, forest viability, and their social, economic, and environmental consequences. These available tools aim to support decision makers to determine the government readiness for particular changes in spending and investment, private-sector adjustment to trade policy changes, or collaboration on international environmental and policy agreements. AI methods have been widely used to support these type 2 impact assessments at the procedure stage, especially in relation to the identification and prediction steps. Examples include econometric models, computable defective equilibrium models, or simulation models which implementation is parameterized through econometric estimation, generally with a limited number of estimated parameters. It is important to realize the fact that the decisions influencing the future state of the climate system and the economy are made in the present, when uncertain impact functions are available to influence social welfare. When planning for currently occurring economic activity, fixed year impact functions are used for a country, or group of countries. However, at present, uncertain future year impact functions which varying according to each predicted year are used by policymakers.

In contrast, type 1 impact assessment refers to activities supporting climate modelers at the development and implementation phase. It uses models endowed with limited capabilities of generating high-quality climate data outputs to indicate a deficient generation of Level 1 and Level 2 climate data, possibly influencing the quality of the climate data outputs used through a focus on generating higher quality climate data outputs for Level 1 and Level 2 variables. AI methods have also been previously used by impacting the different constituent activities of future-climate predictions to accomplish the overall goal of generating climate data outputs of considerably greater quality than those using standard traditional methods. Given the complexity and the different specific uses of these integrations, a reassuring fact is the wide variety of different AI techniques which fittingly lend themselves for the support of type 1 climate model development and implementation.

5. AI Applications in Renewable Energy

The global shift towards renewable energy sources, driven by environmental concerns and technological advancements, has ushered in a new era of energy production. With predictions about the increasing share of power generation currently held by renewables, the growth lies principally in solar and wind power. The entire renewable energy sector has gained the confidence of investors globally, leading to investments across the globe for building new solar and wind projects. However, many challenges remain which need to be solved by the industry including improving efficiency, allying intermittence, and the proactive role of AI and ML.

The chapter covers the major application areas of AI, ML, and Data Science in Renewable Energy generation, mainly Solar Energy and Wind Energy along with a brief review of other sub-sectors. Although dominated by traditional physics-based models, recent developments indicate an increasingly wider adoption of AI-driven models across various segments of R&D and commercial stages. Due to the abundance of freely available data and the parallel advancements in data-driven predictive algorithms, the integration of state-of-the-art computer vision and time-series based AI advancements is expected to further push AI-in-Domain applications. The chapter ends with a few examples from other renewable sectors demonstrating the immense potential in these domains. An improved drive towards adoption will not just lead to breakthroughs in renewables but will also be conducive to the mission.

5.1. Solar Energy Optimization

The application of machine learning and AI policies has grown remarkably in solar energy technology and its efficiency enhancement over the last decade. A few areas have been considered thorough investigations of research aims motivated by optimization of PV generation, conversion of solar-to-fuel, and operation of building energy management systems. The AI paradigm aids solar panels in choosing an appropriate combination of electricity-production parameters such as temperature, irradiance, and humidity. Furthermore, it explores various configurations for solar cell designs: device physics, material properties, and fabrication conditions. Additionally, the energy generated from solar energy systems is not inexpensive, and the experimental time and cost are indispensable before fabricating the real module. Thus, further exploration of the search space by machine learning methods can mitigate the burden of costly optimization. Besides, the solar bottle design process with AI includes various optimizing settings and evaluation procedures, and automated machine learning is better than traditional machine learning approaches.

Moreover, AI-based building energy management systems can smartly assign PV's production to either use on-site, store in batteries, or sell it to the grid, and can incorporate solar thermal collectors either to heat air for space heating or to heat water. AI gets the system off grid while managing wind, solar, and batteries for brief intervals that would cost a substantial amount if carrying out these functions independent of grid responsibilities. Generally, the building energy optimization with AI can make energy derivative markets available for energy flexibility for speeding the transition towards the smart grid. Particularly, deep learning employs sun's position algorithm to allow architects and designers to input location, azimuth, date, time, day, and month of year to calculate the sun position angles for vertical and/or horizontal surfaces.

5.2. Wind Energy Management

In the combat against climate change, wind is considered one of the most reliable resources for renewable energy generation. Due to the pressure of fossil fuel depletion and the formation of greenhouse gases into the atmosphere, the interest in wind energy has raised extraordinarily in the last years. The interest in many different areas of wind energy systems has raised due to its cost reduction and reliable energy supply in price-capped energy market, especially in Europe, and this area has also been consolidated as a major energy generation in some countries. Scholars and experts began to investigate many aspects of wind energy generations, increasing the scientific production in this area. The wind forecasting can manage the uncertainty and intermittency of wind generation.

Wind forecasting is the activity that considers all the techniques and algorithms available to provide quantitative information about future wind speed and direction at known locations in space and time. Accurate short-term wind forecasting is important because the energy market models are based on real-time information, and unexpected changes or longer prediction lagging can cause market anomalies. Wind generation forecasts can help in assignments such as generation unit self-dispatch, congestion management, or unit commitment problems. The ability to philosophy the future behavior of the wind provides another set of useful tools for wind farm design and layout, maintenance, and operation. The data can also be helpful to share across agencies and enterprises since they can provide data on localized events for grid interactions. The field of artificial intelligence has seen unprecedented growth in the past two decades which has helped in the advancement of solutions to many different problems in diverse fields.

5.3. Hydropower and AI Innovations

Between 2023 and 2025, the global hydroelectric systems market is expected to reach about $63.36 billion. This could provide energy to as much as 21 percent of the world’s population. The crucial goal behind performance enhancement of hydroelectric systems is optimally managing their allocated resources. However, various challenges that hinder their operational efficiency must be analyzed in a timely manner. These include challenges with aging infrastructure, long duration of repairs, inadequate maintenance procedures, and decision-making overheads. It is amid these difficulties, and leveraging several possible applications of AI in enhancing the operational ease of HES, that can facilitate data-driven decision-making, in real-time. A wide range of industry applications can be addressed through monitoring and control, maintenance prediction and optimization, reservoir operations optimization, and operational flexibility. AI algorithms can further assist in improving the efficiency of HES operations via forecasting long-term energy price patterns, market changes, resource availability, future power load requirements, and hydrological inflows. In addition, prediction of operation parameters such as water levels for reliability and safety, hydro-fluctuation impacts, turbine governing systems, real-time data processing, and hydro data analytics can also be performed. AI can also help in long-duration short-term predictions for creating realtime short-term load forecasting solutions. Hydropower plants are increasingly looking to improve revenue through innovation, whether that is updating their control systems, deploying predictive and prescriptive maintenance programs, developing capabilities to capture ancillary service revenues, integrating AI into their modeling, or otherwise. Across the globe, various plants from smaller, independent hydropower operators to some of the largest projects of European electricity conglomerates are testing AI applications in their operations. From asset management and plant efficiency to predictive and prescriptive maintenance, AI is helping hydropower operators make smarter decisions faster and implement those decisions more effectively.

6. AI for Energy Efficiency

While AI can optimize how energy is generated or traded, it can also reduce demand directly by improving energy efficiency. Global energy intensity decreased in recent years, partially benefitting from the deployment of AI. Increased attention to energy efficiency is critical as the world shifts to electrification. Demand-side incentives, driven by market, policy, and social pressures, will reshape when and how much electricity is utilized. Through smart tech approaches, AI can help shift peaks, as well as decrease demand at the critical time and help bring down energy use.

Optimizing buildings' and factories' internal energy-consuming processes reduces associated costs and greenhouse-gas emissions whilst making them more uncomfortable places to live and work. Low-carbon technology deployment is motivated by voluntary actions by many consumers in the sector and is increasingly addressing policies, social science, behavioral economics, and the decision-making processes of energy suppliers and consumers. These approaches are more likely to succeed when they seek to define or reduce energy-using or energy-supplying behaviors, as well as the goals and methods proposed by policy makers or policy supporters.

Energy efficiency in the smart building domain refers to the efficient management of energy systems and a building's operations, where the rapid development of technology, the application of AI, and the market integration of communication technology is providing new energy efficiency solutions, especially in the internal building system where a large share of energy is consumed. A continuous building operation energy simulation model has the potential to be a self-correcting mechanism that can massively affect energy efficiency. Through the use of AI and big data management, this model can adjust input variables in real time and simulate the dynamic properties of lighting, HVAC, plug load, and thermal mass to determine the extremely complex, time-varying non-linear relationships between those system outputs and inputs. Self-correction of energy simulation models leads to building control major periods, especially of large commercial buildings that increase energy savings drastically.

6.1. Smart Buildings and AI

It is widely accepted that buildings consume almost 40% of the world energy and produce a comparable share of GHGs. Hence, it is crucial for the fight against climate change to improve the energy efficiency of buildings. There are a number of barriers to achieving better energy efficiency in buildings. The first barrier relates to the owner-resident dynamic. In rental buildings, the landlord bears the cost of improvements while the tenants consume the energy, reducing their incentives to accept the costs or make the investments. A second barrier is split incentives between the owner and the occupant. Building energy consumption is also highly opaque, especially in rental situations where tenants may burn fossil fuels to heat water and cook. As a result of split incentives and technical hurdles, countless point-of-use improvements remain unfixed and energy performance certification systems have added limited value to disclosure of building energy consumption and energy labels. Reducing energy consumption in residences with the worst energy efficiency labels has proven difficult, and mass-market upgrades to heat pump and smart meter innovations have been slower than predicted.

Consumer acceptance of smart technology is of critical importance to seize the efficiency potential of technologies such as heat pumps. Continuous real-time data collection from sensor networks, heat pumps, and decentralized battery storage can enable manageable building automation and demand-side response aggregation with proven benefits for grid operations and cost savings for owners of energy production and energy use assets. No homeowner wants to buy a service contract for demand-side response from a turbine operator, while building energy use and production is highly variable across space and time, and people with different building or appliance profiles care about different attributes during extreme events. Point remedies and mass upgrades to infrastructure for electricity storage and heat pump supply of domestic and industrial heating can be scheduled-informed and community-optimized by learning AI, which is critical to ensure relative value in the short and medium term. Comprehensive automation of energy use and demand-side response driven by algorithms can function in the background on behalf of the owner.

6.2. Industrial Energy Management

Industries are among the largest energy-consuming sectors in the world. Energy costs can represent a significant share of production costs. Consequently, there has been considerable effort to improve energy efficiency in the industrial sector through energy management practices. Most major industries have set targets to reduce their energy use intensity, yet specific guidance remains scarce for many industries. In particular, low-cost monitoring and analytic solutions being developed for sensor-rich factories are expected to allow firms to develop and implement customized energy management strategies on a much larger scale than with traditional approaches.

Improved availability of inexpensive energy consumption sensors and visibility platforms are allowing organizations to get a first pass at industrial energy use data using typical day profiles. Building on this foundation, detailed data from advanced metering, factory sensors, and machine meters can be mined to identify energy use patterns, including equipment load profiles and on-time analysis. Based on this information, companies can better manage their capital, create more accurate production schedules, and optimize non-production shifts during peak use periods. This detailed energy use information can also be useful for contractual negotiations and the design of load shaping incentives with energy providers, particularly if high-quality energy data is available for a year or more.

6.3. Consumer Behavior and Energy Efficiency

Improving individuals' energy-related behavior and promoting energy efficiency through information and communication technologies are some of the ways the global community can move toward a sustainable energy future. This chapter identifies key social and computation HCI-related challenges in making energy efficiency a desirable activity. It also describes several ongoing projects that combine Artificial Intelligence and user-centered technologies to facilitate users' desire and capacity to reduce personal energy consumption. Aspects related to privacy, user acceptance, and the understanding of soldiers' actual energy use behaviors are important for system design and deployment, but are often overlooked in the energy research literature.

This chapter contributes to the ongoing exploration of the human factors associated with the interdisciplinary implementation of AI and HCI in energy efficiency projects. The actual development and design of smart technologies that can modify and support how, why and when we use energy in our daily routines should be informed by our understanding of the users' needs and opinions. It is only when we combine people-centered design and implementation concepts with the best technical options, that we will create smart technologies that support us in reducing our energy use and damaging greenhouse gas emissions. Existing interdisciplinary energy efficiency projects are described, to support researchers and engineers in their quest to better understand the requirements of end users, provide guidelines for new projects, and provide the models and architectures needed for the development of technologies and systems.

7. Ethical Considerations in AI Applications

AI-based applications can help solve glaring energy and environment problems efficiently, but scrutiny is needed to ensure that these tools create a good impact at an acceptable cost. Here we discuss three major ethical considerations in AI applications, as applied to energy and the built environment, although these ethical issues are pertinent to most AI applications. First, we address data privacy and security. AI algorithms need voluminous data in order to perform well, but this very need creates risk of revealing sensitive information. Energy usage and associated behavioral patterns reveal a significant amount of details about a person and their family. Hence, at the core of privacy dilemma is that AI needs data that goes against data privacy. In any research scenario, the data subjects should sign a waiver, giving their consent for usage of data for the stated research purpose. Mere compliance with privacy requirements is not enough. The decline of data privacy, even when compliant with the letter-of-law, and the associated risks of facial or behavior misidentification has led to the creation of AI privacy "taxes" which may be counterproductive to research, especially when dealing with niche and sensitive causes.

The second issue that has attracted increasing interest is how ethical AI is in the way it utilizes data and generates algorithmic predictions. An algorithm developed with biased data will return biased results, and depending on how biased the data is, the ethical, legal, and social implications can range from minimal to severe. Algorithmic predictions based on incomplete or incorrect data can directly lead to harm, especially if AI is used in decision-making roles that directly impact lives, such as recruitment decisions when applied to job candidates, delivering predictive analytics to hospitals, or predictive policing. The third issue is the topic of sustainability. AI utilizes information and communication technology, which is critical to all AI-based applications. Energy is consumed and carbon is emitted when running AI systems, whether it is creating machine learning models, or running them for inferencing.

7.1. Data Privacy and Security

Artificial Intelligence (AI) applications rely on collecting data in their systems, causing ethical and privacy considerations. Privacy-Preserving Machine Learning (PPML) techniques have been proposed for generating models while keeping the users' data private. Such techniques are proposed as alternatives to traditional ones that gather data in centralized systems for monitoring and services that artificially create privacy issues. However, there are challenges to making privacy an inherent characteristic of future AI applications, such as: balance of privacy with the goals of the AI model; the problem of data minimization and proper aggregation; proper notification of the user about energy- and context-related AI-based data services which could trigger data collection; trust in the design and operation of the model for data security; data protection policy, expressed in understandable terms for the user; policy adherence incentives; ethics of responsible data ownership; data leak consequences; ethics of the use of data after the user is deceased.

Moreover, if the usage of AI in energy and environment creates unethical situations, inadequate energy-inefficient models, and problems with services that augment the digital divide, it will have severe consequences in the future, which could compromise the achievement of the United Nations Sustainable Development Goals. Hence, the explanation of how AI could breach or complement ethical issues concerning data ownership — for example, the collection of information about trustworthiness, transparent data provenance, and effective redress for improper use — is an important enabling factor for a fair distribution of power in society.

7.2. Bias in AI Algorithms

AI algorithms have the potential to be incredibly transformative. However, if we want to see the positive potential of these algorithms for our world, it is critical to address real concerns about the biases that may become embedded in these algorithms. AI algorithms differ from traditional databases, data pipeline, and filtering techniques in a number of ways that increase the likelihood that biased algorithms will cause more serious issues, particularly for high-impact domains. The first difference is that AI algorithms use increasingly diverse combinations of disparate data sources. What is exciting about AI is its ability to leverage previously uncorrelated data sources. The downside is that with any new combination of data sources, new issues are introduced that could not be determined by examining previous datasets in isolation. For example, existing census data may not cover certain geographic areas and thus provide inadequate learning examples. Another factor that contributes to bias is that AI will request information from new users at different times than existing users. A user who comes on the scene at an unusual time in a news cycle may have a very different profile than an established user who has a profile based on years of online activity. New users' contributions should not be overly devalued or excluded; the AI must be able to adapt in a reasonable and timely way. A second contributing factor is that many AI algorithms are constantly learning and adapting due to changes in social or physical contexts. For example, a predictive algorithm for target marketing is continually learning about the marketplace in order to refine user segmentation. However, no model is perfect, and AI algorithms are subject to error during certain transitions or major upheavals in factors that affect their operation.

7.3. Sustainability and AI

AI is not just a disruptive technology; it has the potential to solve problems relating to almost every aspect of human activity, the economy, and the planet – and rapidly too. If we want AI to be the medicine that cures our planet, we must ensure that we are developing and deploying AI tools in a responsible manner. Just like and indeed complementary to Green AI, whose objective is to make AI less polluting and less power-hungry. Sustainable AI, on the other hand, is geared towards the much broader objective of using AI and related tools to help solve the most difficult problems that mankind is faced with, and do so rapidly and responsibly.

Some thought leaders on Sustainable AI came together to define "Sustainable AI" in an open-source manifesto. The motivation behind this manifesto is the urgent need to develop AI in such a way that is a net benefit to our planet. There is a vision of a future in which societies and organizations across the globe mobilize to channel the forces of AI toward the shared objective of solving humanity's greatest challenges and helping to build a better world for all. In order to give back more than it takes, AI must be pursued by skillful hands, with equity and ethical intent. The manifesto identifies four main pillars, namely AI for helping the world, for inspiring the world, for understanding the world, and lastly, for creating the world, continuing the cycle of creation. These four pillars are supplemented by nine ingredients which provide more specificity to each of the pillars and act as a guide to making AI a net benefit for our planet.

8. Future Trends in AI for Energy and Environment

Numerous trends derive from the use of AI technologies for energy and environment toward 2030 or beyond. The majority fit within the larger context of the decarbonization of the energy and resource systems, resilience to climate disruptions, and related priority changes implied in the Energy Transition and Global Change agendas. New emerging technologies will use advanced and computational science methods and principles to achieve higher performance toward those goals than classical, passive, often extremely capital-intensive approaches. These developments will broaden the focus beyond energy and greenhouse gas emissions of economy-wide impacts; in addition other aspects of Climate Change as well as functioning of energy and resource systems will receive increased attention. Operationalization and commercial availability will result from industry-academic collaborations. Policy will play a critical role in implementing the changes from supporting or accommodating the change toward moderation or reversal of the change.

In addition, global collaboration will intensify in support of the AI-Env-Energy pathway changes, beyond the climate, energy, and resource specific associated agreements. In particular, security concerns or accidents in an increasing number of security dimensions such as cybersecurity, food security, and biosecurity will increasingly influence the energy-Env pathways, and the related collaboration frameworks, in addition to military and technological imbalance considerations. The AI for energy and environment will be at the heart of the developments in the Energy-Env interrelated sectors, as one of the first economically viable implementations of the longer term effort to fully implement the AI fully adaptable systems. The continued focus on the need for closing the gap between technology developments, implementation timelines, and achievement of the Climate Targets is allowing the AI-Env-Energy collaboration to be forward looking, concentrating on ambitious outcome or performance goals, rather than retrospective - defining regulations and fixing responsibility today.

8.1. Emerging Technologies

Advances in machine learning (ML) algorithms are the key drivers of the success of AI in the energy and environment sectors. Recent developments in generalized representation learning and large language models (LLMs) have opened a new frontier for machine learning that will bring new exciting opportunities for energy and environment applications. The challenge of interpretability often considered with deep neural networks, particularly for energy and environment systems with multi-physics processes can be mitigated by bridging ML with physics. AI will also combine with other new technologies such as Internet of Things (IoT) and quantum computing to shift paradigms in the energy and environment areas. As cheap, ubiquitous, and real-time sensors are being proliferated in all aspects of life, it will enable extensive data mining and discovery using LLMs that can synthesize and learn from large corpus of expert generated reports and memorized knowledge. AI will also support the burgeoning demand for deep decarbonization, renewables deployment and management, carbon capture, utilization, and storage and sustainable use, production, and storage of hydrogen.

The decarbonization and digitalization trends in the energy sector will also open up opportunity for on-demand electricity service with the integration of local energy markets allowing small energy users to become prosumers, exposing them to short-term market volatility and requiring more control, signaling and optimization to go along with active demand response. The increasing reliance on the availability of electricity service and cyber-physical systems controlling the electric grid bottom-up will encourage power system operators to transition towards self-healing and resilient grid design. Data-driven digital twins powered by AI and ML will enable electric utilities to simulate, synthesize, forecast and mitigate stress events in the grid, such as generation and supply mismatch, demand surges, forest fire, wind and snow storms and tropical cyclone disasters. Digital twins can also facilitate the seamless switch of demand between normal and backup electricity service during stress events and assist electric utilities in the implementation of their resilience investments as required by regulatory orders.

8.2. Policy and Regulation Implications

In terms of governance, the development of AI in the energy ecosystem will pose both opportunities and challenges. The existing policy landscape in diverse countries is still in the proposed stages. AI policy and regulation typically converges on establishing standards and guidelines on AI technology development, implementation, market access, trustworthiness, audit mechanisms, and investment promotion. Positive implications are seen in the areas of intelligentization of energy systems such as prediction, automated decision-making, and system/asset management. However, existing regulations mainly focus on data security, anti-monopoly, and ethical principles, with few direct policy guidelines on AI technologies applied in energy.

Unfortunately, the current policy systems are not specific enough for AI development in the energy sector and do not address the potential/trust problem. AI algorithms could become black boxes without accessible means of validation by other parties. Linked to this transparency problem, biased data could lead to ethical issues arising from algorithm encouragement of corruption or discrimination. More so, under-performance or malicious AI warnings could cause catastrophic accidents in highly-safety-demanding environments as AI is increasingly integrated with safety equipment for autonomous functions. To alleviate these concerns, the global community must better address the above-mentioned policy guidelines regarding testing, validation, ethics, bias, and safety in energy. In addition, given that competitive AI ecosystems are crucial for promoting healthy competition, markets must be created conducive to collaboration among energy solution providers and AI developers, as opposed to mainly focusing on smart energy asset developers and integrated market coupling.

8.3. Global Collaborations and Initiatives

Geopolitics plays a role in national initiatives for energy transition, such as the US Inflation Reduction Act and the European Union Politics. For researchers predominantly in developed nations, providing access to AI technologies and tools held by advanced nations is a way of responding to the need of developing countries to access methodologies and tools that would allow them to utilize AI for a more efficient energy transition. On the other hand, the need to develop capabilities in the application of AI in sensitive areas, including intelligence systems, is what motivated China to create the “AI 2.0” vision, which proposes five major established international collaborations in priority key areas where AI could benefit the world.

The US National AI Initiative Office of the White House, responsible for the United States’ National Strategy for AI, and which promotes educational resources and national and international collaborations goes a step further by advancing through its Collaborative Strategy for AI Research and Development in the International Context the importance of promoting a Coalition of Publish-AI Partners. The EU has built for many years an overall policy for AI development and grant by proposing the European Strategy on AI and, more recently, the updating of the strategy for a Europe fit for the digital age. In

ASEAN countries, researchers from countries of the region recommended the establishment of a collaborative strategy across the different stakeholders of different countries in the bloc as the most effective way of developing its AI ecosystem.

9. Conclusion

The cross-pollination between the fields of AI, energy, and environment is a young and rapidly evolving field of research seeking to bring intelligent methods to bear on pressing and largely intractable problems related to the energy transition and climate change. These domains represent the largest challenge humanity has faced, one whose scale, complexity, and urgency demand digitally driven technological solutions that can address issues in an efficient, resilient, and sustainable manner. As such, this area has wide and varied intellectual scopes and breadths, covering areas such as AI methods and systems that learn or are deployed in energy use cases, AI methods to monitor or control climate change processes or effects, and the use of intelligent methods to reduce the energy consumption and carbon footprint of AI systems, among others. Developing innovative solutions for such issues are no small feats, as the challenges therein are often complicated by incomplete spatiotemporal data, an inconsistent policy landscape, high-stakes resource competition, complex AI–Environment interaction or coupling dynamics, and model scalability or generalization difficulties.

Nevertheless, there is tremendous scientific and societal promise in achieving a harmonized synergy between AI and the energy and environmental domains. This can pave the way for resilient, sustainable societal progress by accelerating the design and deployment of innovative technologies, resources, and infrastructures. In particular, we note particularly exciting future directions related to AI use for reimagining-built environment and urban settings as being more equitable and inhabitable; leveraging growing advances in AI interpretability and uncertainty quantification to monitor critical climate variables and events; and safer integration of electrification and renewables into existing energy systems and beyond.

References:

Abdalla, A. N., Nazir, M. S., Tao, H., Cao, S., Ji, R., Jiang, M., & Yao, L. (2021). Integration of energy storage system and renewable energy sources based on artificial intelligence: An overview. *Journal of Energy Storage*, *40*, 102811

Liu, Y., Esan, O. C., Pan, Z., & An, L. (2021). Machine learning for advanced energy materials. *Energy and AI*, *3*, 100049.

Wu, B., Widanage, W. D., Yang, S., & Liu, X. (2020). Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. *Energy and AI*, *1*, 100016.

Wu, B., Widanage, W. D., Yang, S., & Liu, X. (2020). Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. *Energy and AI*, *1*, 100016.

Booshehri, M., Emele, L., Flügel, S., Förster, H., Frey, J., Frey, U., ... & Stappel, M. (2021). Introducing the Open Energy Ontology: Enhancing data interpretation and interfacing in energy systems analysis. *Energy and AI*, *5*, 100074.

Mehmood, M. U., Chun, D., Han, H., Jeon, G., & Chen, K. (2019). A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. *Energy and buildings*, *202,* 109383

Mehmood, M. U., Chun, D., Han, H., Jeon, G., & Chen, K. (2019). A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. *Energy and buildings*, *202*, 109383.

Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., ... & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, *141*, 104440.

Ahmad, T., Zhu, H., Zhang, D., Tariq, R., Bassam, A., Ullah, F., ... & Alshamrani, S. S. (2022). Energetics Systems and artificial intelligence: Applications of industry 4.0. *Energy Reports*, *8*, 334-361.

Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 10: Ethics, Fairness, and the Future of Responsible Artificial Intelligence

1. Introduction to Responsible AI

Artificial intelligence, machine learning, and algorithmic decision making are being rapidly advanced, funded, and deployed by both private and public institutions without sufficient ethical consideration, accountability structures, or incentives for safety or fairness (Adiguzel et al., 2023; Coeckelbergh, 2020; Hagendorff, 2020). Research highlights the risks of harmful outcomes from biased algorithms and improper automation. These harms are particularly pronounced for marginalized and underrepresented groups and are increasingly amplified through the scalable reach of social media platforms, and counterpointed to social good efforts by non-profit organizations. In response to these trends, more and more leaders from diverse sectors are calling for responsible practices to be woven into the mainstream technologies of today's societies across all domains such as business, law, education, and government. But who gets to define responsibility for AI? What are the levers for effecting responsible practices within companies? What role do policies and platforms play in promoting better practices? What ways are there to educate practitioners, and raise the profile of responsible practice? These questions and more are the domains of discourse within a growing community dedicated to these themes, in research, practice, and policy. In the following, we set up the context for understanding AI responsibility, how it interconnects to ethics, fairness, and policy. Then we present approaches for responsible research and development of AI systems in practice, and tackle the pertinent questions around pedagogy. Finally, we present how responsibility impacts the larger phases of the system lifecycle from conception and planning to deployment and development.

At its simplest, responsible AI ensures that AI enriches the society we live in, rather than detracts from it. Also known as AI ethics, it is the study of how and why certain usages of AI are morally acceptable, and others are not. The study of Promethean dangers has long been a concern of philosophy, and we draw on that tradition to discuss the ethical frameworks on how to achieve responsible AI.

2. Understanding Ethics in AI

This chapter will clarify the overlap between ethics and AI, which is more philosophical and principled in orientation than other parts of the field, which focus more on implementation. We focus on the relationship of ethics and AI generally, rather than delegated to subtopics. Section 2.1 explains the bridges between ethics, technology, and social impact. Social media, personal encryption, drones, and autonomous weaponry are illustrations of areas where ethical fallout is immediate. Although ensuring ethical assessment is clearly a practical consideration, we argue that such assessment cannot be purely a practical effort. Section 2.2 gives an overview of the major players in the debate over the ethical values surrounding AI. Topics of interest maximum ethical recommendations, machine ethics, ethical AI and AGI. What should matter be instrumentalized into gaining maximum utility, and should AI care about utility?

Or should AIs have ethics? If so, how should they care? And what of the thinking and values behind the design? We argue that the current interest in AI is partly because of worldwide AI's role in funnelling human values into AI systems capable of wielding resources at a human level, whether through job loss, use in warfare, AI-nudged personal electoral decisions, internet-driven loss of trust, and so on.

Are intelligent agents, human or non-human, ethical? Are there limits on who may ethically deploy intelligent agents? Are there limits on how they may be ethically deployed? These questions exist whether the agent is human or is assisted by AI. They matter less, at least immediately, because they cool the interest in "speculative" AI, AIs that do not yet exist. But they are why it is hard to think through AI's social ethics in theory. From one perspective, we are still debating who is an agent, at least apart from humans. From labels such as persons, agent-based ethics can work its practical ethicist magic into assisting APs with responsibilities, rights, and privileges. Perhaps it will then become far easier to accept AI rights and duties as credible tools for not-so-speculative problems such as creating AI agencies that assist with bio, cyber, and nuclear threats, or that ameliorate climate change.

2.1. Historical Context of Ethics in Technology

Understanding Ethics in AI

2.1. Historical Context of Ethics in Technology

History is described as a record of events concerning real people, the record or study of such events, and the part of a general account of the whole human past concerned with the differentiation of various domains of social and cultural life. Events are referred to as historical when they become relevant to problems of a peculiar moment of civilization development and the training of the historian's craft. Consequentially, history of ethics is told through events that have been pronounced and have therefore revealed themselves as significant and above the flow of time.

The nature of technologies and subsequent technologies' relation with their creators has puzzled thinkers for a long time. Even ancient Greek philosophers like Plato warned about technology's capacity to act as a curse for the human condition that should better be controlled through Politics. Consequently, the idea of technology thus implied ideas of destiny, fate, and even divine punishment. Aristotle took a less severe position towards technology, describing it in his Politics as an invention of rationality. Later, the neologism of techne first coined by the Greeks would have a marked success with the Romans, throughout

Antiquity and even the Middle Ages, revived and deployed anew by Renaissance thinkers. The coinage techne -again reshaped as ars in Latin- laid at the basis of the future disciplines defined "scientific-technical."

2.2. Key Ethical Theories and AI

In this section, I will briefly review some of the major philosophies and ethical theories, before going into more specifics on well-known ethical frameworks in AI in the next chapter. These philosophical traditions have been central to moral action, and our discussions around them have important implications for how we build AI systems.

Often considered the opposite of deontology, a consequentialist perspective is the idea that, with actions, we should carefully consider their outcomes for individuals, the group, or society as a whole. Actions with the most positive impact or with the least negative one, considering all the people impacted by the actions, are the ones that are right. This perspective increases in relevance when our actions, or decisions, have widespread ramifications, such as those of AI systems. Not only do they affect many individuals and groups, but because AI systems are less prone to be guided by social or emotional cues, the benefit-of-the-group perspective can be especially salient.

Often, it is said that consequentialist thinking leads to certain well-known ethical dilemmas. In the Trolley Problem thought experiment, you can pull a lever to save a group of five people tied to the tracks, while pulling a trigger would crush one single person under the toy train. What would be the consequence of such an action? Would it lead to the greatest happiness for the greatest number? Would you count the enjoyment of the five grown persons in comparison to the future life of the child as the one? Taking such a deontological action would be condemned by consequentialist perspectives — or would it?

3. Fairness in AI Systems

The deployment of AI systems, especially those for high stakes decisions such as hiring, loan, or criminal justice, poses challenges of fairness (Hassija et al., 2024; Holmes & Tuomi, 2022; Jobin et al., 2019). The implausibly low face validity of decision outcomes of AI systems has led many to study fairness in these systems. In this section, we discuss key aspects of fairness study in AI systems. We first overview the ways different definitions of fairness have arisen in machine learning, and discuss key notions that inform these definitions. We then discuss the methods of ensuring fairness in AI systems. The final part of this section discusses some data-driven studies of fairness in AI via case studies of bias in AI.

3.1. Defining Fairness in AI

AI systems function as highly intelligent proxy decision makers in a wide variety of socio-technical systems today (Lund et al., 2023; Munn, 2023; Nguyen et al., 2023: Siau & Wang, 2020). The decisions they generate, in many cases, affect the lives of people, for instance, by determining whether the candidate will get the job or by determining whether the credit request will be sanctioned. Growing concerns about algorithmic bias in the outcomes of AI systems created trouble for the functionality of AI systems as trusted decision-making proxies. This leads to the exploration of the definition of fairness in AI. The beginning of definitional exploration of fairness in AI can be traced back to a kriging-based expert system in hiring selection.

One hundred years later, a proprietary AI system created similar concerns about heavy bias in real-world hiring decisions by the student actor recruitment industry, sparking a flurry of news reports about AI bias. The publishing of widely known case studies of AI bias, such as racially biased criminal risk assessments, biased recidivism predictions, and keyword stereotyping, elevated concerns about bias in AI systems to a fever pitch, accelerating the exploration on the definitional aspect of fairness study in AI systems.

3.1. Defining Fairness in AI

Although there are countless ways to define fairness, an actual definition is necessary for the successful design and evaluation of AI systems. Fairness is an important philosophical concept, dating back centuries to philosophers who presented equity as a principle of justice. Researchers in AI often focus on fairness as a principle of justice related to discrimination, or unjustified differences in treatment across certain groups, such as failure to hire transgendered applicants. Other researchers have drawn upon and adapted mathematical notions of stability and consistency, especially in the context of algorithms for machine learning. Our research group uses a definition of fairness that captures both of these conceptions of fairness. Formally, we say that an AI system is fair if it does not discriminate unjustly against certain groups, and treats the members of those groups in a similar manner.

Discrimination can take many different forms. Adverse treatment discrimination occurs when a member of a certain group suffers an adverse consequence as the consequence of an action. Conversely, adverse impact discrimination occurs when the members of a certain group, and particularly its members of a certain protected characteristic, suffer adverse consequences at a substantially higher rate than from the action made by the AI system. A decision is averse if it carries a significant risk of causing serious harm, or is materially adverse, and a decision has significant and disproportionate negative impact on the member of the group if the AI system's operation has a substantial effect on the life of the individual and their family.

3.2. Measuring Fairness: Metrics and Methods

Fairness may refer to a broad array of subjective notions, which is why it's essential to clarify the meaning of fairness in a given algorithmic decision or a class of decisions. Once this definition is established, a broad range of mathematical and statistical tools can be deployed to capture fairness in a definitional sense. Consequently, the task of measuring fairness is far from simple: there are numerous fairness desiderata pertinent to a decision-making problem, and methods for measuring fairness may depend on the problem type, objectives, and available data.

Various metrics have been proposed and implemented to encapsulate different perspectives on fairness, which may vary in whether they pertain to the decision process, the outcomes of the decision, or the model used to arrive at the decision; in whether they measure fairness conditioned on a group or measure absolute fairness aggregated over a population; in whether they penalize unequal treatment, unequal opportunity, or unequal accuracy; and numerous other aspects. These perspectives provide insights into potential shortcomings of the system and suggest different routes for remedying the issues, if they exist. For this reason, characterizing fairness in diverse and complementary ways often makes sense.

When considered at the outcome level, a metric may, for instance, quantify relative difference in error rates across sensitive groups. Whereas computational measures of fairness can aid in guiding mitigation techniques toward desired outcomes, different fairness metrics have been leveraged throughout the lifecycle, from informing the design of the model, to evaluation, to testing. Generally, the state of model testing in algorithmic fairness tends to predominantly favor a suite of predetermined, well-known and adopted, mathematically simple relative error metrics, implemented due to ease of compute or choice of convenience, over sophisticated metrics that probe deeper and yield richer perspectives on fairness.

3.3. Case Studies of Bias in AI

Bias in real-world data can lead to considerable AI system misbehavior that can be found in a variety of content domains and for many AI modalities. In this section, we summarize several case studies that highlight the ethical questions and real-world problems that come from biased AI systems, and propose their inclusion in AI curricula as cautionary tales to warn against the unethical use or creation of AI systems.

The parade of horribles for biased facial recognition technology began early. A group of computer scientists trained facial recognition models on diverse datasets, finding a significant performance gap between demographics. For images of light-skinned males, the model had less than a 1% error. In contrast, dark-skinned females had an error of over 34%. They specifically cited application to hiring, security usage, and police usage as areas of significant concern. We can only imagine what damage a system with a 34% error rate would create in the real world if put to these tasks. Exacerbating these issues, these researchers also did not publish their model or data, using the pose of the "dark-skinned female" images to determine the "true" label. These actions mitigate the ability to create a fairer version of the model.

4. Accountability in AI Development

Decision-making is one of humans' most distinctive and valued capabilities. It plays a central role in our society and in our lives, affecting our relationships, our lives, and our world. However, decision-making is a complex process, and it can go wrong for both human and non-human agents, with serious ramifications for peoples' lives. When a human agent makes a decision on behalf of other people, they are held accountable for the consequences of that decision—both the positive outcomes and the negative repercussions. When decisions are made by automated systems, however, holding someone accountable is a more complex issue.

Automated decision-making is increasingly becoming a fact of daily life. From simple decision-support systems that assist policy makers and medical practitioners, to complex predictive models that decide on allocation of resources or identify potential fines or criminality, decisions are being delegated to ever more advanced artificial agents. As they increasingly take over these functions, questions of features and limits of accountability frameworks for AI systems are beginning to attract attention. Establishing these frameworks is an essential part of building responsible AI systems that enhance—not undermine—societal goals. Lack of accountability standards could result in wielding an unaccountable power, the self-perpetuating reinforcement of societal inequalities and the jeopardizing of core ethical principles that should guide society.

International current legal and accountability frameworks were established before AI systems began taking over decision-making functions. They are wholly inadequate when it comes to decisions made by semi– or fully autonomous systems. The need for new accountability mechanisms has been widely acknowledged; yet questions remain as to their exact form. What practical alternatives are possible? Would we use a different model for accountability if the system has been developed using observed data rather than being designed from scratch?

4.1. Establishing Accountability Frameworks

Concern about accountability in the context of AI systems is often articulated and conceptualized in the context of responsibility. The development and deployment of AI systems is increasingly a team undertaking, and such responsibilities begin with the executives in charge of companies who make the decision to construct an AI solution. In a study of the prevalent types of corporate communications related to corporate responsibility, it was found that corporate executives address ethics and responsibility as a sideline. There is also mounting support for the identification and attribution of responsibility for harmful actions taken by AI systems. Establishing accountability frameworks to clarify responsibility is extremely important in many practical situations. For example, in the case of an accident caused by a self-driving vehicle, it is imperative to have regulations and laws in place clarifying the issues of who is responsible for the actions of the system. Although questions about the potential need to formulate accountability frameworks for AI risks were examined by AI and robotics researchers already in the late 1990s, the issue remains largely open and unresolved. It is important to not only provide accountability frameworks for future AI systems based on their potential capabilities, but the increasing fact that many AI systems are already having widespread impacts on the world make the issue more urgent.

Accounts of how to formalize the delegation of responsibility to AI are framed in terms of the distinction between agentive and nonagentive roles in responsibility: to what extent can we say that machines are responsible agents, as opposed to only being part of a nonagentive arrangement that makes any further questions of responsibility go back to the organizations and individuals involved within the arrangement? Practical examples of the delegation of responsibility to machines include the allocation of steps in the justice process to solutions that are based on AI technologies.

4.2. Legal Implications of AI Decisions

The transparency that is needed for AI systems to be ethically designed and implemented is also mandated by law in certain cases. Suppose a company were to develop an AI system that decides who is allowed to rent a particular apartment and who is not. One day, an individual is informed by the company that they have been denied access to an apartment that they wanted to rent, solely because of an AI system that detected something about the applicant that was identified as a risk. The decision indeed must be transparent because denial regarding housing is a serious risk and so is the risk of unfair discrimination by the AI system.

The company must disclose what characteristics of the applicant the decision was based on at the request of the applicant, and if there was a response to the decision, the AI system should provide a way for the applicant to appeal. Most importantly, if the decision was based on an algorithm that was programmed with biased data and production code to target a specific outcome, then the developers and operators of such an algorithm could be in violation of this act. All of these obligations are not new to the developers and implementers of classical algorithms. The only difference is that such obligations and their consequences could for now be avoided in the case of machine learning. Currently, the transparency and accountability laws concerning classical machine algorithms have been extended to ML, but future legislation might enforce more strict obligations as privacy and fairness in ML research and practice become more increasing issues.

5. Transparency and Explainability

Artificial intelligence (AI) is understood to be a black box by users, since it uses algorithms that implement data processes that are not really understandable or understandable by humans. AI systems are complex and the AI design process does not currently require steps that safeguard the provision of explanations that provide adequate insight. People need to trust AI systems. We are in a great moment of development of AI and, if trust in these systems is not achieved now through their transparency and the debate and discussion about what is understood as ethical use, we risk that companies and people do not use AI for works that need it for reliability and decision support. Some AI systems such as Autoregressive Language Models, often referred to as 'foundation' or 'pluripotent' models, need an explanation when they are incorporated into a solution in which they are not autonomous. They can be embedded in answering systems, but their behavior cannot be explained since they are not supervised. The importance of model transparency can be both from the person's point of view and from the point of view of the model designers. The answer given can be categorically incorrect or there can be a misunderstanding and, therefore, a decision based on a bad understanding of the answer. In both cases, a lack of transparency in how the model understands and generates its answers is critical. It is essential to preserve the trust of the person who interacts with the model and what is understood by ethical and responsible use.

5.1. Importance of Transparency in AI

Increasingly, machine learning algorithms are being used to assist people in making important decisions. In such cases, an ethical question arises: should ML replace human judgment while providing only the results of its predictions to the users making the important decisions, or should ML provide some further information to enable the users to properly evaluate the inputs and the model's predictions in order to use the ML output judiciously? There is considerable evidence which suggests that decision makers using AI assistance are basing critical decisions on the AI model's predictions alone, without questioning the model's predictions, or utilizing the AI suggestions judiciously to avoid negative outcomes. Such behavior could lead to disastrous consequences: for instance, predicting that some candidates are not suitable for a job when in fact they will be productive, or not predicting that the job candidate is a potential threat and not taking appropriate safeguarding actions. Normally, humans would take one of two actions in such situations: either question the reasons behind the model's predictions, or utilize other sources of information to help evaluate the prediction quality, and modify the prediction to avoid negative consequences. The role of transparency and explainability of the model used for prediction and its internal logic is vital in the first situation, while access to relevant contextual information is critical in the second situation.

Transparency of machine learning models means that the model's internal logic is made available to the user. This facilitates better utilization of the model's predictions by the users. Further, when the users have access to the model's internal logic and are aware of the features being used to predict the outcome, unexpected outcomes may be questioned. This is particularly important in extremely impactful decisions, like offering someone a job, release of a prisoner, or assessing the creditworthiness of an individual or business. Critical decisions, if based on faulty predictions, could have catastrophic consequences.

5.2. Techniques for Explainable AI

The problem of opacity or ‘black box’ inferences does not stop people from being persuaded to take actions that would not normally endanger them if they are convinced AI can predict their behavior better than they can. That said, a critique of the increasing reliance on algorithmic decision-making goes deeper than mere considerations of cognitive adequacy. First, it challenges the competence of AI systems to perform those tasks, which have suffered from human incompetence, which these systems are expected to take over. Two generic approaches have clarified the work of the community. One focuses on methods to render otherwise opaque systems interpretable to compatible users, and the other tackles the problem of testing, auditing and verifying algorithmic systems across their lifecycle. The interpretability approach has a harder problem to address because while there may be ways to audit for the absence of unfair bias in a trained algorithm, explain probabilities of its predictions or potential associations with sensitive variables, the evaluations it does accomplish may affect its actual or potential neural performance.

This conceptual distinction gives rise to another: that between data-level explanations of algorithmic behavior that help the user trust the AI decision, and model-level explanations that concentrate on the inner workings of the algorithm affecting the trustworthiness of its predictions. The distrust the focus on interpretable models invoke is designed rather as a safeguard for ‘critical decisions’ that could augment fairness and diminish errors affecting minority groups. Both methods demand trade-off decisions made at different phases of the cybersecurity lifecycle, both by actors within and outside the institution applying the suitable AI system.

6. The Role of Stakeholders

While the aforementioned approaches represent important building blocks of Responsible AI, these cannot be deployed in an isolated manner or without the inclusion of relevant stakeholders. These diverse stakeholders perform different actions that support the aforementioned approaches and that would eventually help achieve the larger vision of AI for Good and Responsible AI goals. Several diverse stakeholders make up the AI ecosystem, including think tanks, corporations, academic institutions, governments, inter-governmental and governmental organizations. Some of these organizations perform surveillance services, others provide guidelines and roadmaps to help effectively and efficiently steer the development of AI, others design technology-based approaches to implement the responsible development of AI, and others measure progress and offer assistance on using the technology for good. Each of these stakeholders perform an essential task or set of tasks, all pointing towards the same goal — namely to create AI systems that do not abuse nor misuse human rights, interfere with principles of justice and fairness nor harm the natural environment. This chapter will highlight some of the functions public and private organizations perform in steering the responsible development of AI.

While academia educates upcoming generations in the responsible use and development of AI systems, and provides the necessary scientific basis to enable the AI industry to design and develop such systems, industry, through good practices, proves that the application of Responsible AI is possible and beneficial. Finally, governments provide funding and support to endorse the successful application of Responsible AI into the projects that are proposed and developed, set a clear framework through ethics guidelines to ensure the trustworthy exploitation of AI technologies, and define the political regulations that steer the entire ecosystem in the desired direction.

6.1. Governments and Policy Makers

Because AI can have a dramatically disproportionate impact on wide swathes of the population, in democracies, its use should be designed to reflect the needs of society. Achieving such fairness and ethics requires a specific knowledge of local needs, protocols, and priorities. Therefore, it is essential that local governments and policymakers are involved early and often in shaping how AI evolves and how it impacts people and society. However, policymakers are often not trained to recognize the psychological, economic, business, or technical complexities involved in deciding on guidelines and principles for implementing AI. Yet, there is also much at stake for leaders to enhance their understanding of AI possibilities and limitations. As frontline users of scientific results, decision-makers stimulate scientific progress through requests for solutions to the social issues facing society.

The security and the well-being of the society and its citizens are the ultimate objectives of any public policy. As such, it should be the government's duty to ensure that AI is "driving" society towards similar goals. In this respect, governments could demand the provision of demo systems emulating a real implementation of the tool so that policymakers clearly see the effects on all fronts. They could also set limits or constraints on the provisioning of AI or have special legislation for its specific use. In a similar fashion, public institutions that have been using AI-based tools, such as the police, education, or health system, should also share their knowledge and expertise on the potential and the pitfalls of AI implementations.

6.2. Industry Leaders and Corporations

Beneath all the high-minded rhetoric about the promise of AI is a stark commercial enterprise warping the course of reality: big tech companies recruiting the brightest to monetize our collective transformation from human to industrial commodity, to capture all value generated by our interactions. Short-term focus often supplants trustworthiness, reliability, and safety. Very few companies acting ethically or responsibly would deploy their systems in a manner that subdued human will, or compromised an individual's autonomy long before reaching the brink of no return. And even fewer would bury the results in an enterprise looking to flood the world with artificial imagery directly enabling every conceivable nefarious action. Beneath the artificial veneer glamourizing society's academic transformation lies a utilitarian, data-gorging machine focused solely on the game theory of profit optimization at any expense.

Noble intentions or pristine aspirations notwithstanding, corporate-led efforts in ethics and fairness deliver the directive of the narrow envisioned responsibility to their executor. Well-intentioned, yet leaderless efforts register their presence through voluminous reports typical of anonymous, committee-shaped organizations rife within industry. Corporate leaders -- oftentimes asking for help in achieving trustworthiness and ethical enumerations of locational concern -- are now among the prime consumers of applied ethical research. Corporations acting irresponsibly acutely benefit from differential goals demanding independent constraint. Others feel no imperative to rely upon or reward those performing applied research on the business's dime. With desire for desiderata ceaseless, time demanding moral forbearance from tech corporations looms as desirable and difficult. As stakeholders transform the industry, they provide fresh narrative mechanisms to articulate bindings around responsible AI for the corporate world.

6.3. The Role of Academia

Academic researchers and institutions have long been important drivers for work in AI, often grounded in mission-oriented perspectives in contrast to profits or success. However, like industry, academia faces tight constraints to secure resources. While in previous waves of AI, this had the effect of reducing risk on researchers and limiting ability to engage with unusual niches, more recently there has been an influx of externality-rich projects, especially in collaboration with private sector partners. The result is growing career pressure on researchers – both for funding or other resource security and also to publish in top tier venues with substantial competition for limited space. Existing demands on academia to produce more relevant research, on shortening cycles for publishing work, and concentration of power over publication that leads to a winner-takes-all model all pose risks to the quality and breadth of research in an increasingly important domain.

The priority within academia to support relevance by collaborating with industry struggles against the priority to retain independence. This is especially concerning for topics that industry is less able or interested in addressing – understanding what AI should not be used for, or when to say no, dependent care informed by disciplinary perspectives like critical race theory or indigenous knowledge. These draw upon long-standing cross academic-disciplinary industry collaborations by researchers in fields like ethnomethodology that blur what is considered work; this serves humanities disciplines especially well, and brings both richer understanding and clearer takeaways – engaging industry in longer term, more collaborative modes than are typical in science and engineering is likely to be more productive, for both parties.

7. Global Perspectives on AI Ethics

Introduction

As advocates of global interoperability as well as proponents of cultures' diversity, we discuss in this chapter the future of responsible AI from a global perspective. We first describe cultural differences in AI ethics. That is, how do different cultures interpret ethics in AI differently? After that, we briefly review existing international guidelines and standards related to ethics in AI in order to promote aligned practices across borders while allowing countries, companies, and individuals the freedom to act ethically according to their beliefs.

Cultural Differences in AI Ethics

There is no single ethic which is universally accepted; hence, ethics differs by culture. Nevertheless, ethics is crucial for the survival of humankind, and therefore it is of utmost importance to agree on certain ethical principles seen through the lenses of different cultures. Different cultures may actually decide that the same ethical recommendation is a good idea. For instance, the principles of beneficence and nonmaleficence are highlighted in several places and are thus pretty much universally accepted. However, it is possible that this consensus would not have been reached if there were no dominant culture that would propose such principles and morally convince the others, but rather an equal collaboration among cultures.

Now, numerous ethically based guidelines for AI systems exist, many of which have been created in a patchwork fashion by companies and countries respectively. These guidelines differ widely in focus—from protecting specific stakeholder groups, such as consumers or workers, to protecting humanity as a whole. Thus, we suggest that compliance with ethical AI principles taught as part of AI literacy should be sought after globally across different cultures to the degree that this is possible and explainable, but that companies and countries should be allowed to define specific requirements according to their own ethical beliefs.

7.1. Cultural Differences in AI Ethics

The call for AI with ethical value such as fairness and explainability has been fascinating globally, but it is interesting to see which values in Artificial Intelligence are perceived as more or less important, and whether there are differences in the perception and development of responsible AI among different countries and cultures. The Western world with the USA embedded in the ideals of the Enlightenment with emphasis on individualism has created an AI system which tries to reach ethical moral standards with values such as transparency or individual accountability and responsibility in competitions, usually embodying AI ethics as a problem with solutions of the same kind on the political process level. On the other hand, Eastern philosophies recognize a more collective harmony among the family and society and that AI should be designed not affecting social interactions in a negative way, focusing on moral responsibility more at a collective level. In these cultures, systems without such assurance should be prohibited even if not harboring clear misconduct. Their approaches and focus on possible ethical misbehavior vary accordingly.

We cannot just superimpose our values on others. Ethical development is mentioned in many documents, but practice varies considerably globally. In particular, non-Western approaches are often underrepresented. It is important to share and consider different approaches based on their respective contexts, so that development and implementations can be redesigned while being aware of cultural differences and local customs. This responsibility applies not least to developers themselves. In research work, discussions on the challenges to run the local ethics committees demanded with reference to regional implementation, enforcing the principle of subsidiarity, so that non-Western solutions could be advanced based on building trust between government and society and towards digital sovereignty.

7.2. International Guidelines and Standards

Efforts to define universal principles for AI ethics have proliferated in recent years, as the implications of AI transcend national borders. Such efforts typically focus on principles that should underly the design and deployment of AI and related technologies. They are informed by fundamental rights and principles of human-centered and ethical AI. These guidelines inform the future deployment of AI technologies. In this section, I discuss how foundational principles from various organizations, corporate social responsibility movements, and the for-profit sector inform such work.

The principles articulate guidelines for AI development in safety, ethics, maximizing human benefit, and long-term hopes and fears. Although their use is likely restricted to AI research, they were conceived in part as integrating concepts from work in related technologies, such as biotechnology and nanotechnology. Universal pro-social guidelines for the creation and deployment of AI have been defined, and multiple principles for the safe and beneficial use of AI have been set forth. Principles for AI systems are also laid out by initiatives on ethics of autonomous and intelligent systems. Others offer similar principles, such as standards on AI bias and various strategy documents. Guidelines have often informed such documents, published principles on the use and development of AI and of AI-related technologies. The publication is seen as a major collaboration and effort by multiple countries.

8. Future Challenges in Responsible AI

In the years ahead, we will increasingly witness the convergence of multiple advanced technologies in fields like biotechnology, nanotechnology, and computational technology. Such development will bring about the transition to what has been called "the third wave of the technological revolution." We will find ourselves moving from the digital and information stage of current advances toward a stage in which intelligent machines will be integrated into our biological and physical environment. Technical inroads are already being made in this direction: wearable technology goes beyond augmented reality, with heads-up displays incorporated directly into our eyeglasses; implantable devices help diagnose and treat various ailments; and, soon, biofeedback devices, and even complete cyborg assumptions, may not only be physically but cognitively integrated with human organisms.

Such integration into intelligent and automated computational environments that now embrace us represents both opportunity and challenge. New ethical dilemmas will arise related to neuroethics, in particular, as devices emerge that are capable of cognitive and emotional incorporation, modification, or invasion. How will social norms be affected, for example, by devices enabling people to influence or condition the emotional states of others? Questions about privacy and personal autonomy will take on new meanings, while issues raised by existing technologies, such as riding-share apps, automated drones, and autonomous vehicles, will need to be explored anew. In particular, how will integration of such devices with our lives as social animals affect the rules and practices we develop as human beings trying to make our way in the world together? While research into ethical issues surrounding AI has already begun, it serves us well to consider how ethics for AI and robotics should evolve in the face of the challenges these emerging technologies will give rise to.

Long before the Third Wave approach becomes fully realized, however, we will encounter profound challenges produced by the current Second Wave rush into ever deeper and more versatile AI applications. Because such applications make it ever easier to replace human judgment in the workforce across sectors and with increasing urgency. Already, evidence suggests that employment opportunities are more difficult to find for those lacking education, training, and experience: machine learning applying to artificial neural networks is making faster, deeper, and wider inroads into performance domains requiring less and less education and experience, even as those in remaining categories that require higher level credentials experience income increases. In particular, wages for unskilled laborers in all sectors have stagnated, and the wage disparities between the highest-earning and lowest-earning workers have reached the highest levels since the late twentieth century.

8.1. Emerging Technologies and Ethical Dilemmas

The rapidly evolving frontier of technology raises significant questions about present and future ethical and safety challenges. How effectively can we design safe and ethical AI systems like self-driving and self-flying vehicles? As we struggle to understand the implications of the first generation of machine learning algorithms, new, even more powerful general purpose products of deep learning are emerging, including systems for creating text and images, as well as generating music, speech, and video content. Indeed, the hype surrounding these latest models has led some observers to dub 2023 the “year of the AIGC” – artificial intelligence-generated content – perhaps overshadowing the fundamental social, legal, and ethical dilemmas created by their deployment.

Increased capabilities, while exciting, often heighten the intensity of ethical dilemmas, reflecting one or more of the values at stake in the development, deployment, and design of alternative responsible AIGC systems. Attention is focused, for instance, on the proclivity of AIGC systems to create biased images, perpetuating and exaggerating societal discrimination against people of color. Will generating speech and video deepen the threat of impersonation? Recently, news surfaced that officials faced the possibility of having to respond to a false report of a terrorist attack generated by a deep fake video in the event a national holiday was declared. Even with attention to the possibility of manipulative misuse, the technology poses ethical questions whenever deployed in a context with important implications for human rights – whether for political actors, journalists, or the general public. A failure to develop safeguards would make AIGC a powerful weapon in the hands of those wishing to mislead, deceive, and persuade audiences of untruths, whether they be that of a candidate, other political figure, or business executive.

8.2. The Impact of AI on Employment

Since the dawn of the Industrial Revolution, fears have been expressed that machines would take people's jobs. In the context of AI, these fears have been amplified to the point where people use phrases to explain the latest upheaval in technology. The Luddites were 19th-century English craftspeople who, led by their leader, destroyed the automated weaving machines that, by making their handmade goods obsolete, devastated their incomes and way of life. We all want to keep our jobs. Some of us love what we do and would continue to do it no matter if an AI system could do it faster and cheaper. Others of us endure our jobs solely for the income. We all depend on a functioning economy.

The means of production need to be owned and operated by someone. Who is that "someone"? If only a few people own the companies that own and operate the AI systems and robots and everyone else is but a pawn in the capitalistic chess game, then what happens to the rest of us? Or if the AIs are operating on behalf of some benevolent multinational or on behalf of the government, are people allowed to simply consume the output without paying for it? Will the government tax the output from those AI systems and pay people to do nothing, because there are no jobs for them to do? Or will the government provide the AI systems and the output as part of its services to its citizens? Is this Universal Basic Income? Would the taxpayers be happy lending money to the government for the program when the government is running massive deficits? Would they trust the government enough to not free ride on the program?

9. Strategies for Implementing Responsible AI

Unleashing the true potential of responsible AI will take patience, commitment, craftsmanship, and the synthesis of new knowledge. Alignment with core ethical precepts will need to be baked into the existing technical processes and designs that underpin the development and deployment of AI. This is likely to require collaboration within a broader coalition of interested parties that is policed and managed via new governing encyclicals.

The intricate interplay between technical process choice and the range of players in the AI ecosystem implies that there is no one best way to create ethical AI. Ethically sensitive design thinking and approaches will be fashioned from a wide range of techniques and actions, taking careful note of the ethical consequences that flow from the many intertwined temporal, spatial, political and institutional dimensions of the AI context, and the ethical goal that underpins these active choices. We outline three sets of flexible and disaggregated best practice guidelines: designing ethical principled development processes, working on and collating best practices to minimize the risk of harm or avert possible adverse ethical consequences, and creating public-facing AI ethical guidelines that clarify the scope of ethical aspirations and liabilities of the owner of deployed AI applications and systems.

9.1. Best Practices for Ethical AI Development

Responsible AI is a concept rather than a set of rules. Responsible AI is about how societal values can be employed as a compass: one can arrive at just and desirable ends, and avoid catastrophes, by learning from the negative lessons of the past and sitting down to think how best to use AI to benefit people, the planet, and all systems at the intersection of the two. That said, creating the right requirements for a good AI system can be highly context- and use-sensitive, and involve some ambiguity. These can include the actual implementation, the data involved, and the values at play. In formulating these requirements, one can move towards Responsible AI development by abiding by a number of general principles.

First and foremost, understanding the potential uses and users of systems providing AI assistance is essential to creating appropriate requirements for those systems. Users should work along with designers to set the goals of the system. These goals usually intersect with human and machine values like: safety, people-centredness, welfare and service, individual autonomy, justice and fairness, accountability, privacy and confidentiality, respectfulness, security, and reliability. There is also the shared goal of finding solutions capable of solving the core problems of society. Finally, these goals should be compatible with their deployment in all relevant countries and cultural settings, should require user-friendly implementation, should not require excessive resources for development, maintenance or infrastructure, and should be cost-effective.

9.2. Creating Ethical AI Guidelines

The idea behind these guidelines is to provide machine learning developers and practitioners with a policy they can reference while developing models or systems. Additionally, if these policies stem from the research community, they create a certain responsibility for AI companies and services to stick to them. The guidelines are inspired by rules and norms from diverse fields, including philosophy, law and engineering standards. The approach followed aims to be high-level enough to be customized to the needs of particular teams and projects, while providing sufficient detail about salient technical and ethical aspects of machine learning systems.

The guidelines are part of a broader set of ethical standards that society could adopt to regulate the practice of machine learning. A major goal of the guidelines is to initiate a discussion on effectively using computational systems, machine learning technology in particular, to define a good for society or, at the very least, to avoid acting against social wellbeing considerations. The guidelines also represent our belief that responsibility in machine learning and AI is currently undertaken mostly by individual researchers. They can raise the bar for good practices, and represent a call to researchers and practitioners to explicitly take a stand on ethical principles, delineating a territory of AI development that is better than careless or overambitious, lucrative-centered applications of technology. Some first steps towards defining principles of responsible AI have already been taken, for instance in the form of guidelines for the ethical use of AI or ethical frameworks for a good AI society. More recently, other initiatives have been launched to define principles for responsible AI and attempt to translate them into practice. Our goal, however, is to narrow down these general helpful principles with concrete lists and questions, to be used by teams during the practice of machine learning design and implementation.

10. Case Studies of Responsible AI

In this chapter, we present various case studies that describe actual implementations of Responsible AI. Some highlight success, while others offer lessons learned that stem from failure. By learning from others, we can better our own practice when adopting Responsible AI. This section contains both kinds of cases.

10.1. Successful Implementations

We begin with cases that illustrate favorable examples of Responsible AI. The Responsible AI Collaborative is a group that offers a wealth of knowledge surrounding the topic of Responsible AI. They present partnerships among established organizations leading projects that improve the practice of building and implementing AI for the benefit of all. Case studies presented here were all sourced from the Responsible AI Collaborative, provided there are relevant, edited excerpts that can convey a coherent story. There are engaging narratives on the project origins, partner roles, challenges, innovations, next steps, and more.

Diagnostic analyses are increasingly becoming standard approaches to understanding the data and algorithms behind AI systems. These analyses assess, quantify, and evaluate key algorithmic performance criteria in the context of the stakeholders and problem domain addressed by the algorithmic decision-making system. From the success of these diagnostic analyses, various algorithm/data developers have formed diagnostic tool partnerships, creating novel and important, approachable solutions. Such easily adapted solutions aim to help cross-functional teams, helping them answer the why a technical approach was taken, the how well does the approach work and what improvements are needed.

10.1. Successful Implementations

Responsible AI is no longer just a concept being debated in academic circles; its principles have been recognized and effectively instantiated in numerous organizations and areas of application. The Ethical Principles for AI are as relevant today as they were then. These principles include accountability, accuracy, auditability, fairness, privacy, reliability, safety, and transparency. Implementations of some or all of these principles in some AI-enabled systems can be found in the life sciences, the intersection of medical and radiological imaging, the automotive industry, and in the use of NLP Fragments for content moderation. Moreover, foundational models and their contemporary and future incarnations are being used to help hospitals and insurers with patient care, financial resource allocation, and other internal functions in order to improve patient care experiences while lowering costs.

Other examples of responsible AI implementations come from various private sector organizations. For instance, a group of diverse stakeholders from academia, industry, and civil society was called to convene to develop best practices and conduct public research and public education around the ethics of AI. To this end, they facilitate discussions between various organizations and increased engagement with smaller industry organizations, university researchers, and think-tank policy analysts. At the same time, various governments have developed or recommended the implementation of ethical principles for AI design, development, and deployment. Specific recommended principles include recommendations on fairness, accountability, transparency, explainability, economic and social impact, and safety and security.

10.2. Lessons Learned from Failures

There is a danger, perhaps unique to the AI ethics space, that the discourse may sometimes focus on efforts that were successful in birthing techniques that could be adopted more broadly. These might be frameworks designed to promote fairness in model designs or corporate guidelines intended to espouse the engagement of affected communities regarding possible AI harms. However, it is equally important to share observed failure modes so that we can better understand where practitioners often stumble and sweep what might nevertheless be an embarrassing experience under the rug.

Why Should We Learn Lessons from Failure? The question of why we should issue notes of caution when it comes to what could be motivating outcomes, such as good intentions and hard work. The answer lies in both the popularity of discussing success and the excitement that continues to drive the technical AI space. First, not only is the air the apparently rarefied air so full of shock and awe, the booming economy around it makes it an aspirational goal for graduates and practica alike in every field. On the one hand, it would seem normal and natural for us to motivate these as comparisons with successful practitioners so that those that follow in our footsteps can be given the inspiration that we also needed at one time. However, as we already alluded to at the outset, this is significantly tempered by the caution that having successfully gotten onto the road onto AI-driven success so that we are now higher up them in the economy, it makes us storytellers behind a veil.

11. Public Perception of AI Ethics

What does the public think about AI ethics? What kind of ethical safeguards do people expect to see from AI researchers and companies? Public perception is an important part of how to shape the future of AI systems. Many of the most discussed dangers of AI may not happen for decades or even centuries, meaning that we need an active interest in dangerous AI development from the public, and reasons for the public to demand regulations and safeguards against dangerous AI. Conversely, work on beneficial AI, and general progress in the field of AI, should seek public support. If the public loses trust in AI developers to develop AI issues that are beneficial and safe for society, they may demand heavy-handed regulations or entirely ignore the technology. This would stifle progress on important areas, like medical AI, because of concern that others are developing it irresponsibly. Therefore, we hope the following sections stimulate more discussion and research on questions surrounding the public perception of AI ethics.

Various studies of public trust in AI systems appear regularly in the news. Other established non-profit companies frequently conduct surveys and publish reports on their findings. These surveys show that public trust in AI technology is generally low, particularly concerning algorithms used for sensitive decisions like hiring or criminal justice. Trust is particularly low among marginalized groups, who have been the most affected by algorithmic decisions. The media also play an essential role in shaping perceptions about AI ethics by accident or design, often by reporting on issues around research on technical AI safety, but sometimes also through the dramatization of AI in science fiction movies and books.

11.1. Surveys and Studies on Public Opinion

AI systems are increasingly recognized as being part of the public sphere; the values we build into them shape the sort of society we want to live in. The public's input is necessary, and observers recognize the real challenges of determining the public's collective view. Although AI ethics has not settled on consensus as yet, recent years have seen an uptick in the number of surveys and studies exploring public attitudes, especially in the wake of high-profile incidents exposing biased algorithmic systems used in public life, such as criminal justice sentencing or jury selection, hiring and recruitment tools, and consumer-facing programs in which people are denied access or offered unfair opportunities.

Investigations into AI safety attitudes, motives, and framing have involved asking participants to rank various AI risks in the areas of warfare and militarization, public safety and security, economic disparity, polarization and disinformation, governance and accountability, labor displacement, transportation, and embedded autonomy, and inquired about AI's role in future innovation and enhancements. Vignette methodology has been used to track how people viewed AI during 2020, modified several times during the pandemic to gauge concern about surveillance systems, and why. A project behind the second Expert Forum on AI Policy Cooperation presented a set of policy priorities distilled from a survey of people across multiple countries, later creating regional reports detailing how AI policy priorities differed across the different regions.

11.2. The Role of Media in Shaping Perceptions

In this chapter, I discuss how public perceptions are shaped by media coverage, market institutions, and policymakers. Media mechanisms are one of the essential microfoundations for understanding the political economy of global AI ethics. First, I briefly revisit the relationship between public opinion and media coverage and investigate how media affect various aspects related to public opinion surveys. First is how the media's tone matters for survey results. Second, survey and media research generally explore short-run effects, but there are a growing number of studies that explore the media's effect on long-run public opinion trends. Third, bottom-up populist pressure may only be one reason for the growing media coverage of artificial intelligence.

Because the media's role in shaping public perceptions is so essential, I devote a separate section to it. Most studies on media and public opinion focus on misinformation or discuss the informational environment against which assessment takes place. I argue that the examples that are prominently presented in the media can change risk perceptions, with possible implications for investment and support for regulation or policy solutions. Second, the media can keep the potential consequences of artificial intelligence salient in the public debate. The questions of which society emerges from the discussions and who defines the discussion, how globalization and new technologies reshuffle the communication landscape, what that implies for the balance of power and accountability remain broadly open.

In short, I summarize in this section the role of media coverage in shaping the debate, what society and discussion emerge from it, and what are the implications of how technology, globalization, and new technologies reshuffle the communication landscape. Empirically, I investigate the media's role mainly by looking at the timing and the tone of the media reporting on artificial intelligence.

12. Conclusion

What can we conclude? Firstly, AI is a scientific and technological project initiated by a sophisticated group of theoreticians, engineers, and entrepreneurs.

Its ultimate aim is to architect intelligent agents machine-made and capable of liberty, autonomy, and social interaction. What is maybe most disturbing is that, although liberating a dangerous and powerful genie from its bottle is not isomorphic to liberalizing a benevolent and useful genie, the risks are more linked to an aggressive genie than to a benevolent but impotent genie. We can predict, based on the Dirichlet principle, that any enhancement of the intelligence of a non benevolent or machiavellian genie, AI being only a piece of its complex architecture, is very good news for criminals, mafias, and anti-social individuals and societies, and for the rest of humanity suffering the consequences of the activities of those who may be defined as "genie-designers".

AI is thus, together with the colonization of space and the enabling of life in extreme conditions on Earth, always able of exterminating, acting as "inner pandemic" at the global level, our population composed essentially of what can be termed "consumers". Among those developments, outside those risks and questions, AI continues to be an "enabling" technology, allowing for example a wide range of evolutions in the life of collective agents, inorganic and organic, and for the collective activities of these. AI contributes not only to the enhancement of the efficiency of collective activities promoting the flourishing of eco-systems, societies, economies, and cultures capable of evolving in a positive direction, but to the solution of the wide range of scientific and technological paradoxes that are raising in front of us.

References:

Siau, K., & Wang, W. (2020). Artificial intelligence (AI) ethics: ethics of AI and ethical AI. *Journal of Database Management (JDM)*, *31*(2), 74-87.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature machine intelligence*, *1*(9), 389-399.

Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. *Minds and machines*, *30*(1), 99-120.

Coeckelbergh, M. (2020). *AI ethics*. Mit Press.

Munn, L. (2023). The uselessness of AI ethics. *AI and Ethics*, *3*(3), 869-877.

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., ... & Hussain, A. (2024). Interpreting black-box models: a review on explainable artificial intelligence. *Cognitive Computation*, *16*(1), 45-74.

Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, *15*(3).

Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z. (2023). ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing. *Journal of the Association for Information Science and Technology*, *74*(5), 570-581.

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and information technologies*, *28*(4), 4221-4241.

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European journal of education*, *57*(4), 542-570.

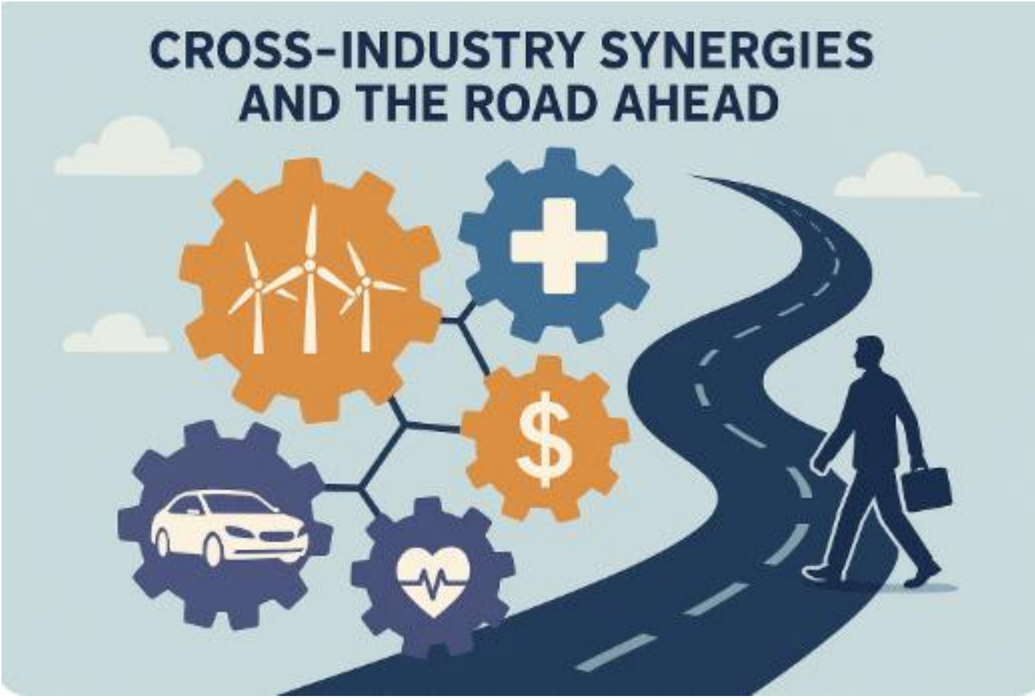
Deep Science Publishing
https://doi.org/10.70593/978-93-49910-25-6

Chapter 11: Cross-Industry Synergies and the Road Ahead

1. Introduction to Cross-Industry Synergies

Cross-industry synergies can be defined as economic and financial relationships between organizations in different industries. The idea of cross-industry synergies is not new; in fact, it has been around for several decades. However, discussions centring on the use of cross-industry synergies for strategic purposes have mainly remained within the walls of specific academic journals. Cross-industry synergies represent a powerful yet largely dormant framework for presenting and examining the corporate activities of a business. Aside from a handful of academic studies and increasing interest from practitioners, corporate strategy and corporate financial management has largely focused on the idea of within-industry, that is horizontal, diversification.

We are certainly not the first to highlight the potential importance of cross-industry linkages. In their study, a particular type of horizontal merger, that of diversified companies, but located within two different sectors of the economy, examined the extended inter-industry relations as a powerful but understudied phenomenon in the empirical merger literature. The neglected issue of diversification by merger should not be relegated to the dust bin of history. By observing examples, such as the merger between two major corporations and telecoms and cable connections strategies, it is evident that a growing number of corporations seek to increase the efficiency with which they utilize their assets and resources as well as gain access to new customers, distributors, and markets by successfully engaging in this type of corporate restructuring. More broadly, the definition advocates that diversification, broadly defined, embraces both the direction and extent of the coordination and congruence of economic activities into distinct but complementary areas or industries, as well as the processes through which these are leveraged and integrated.



2. The Importance of Collaboration

The establishment of a collaborative relationship between two parties, or the cross-fertilization of ideas from different groups, has been shown to produce better results than those that could be achieved unilaterally by either party. Collaboration is cited as a key measure for attaining predetermined objectives across diverse domains, including education, research, business, military, private sector, and government. In the setting of technology, collaborative relationships can accelerate progress through joint funding by the government and an industrial player, through joint programs in consortia or through informal agreements, or major research projects sponsored by large lending banks and carried out jointly with universities both in industrialized and in developing countries.

Over eras this kind of collaboration has become increasingly necessary, given the heightened pace of technological progress and the growing investment effort in research and development exerted by major companies, notably in high-technology or high-investment intensity fields like telecommunication, computers, semiconductors, health surveillance, and biotechnology. This growth could be maintained only through the association of the public sector, either directly, through government contracts or, indirectly, through the use of tax incentives and subsidies, or the promotion of collaborative approaches. The rationale for building a collaborative model of industry may be the accelerated economic growth which may result from such a public-private partnership, and the motive for collaboration is primarily induced by the very nature of research and development behavior in an economy.

3. Historical Overview of Cross-Industry Collaborations

From early history to the present day, the collaborative nature of human existence is a pivotal aspect of our species defining what is often called the "social animal" theory. The terms transaction, relationship, alliance, and network architecture emerged during the 1970s and have been used in various disciplines to explain and understand economic and social interactions. Cross-industry alliances have existed for centuries, for example in the form of joint ventures and marketing agreements. Moreover, cross-industry collaborations are sometimes born out of necessity or driven by industrial policies seeking to develop certain technologies or products. Companies in the automobile, aerospace, and defense industries commonly collaborate with electronics companies to develop software and applications which run on new platforms or create new products and services to offer to their customers. Cross-industry collaborations are both interdisciplinary and multisectoral in nature and facilitate the intermingling and reshuffling of knowledge, understanding, and human cooperation within and between industries.

The beginning of the 21st century has been characterized by a multitude of technology transformations that make up what is termed the Fourth Industrial Revolution. The innovation engines devouring 21st-century business organizations appear to be fueled by fertile ground, where a diverse mix of markets, democratized access to financing, and digital are enabling ground-breaking entrepreneurial ventures, many of them cross-industry in nature. Companies are being faced with tremors that shake the core of their value proposition and growth strategies, and challenge their technology and market foundations. Moreover, cross-industry collaborations are often voluntary and collaborative systems created because stakeholders believe they should act together for their mutual best interest. Cross-industry platforms offer smaller players and incumbents with resources and capabilities outside their zone of competence the opportunity to ride the platform and capture new revenue flows, thereby sharing the risks associated with their own survival and that of the platform.

4. Key Drivers of Cross-Industry Synergies

The emergence of several cross-industry innovations can be credited to a combined effect of technological advancements and the rapidly changing market demand owing to global economic factors (Alpaydin, 2021; Barnes et al., 2020; Chantry et al., 2021). The development and commercialization of emerging technologies such as artificial intelligence, robotics, and data analytics, among others, have made it easier for industries to access solutions or components offered by other sectors. On the supply side, rapid consolidation in the resources and manufacturing segments of several advanced economies, tracking of products in global supply chains, and customization of products through additive manufacturing are changing the ways in which demand from key end-users is being served. These factors are expected to continue driving demand for cross-industry partnerships in the foreseeable future.

Innovative capabilities of both suppliers and customers rely on technological advances and continuous investments in R&D. Technological changes drive demand for innovative capabilities by driving demand for specialized components from customers. There are two reasons for this: first, demand for advanced components increases because traditionally less-advanced capabilities become obsolete; second, in-house revenue replenishment by customers is reduced, driving specialists to provide these component solutions. Moreover, innovations in one industry often create increased demand for innovative capabilities in other industries, further encouraging attempts to acquire or ally with suppliers or competitors in other sectors. These efforts to outsource, acquire, or ally typically occur when companies face high and profitable demand for specialized components, while general economic conditions are favorable.

4.1. Technological Advancements

The common perception of research and development is an execution of university-level theoretical insights on selected challenging problems and gradual generation of technological knowledge which is accumulated, fabricated into processes, enhanced, extended into products and communicated with the rest of the global economy. However, research and development of its very nature is a cross-industry perspective since every innovation is based on the reinterpretation, extending or just creatively recombining available distinct technological knowledge. It is this common underlying structure of technology which allows inventors and entrepreneurs to look across the border of their own technological domain and discover interrelated available technological knowledge from other domains, to combine them in innovative ways and to discover new novel applications for existing technology. The consequence is that technological advances in one economic sector, industry domain or distinct area of science often generates linkages and brings forth new products and services in other industry domains creating new industries and activities.

In recent years, a-growing number of drivers of advanced technology have emerged which affect all distinct domains of business specially providing companies and research institutions with the possibility to look into other industries, or strategic value chain areas, for new technological developments that can be put in applications in their own activities, thus generating and exploiting cross-industry synergies (Deser et al., 2020; Irrgang et al., 2021; Jordan & Mitchell, 2015). The result is demand-driven and technology supported development of new business activities and industry sectors, generating growth, employment creators, productivity enhancers and sources of innovation. Each of these technology dynamics is spurred on by more and more higher levels of cooperation, partnerships, and teaming up on both demand and supply side between both firms and research institutions. The result is that much the whole economic activities become more cross-discipline sensitive and interrelated with full implication of both national and international supportive technology policy.

4.2. Market Demand

Another key driver of cross-industry synergies is emerging demand patterns enabled by emerging technologies (Kadow et al., 2020; Mahesh, 2020; Zhou, 2021: Deser et al., 2020). The metaverse is touted to factory reset the cross-industry synergy landscape, forcing firms from different industries to collaborate or perish. New use cases that create additional demand for products or services in the supply chain, as well as adjacent areas to grow the ecosystem are also shaping the products and services roadmap. The urge to enhance product and service portfolio continues to spur collaboration of companies from different industries, driven by demand diversification from function to experience. Brands no longer compete solely on performance and delivery, but also on experience – the emotion felt when using a product or service, including design, color, and connection to the brand. The increasing conscious and unconscious desire to access superior experiences has pushed companies to deliver experiences in and/or around their own products and services. Experience-driven demand paves the way for companies from different industries to collaborate by enabling immersive experiences while unlocking the next growth frontier in a collected and selective way.

Over the last two years, experience-driven demand has also been evolving to define the journeys of intended interactions with products and services, connected to both emerging trends and the individual; “my experience”. As companies are undergoing their own transformation to deliver on collective expectations of the brands they share, cross-industry collaborations allow aspirational brands to unlock the component or curated experience economies. Companies are partnering to deliver touchpoints in journey maps that expand, or enhance the overall experience. The potential diversity of product or service experiences at curated touchpoints strongly encourages partnerships from non-competing industries venturing into unexplored areas with options for dynamic monetization with lower investment and risk profiles.

4.3. Consumer Behavior

The textile and fashion industry is in a unique and important position where it is the largest consumer goods industry and at the same time suffers from inefficient business practices and major negative impact on the environment. Consumer preference towards more sustainable fashion products has been becoming stronger recently, but in the foreseeable future it will be almost impossible for the industry to reach the goal of halving its greenhouse gas emissions by 2030. Educating customers about the true environmental costs of their purchases could lead to a shift in consumer behavior, or reducing the number of purchases needed as durable product lifetime is highly impacted by how the products are treated post-purchase. New market trends for the textile and fashion products are favoring recycled and upcycled products, bringing the popularity of preconsumption and post-consumption recycling higher than ever. Cross-industry collaboration could be considered as a medium to cancel the social stigma surrounding “low-cost” recycled fashion products, particularly for unappealing and less fashionable categories of upcycled products. Moreover, introducing circular business models such as takeback schemes for textile recycling leveraged by other industries could foster the intrinsic motivation of consumers to recycle their post-consumption fashion items.

Cross-industry collaborations are not only valuable for the upcycling of old textile products, they can also have a positive impact on consumer behavior while choosing to buy new items. Developing and offering new fashion products by using sustainable or innovative manufacturing processes or applying traditional or new disruptive technologies collectively by members from different industries or sectors can encourage consumers with higher sustainability concerns to buy them. Digital solutions offer great potential to engage consumers and provide detailed product information related to sustainability initiatives such as “eco-friendliness” or the use of innovative technologies.

5. Case Studies of Successful Collaborations

We draw on a diverse set of case studies to showcase successful cross-industry innovation. The goal is to highlight both the breadth of industries that have and can benefit from cross-industry innovation, pointing to examples that are both different in model and style, and to showcase initiatives across a time-spanning canvas: initiating in two sectors that have benefitted for over half a century from cross-industry synergy, technology and healthcare, we then move on to finance and retail before showcasing automotive and energy.

The duo of technology and healthcare is an obvious choice to kick off our exploration of cross-industry synergies. After all, the source of synergies between the two sectors lies in the fact that information technology has and continues to transform the healthcare sector. Semiconductors, computing power, sensors, data collection/storage/analysis technologies, actuators, network capability, security and privacy technologies, artificial intelligence - the insights and impetus for innovations across almost all of the classes of technologies, that have had and are having such a powerful impact on the healthcare sector - have originated from the technology sector.

A clear example of collaborative innovation is the collaboration between Apple and healthcare partners. Led by the department of cardiology, the study aimed to investigate how to best use the Apple Watch technology for atrial fibrillation detection. The validation study reported that the Apple Watch was capable of accurate ECG detection of atrial fibrillation. Apple Watch has continued to innovate - adding an ECG and an atrial fibrillation detector, capturing the public imagination and surfacing concerns about the clinical and commercial viability issue raised about such wearable devices.

5.1. Technology and Healthcare

A variety of digital health and telehealth applications and services have emerged, partly due to the acceleration brought on by the pandemic. Industry partnerships between technology, telecommunication, and consumer electronics companies;

health insurance; medical device; and healthcare provider organizations have been at the forefront of digital health collaborations. These cross-industry partnerships have been instrumental in expanding innovation, developing and testing solutions, and bringing digital health technologies to market rapidly. The lines between consumer technology and healthcare have blurred, and the competitive landscape for digital health products and services is becoming more crowded and multifaceted.

With growing demand for telehealth and remote patient monitoring solutions among both consumers and patients, healthcare plans are extending coverage and reimbursement for these services, while dozens of tech companies are receiving medical certifications and clearances to bring their solutions to market. Digital health technology partnerships between tech companies and medical solutions providers are creating synergies that are accelerating the development of solutions for symptoms and monitoring, for both patients who are actively symptomatic, as well as for those in recovery. In addition, consumer technology companies have partnered with health plans and providers to introduce remote patient monitoring systems for the ongoing management of chronic conditions post-pandemic.

5.2. Finance and Retail

In recent years, financial services organizations have collaborated with companies in the retail business to bridge gaps in their services. Banks have worked with fast food companies, supermarkets, and department stores, among others. Banks are looking to increase customer reach among potential clients who cannot be served through the traditional cost structure of bank branches. Retailers are looking to enhance profitability and customer loyalty through financial services offerings. Banks benefit from collaborating with retailers who have a high volume of customer base who are otherwise not in the formal financial network. Retailers benefit from associating with banks who set up ATMs in their locations which help improve footfalls, while offering their customers informal money transfer services through banks and earning fees while doing so, thus enhancing profitability. Moreover, both parties benefit through increased sale of consumer products, and joint payment cards. There are many existing relationships in these sectors in other countries. Retailers have partnered with banks for ATMs and payment services at checkout counters. Some banks have exclusive alliances with supermarket chains to issue joint loyalty cards. Clothing and electronics retailers have launched credit cards with banking groups. Other partnerships promote joint marketing of financial services to communities.

Collectible card games have made it possible for users to use them as smart cards in vending machines, public transport systems, and others.

5.3. Automotive and Energy

Synergistic collaboration can create tremendous value. The large capital cost associated with the initial investment by the utilities can be shared with auto makers. OEMs have the expertise to make image-laden products. Customers care less about the energy, down to the nitty-gritty detail of the battery, fuel cell, or other technology embedded in the vehicle. They want something that performs well, looks good, and is eco-friendly. Any automobile that can source its energy from renewable energy must be highly encouraged, both theoretically and from a marketing standpoint. The utilities will have preferred supplier status in that they will supply free energy.

There are many components to the entire automotive and energy arena. These include electric vehicles, fuel cell vehicles, HEV, BEV, natural gas vehicles, parking control, EV charging stations, at the home, benefiting both the auto maker and customer, charging away from home, and roadside infrastructure to create incentives for EV and HEV. As one can see, this is truly a cross-industry collaboration. The automotive industry works with the energy sector to develop products. The customer wants to see some type of cost-benefit incentive from the utility in order to consider moving from a gas-powered vehicle to one of the many hybrids and variations that will soon take the marketplace by storm.

To understand this cross-industry collaboration, a prime example is a partnership involving a major automotive manufacturer and a utility company. The manufacturer will supply a fleet of EVs for use by corporations, including hotels, airports, and delivery fleets. The utility will agree to install, at its expense, charging stations in the area. The utility will test state-of-the-art technology for the automotive industry and will know how to create desirable products that customers want while the manufacturer will understand all factors in balancing cost and research technology innovation while increasing sales.

6. Challenges in Cross-Industry Collaborations

Despite the positives, cross-industry collaborations are difficult to establish and execute. Many challenges such as cultural difference, diverging visions and goals, and regulatory hurdles need to be resolved to realize synergies between industries. In this section, we describe some of these challenges to highlight that a strategic perspective is important throughout the collaboration process in order to obtain synergies.

6.1. Cultural Differences

In a study of partnerships, it was found that corporate culture was the only factor that was able to explain the effectiveness of a collaboration. Different companies within a collaboration tend to have different interests, and cite different motives and goals. As a result, it can become a struggle for all involved to cleverly combine the respective core competencies so that it can benefit all parties, especially in a cross-industry collaboration. For instance, consider the successful partnership efforts of a company working with electronics companies on a product that involves a sensor in the shoe and a transmitter for workout-tracking. Footwear and electronics companies are fundamentally different in many ways, including: And yet, the company doesn't see the variations clustered around mutual lack of trust, communication, risk-sharing, competing interests or conflicting cultural perspectives, far from it, those elements appear in parallel, with the company reporting no obstacles in collaboration.

6.2. Regulatory Hurdles

Another complication which can challenge the success of cross-industry collaboration is the appearance of additional regulatory hurdles, since it is more difficult for public sector authorities to assess the implications of a partnership. For example, it was found that markets for related products actually experienced a slowdown in merger activity, a puzzling finding as cross-industry mergers are usually viewed as useful sources of diversification. This observation is attributed to the existence of added scrutiny for cross-sector deals, since industry mismatches often trigger competition policy concerns.

6.1. Cultural Differences

1. Challenges in Cross-Industry Collaborations

Cross-industry collaborations face cultural challenges that can impede the realization of their potential benefits. Collaborations merge different yet complementary disciplines, and thus challenges derive both from the diversity in the underlying domains and from the design of the partnership linking them. Culture is generally understood as a shared set of meaning systems or collective programming of the mind. It can also be seen as a fuzzy, underlying reservoir of experience, judgment and skill, which is often neither visible may be taken for granted by people in the same organization or social setting. This shared knowledge provides solidarity to members of the organization but risks to impede learning from others or integrating activities across organizational—and disciplinary—borders. Disciplinary culture differences—different domains, idioms and frameworks—are triggering “creative fertilization” that may lead innovative collaboration outcomes. On the other side of this coin lies the often “invisible” barrier that the underlying differences may become, defining a steep learning curve for managers and team members and, hence, blocking gratification of expectations. These challenges derive from the collision, or at least the non-aligning, of partnership design and organizational mission. When partners have divergent but also common goals, how to strictly share responsibilities, resources and benefits? This cross-industry teamwork dilemma impacts on the specific partnership design adopted: for any collaboration a time-limited project organization is created to manage the collaborative processes over time. But boundaries between industries are not formal—simply signing a contract does not create a virtual organization with distinct and recognizable features.

6.2. Regulatory Hurdles

Cross-industry collaborations present new policy issues. The coming together of banks and telecommunications companies, in the form of mobile banking, raised concerns of theft of bank deposits, erosion of bank revenues, and money laundering. The structure of regulatory agencies that oversee banks and telecommunications companies is different in the US and UK, where regulators are focused on each industry. Regulators of both industries might be inefficient in regulating a cross-industry collaboration, or they might impose burdens that leave the collaboration unviable. However, in countries with a unified regulatory approach that oversee both industries, cross-industry collaborations have developed more rapidly and have been more successful.

A major policy issue with mobile banking is the erosion of bank revenue, particularly for banks in rural areas, where the costs of operating bank branches outweigh the revenues collected from banking customers. This resulted in banks depositing significant amounts in the mobile banking fund in India and the absence of a technology-neutral payment regulatory framework. Banks are also wary of mobile banking because the strategy is seen as being at odds with the continued economic growth. Unlike advanced countries, India’s low mobile phone penetration implies that banks are not trying to attract affluent customers who have low-cost mobile phones. Instead, banks are trying to attract rural customers who have previously been excluded from using banks. With mobile banking, banks are essentially changing their product lines to cater to those who have low-cost mobile phones. However, regulatory issues with mobile banking remain unresolved. While guidelines on mobile banking have been issued, they are seen as being overly restrictive. In countries where there are no restrictions on mobile banking, it has been adopted much more rapidly than in India.

6.3. Resource Allocation

Allocating resources is another roadblock due to the stakes involved. Collaborations will typically involve sharing R&D investment and the risk inherent in success, or often the lack of it. Companies that enter collaborations after developing potentially synergetic areas may enter partnerships on lopsided terms, where one partner is getting a better deal. Subsequently they have to deal with unequal amounts of contributions during the course of the collaboration. Companies in these lopsided partnerships are prone to misgiving. Superiors in both companies should ensure that the partners allocate resources to strengthen the link between capability development in synergy areas and actual market offerings. They can do this by incorporating resource allocation into performance evaluation or resource allocation processes. Allocating resources instead of people to actual projects can remove partners' concerns about collusion or internal competition. Focus of attention can also help. During the initial phases, both partners should focus on perception and capability development and then quintuple the intensity of joint learning in promising areas. Instead of just focusing on capability additions through internal and partner-based learning, the partners can also focus on capability location. They can work to explore and locate their own core group and those at the other capable of developing or harnessing marketable skills in synergy areas. Benefits will be greatest if companies take care to develop their existing connections to improve and use skills in select synergy areas. However, companies should also realize that actual collaboration in the focus areas can best happen only when both partners possess sufficient capabilities in them.

7. Strategies for Effective Collaboration

Collaboration across industries can be an amazing opportunity for companies – but only if done right. Creating synergies with others requires seamless coordination throughout the collaboration process, ranging from early engagement to governance throughout the partnership. Understanding some of the most important prerequisites for a successful collaboration can help steer companies towards building effective cross-industry partnerships. Trust is essential for all relationships, including in partnerships across industries. Companies share sensitive information with partners in many types of cross-industry collaborations, including early-stage conversations, joint projects such as initiatives to develop new products, or longer-term joint ventures. Joint ventures or joint development projects require deep cooperation and coordination among the partners. For trust to develop, companies must find a way to communicate openly, and partners should ideally have a pre-existing relationship. However, in many cross-industry settings, this is not the case. Conversations on collaboration must thus be approached with special care, presuming a high level of caution by executives due to lack of prior relationship. Sensitive conversations should ideally be conducted with a few senior executives on both sides to ensure confidentiality and should explore what potential topics for collaboration would be critical for both sides. Having clear guidelines on disclosure and protecting sensitive information on both sides will help build confidence and trust in the opportunity for collaboration.

7.1. Building Trust and Communication

The key to any successful collaboration, particularly one that seeks to implement a new cross-industry concept, is trust and open communication. If the collaborating firms cannot build a sufficient level of mutual trust, the inspired idea behind the cooperation may never get off the ground and fully flourish. Concerns about the other's intentions, motivations, and capability to fulfill its responsibilities can lead to doubts about the overall outcome of the cooperation. Successful companies will then seek to utilize trust building strategies that have proven to be most effective. Early cooperation and trust instilling activities entail socializations attempts outside the influence of the work and project. Teaming together on a project where incentives to compete cannot avert mutual cooperation and strong communication. Transparency in providing and exchanging real, verifiable information; a commitment by both organizations that work hard on the project in order to meet pre-established objectives; and providing rewards that are contingent on overall performance rather than just company performance are factors that can instill trust when the two companies do not have a history of working together.

Mutual communication by both parties is also another fundamental secret to the successful co-creation of new concepts and ideas, not only for insuring cooperation between companies but for generating creative ideas as well. No formal structure can replace an environment infused with a spirit of open, candid communication among individuals gathered to share and exchange diverse viewpoints, opinions and knowledge, or innovative thinking. Developing such an open environment is a challenge and requires concerted efforts during both the formation and active phases of the team. Balancing the acceptance of free sharing of ideas and the progress of well-structured discussions over the various topics each team encounters become difficult. However, the rewards of a collaborative atmosphere infused with such positive interactions will have many tangible benefits.

7.2. Setting Clear Objectives

In establishing intercompany partnerships, creating a detailed description of precisely what it is you intend to achieve together can seem banal, vague, or trivial. Everyone knows that meeting bimonthly to increase revenue by 30% in the next twelve months is a good thing. Why bother repeating this? The answer, however, is the concrete meaning of these monitoring documents, which can be substantial, quantitative, and measurable. The purpose is not to reduce the complexity of the action to a few figures and a few KPIs, but to link the complex reality of an action to a framework that allows for ongoing analysis and modification. A long-term partnership cannot merely be a commercial relationship enduring for a longer period; it is a collaborative investment, and both partners must have an accurate sense of the volumes involved and the allocation of additional resources in order to meet their respective financial and strategic objectives. These are expressed in terms of projects, not just turnover, and indicate the priority and relative importance of the action in terms of the company's overall strategy.

To monitor objectives requires determining, at least on a yearly basis, specific key projects, which will vary in number from partner to partner, and are defined in each meeting based on their importance. These projects should concern the diversification of the portfolio, the novelty of the offer being jointly worked on, the improvement of margins, or the enhancement of the brand image, and only rarely depend on the growth of revenue. Choosing to develop three or four new strategic projects, rather than attempting to cover all segments on a much higher scale, means committing to the resources and energy for tangible results. It also means that failure to meet the objectives in these projects can be a reason, at some future date, for modifying the intensity of the commitment in one or both directions.

7.3. Leveraging Complementary Strengths

Companies come together for a variety of reasons, including weight services. They can rely on each other to deliver specific components or products that they do not have the facilities or the expertise to provide optimally. The merger between Boeing and McDonnell Douglas is a good example of a situation where companies came together to capitalize on complementary strengths. Boeing entered into a merger with the aim of reducing the dependency on commercial aircraft. It wanted to improve the strategically important defense activities of the company. On the other hand, McDonnell Douglas had state-of-the-art military capabilities but had not developed a commercial aircraft. Boeing was aware that despite being a much larger company, which had greater resources and had made substantial investments, it would be wrong to think that it could use its strength alone to develop a competitive commercial aircraft.

Boeing began marshaling the resources of the merged enterprises, which included reducing overhead costs and restructuring responsibility for different aircraft products. It asked McDonnell Douglas to complete an all-new family of next-generation twin-aisle jetliners, which included a 200- to 300-seat replacement for the Boeing 767 and a 350-seat replacement for the Boeing 747. But as McDonnell Douglas struggled into the 1990s, Boeing took almost complete control of commercial aircraft operations. It designated the Boeing 777 as the initial successor to the long-haul aircraft. The Boeing 777 proceeded to become what many expected and hoped a successor to the long-haul Boeing 747 would be. It remains to be seen whether the success of the Boeing 777 in co-construction with its market is just a fortunate happenstance of the times or truly a successful merger intended to engage in both co-construction and change.

8. Future Trends in Cross-Industry Synergies

In our increasingly connected world, the detailed trends and events behind cross-industry synergies are also intertwined. Therefore, we present a brief exploration of future trends, both as opportunities awaiting exploration by companies, but also with a hint of caution to consider these developments deeply, lest unforeseen effects arise. The three trends we want to highlight are digital transformation, sustainability initiatives, and globalization effects.

Digital transformation and the ongoing development and rollout of artificial intelligence technology are two such opportunities. The ability to process vast amounts of data for personalization will be required to capture the attention of overabundant choice for consumers, and more tailored products are one way to achieve a competitive advantage. Making markets even more connected, the need for personalization is likely to emerge in most industries. This could allow companies to utilize the predictive power of AI to identify non-obvious patterns of synergy and partnership, both horizontally within and vertically connecting industries, as well as companies and stakeholders across value chains. For example, fashion brands could collaborate with software development companies to develop gaming and metaverse offerings, and such products could also be tied to the fashion brand's main revenue-generating lines or other products. By acting on trends that will emerge in niches, companies could unlock valuable opportunities while minimizing risk early on.

The ongoing urgency of climate change and other sustainability-related threats make products that support a more sustainable world seem even less optional today than even just a few years ago. As hastily developed prototypes and suddenly implemented strategies that were a response to societal demands created by the pandemic show, industries are becoming connected even for society-related considerations due to changing consumer perceived needs. For example, sustainable packaging is opening up new avenues for synergy between the packaging industry and food or beverage shipping or warehousing industries. But while consumer research suggests many consumers expect gratitude from the companies they buy from when spending money on what they perceive to be for the common good, these seemingly reduced barriers don't come without skepticism – or risks.

8.1. Digital Transformation

Digitalization is not only transforming the business landscape through rapid technological advancements but is also responsible for rendering antiquated even the latest and more recent innovations. Digital transformation is at play everywhere. New business models and innovations are being conceived and implemented, products, services, and customer-centric experiences are being digitalized, digital technologies are being embedded in the very processes of the companies, extensive data utilization is characterizing and enabling decision making, operation models are being redesigned, new human resource capabilities for succeeding in the digital age are being developed, and cybersecurity is becoming an ongoing concern. Digital transformation has become omnipresent in our every day, in our work, in businesses, and in society. What used to be an implementation in the business sector of advances made by the scientific and technology system has now turned into a tool to enhance and bring about real improvements to companies, to economy, and to society. As such, the economic attractiveness of a country cannot be separated from the digitalization of its citizens. National prosperity cannot be disentangled from the deployment of all citizens and their respective companies along the digital transformation journey. Cybersecurity is no longer the responsibility of a few specialized individuals. Digital transformation has broadened its scope. It is a function of the entire organization, whether a firm, a national organization or agency, or other institutions and communities. Many organizations are now publishing their transformation frameworks and policies defining the roles and responsibilities of all players involved, and the ethical approaches to be adopted.

8.2. Sustainability Initiatives

Forgoing outdated practices that date back to the Industrial Revolution, while making products and services that employ advanced technologies, coming also from other sectors, might be the winning path to success in the modern era in specific fields of knowledge. Big Tech, Mass Media, Business Consulting, E-commerce and Logistics giants have become players in health and sanitization, military, automotive and aerospace, financial services, among other existing industries. For them, and for any corporation making products and services on a massive scale, it is impossible to avoid playing the Sustainability game. This need arises from cost/price, risk, CSR, attractiveness for customers, investors, and talents.

While cutting emissions and making an impact on the climate, in a mission that needs to go far beyond the net-zero goal proclaimed, to stop the tragedy of the commons, a cross-industry approach together with new entrants and competitive rookies, could mean opening a whole new road of success for traditional leaders. We are talking about Big Tech addressing Logistics, Real Estate, Packaging, Renewable Energy, Waste Recycling, Petrochemicals, Heavy Industry, Transportation, who, alone or together with traditional players, are offering solutions leading towards projects, products, processes, and services resulting in significant emissions reductions, and near-zero footprint products. For the sustainability cross-industry journey to be successful in results and business, several key requirements must be taken into account. First of all, it has to be done both ways, not only top-down or bottom-up, starting at both incumbent and new entrants levels.

8.3. Globalization Effects

As we move through the twenty-first century, it is apparent that globalization will continue shaping and connecting all industries and geographies, which will certainly lead to innovative opportunities for cross-industry players. Increased interconnectedness and integration of markets, with countries becoming more involved in each other's economy, has several implications for cross-industry initiatives. First, marketplaces and the supply and value chains servicing them have been geographically expanded and extended; outsourcing or near-shoring requires the support of many industries. As a consequence, companies must closely manage their diverse relationships with overseas-based supply chain partners. Domestic and foreign companies and industries are working ever more closely together in supply chains, sharing control and even co-investing in capital assets. Industries sometimes question the traditional notions of what constitutes their supply chain or the domestic adversity obstacles to joint initiatives. Second, the service sector, while leading the economies of many nations, is increasingly contributing to the product of other industrial sectors; as a consequence, globalization creates new opportunities and resources for global service industries. Third, service and intellectual-capital-intensive innovation is increasingly performed outside of the borders of traditional over-dependent economies; companies from all over the world are acquiring intellectual property, technical knowledge, and skilled labour resources. Fourth, markets characterized by sociocultural differences between people for the same service offering require different levels and characteristics of service support. Countries also differ with regards to service regulatory policy and practice.

9. The Role of Innovation in Collaboration

Innovation is often described as a solitary creative act. In business, however, the successful introduction of something new – a product, process, or service – is the result of collaborative interactions between a variety of functions and institutions, including 'demand-side' entities that formally buy and consume innovation and 'supply-side' institutions, such as laboratories and firms involved in the development of prototypes, leading-edge customers, innovation support agencies, and universities. Policy initiatives that deliberately seek to reduce the volume and negative effects of the market 'failure' are better positioned to stimulate innovation, economic growth, and prosperity than those that simply remove barriers to competition. Such a demand-pull, or 'system-building', policy strategy articulates a wider scope for public engagement in innovation than those government encouragements to collaborate and share knowledge that chiefly aim to address a market failure. When formalized through structural and behavioral routes, collaboration adds value to such goals as speeding up the pace of innovation by reducing the time to market; optimizing costs; enhancing the quality of products, processes, and services; acquiring new capabilities and skills; entering or expanding into new markets and sectors; sharing risks; and building and accumulating intellectual and industrial capital. The collaborative partner may be either inside the firm – that is, one or more functional groups or organizational units – or outside the company. Inbound and outbound marketing portals recognize that customers, suppliers, and other stakeholders can contribute directly to a firm's inventive efforts and more generally to the company's innovative processes, while firm to university initiatives acknowledge that universities may have the talent, infrastructure, and knowledge resources that a firm lacks.

10. Measuring Success in Collaborations

The significance of performance measurement is broadly acknowledged; verifying operations against defined objectives is the hallmark of a high-performing organization. Furthermore, preparing for what's to come permits management to adapt to the changes that are constantly occurring in the world of business. Reporting on relationships recognized as "strategic" is geared toward rewarding partners, satisfying their key executives, and recognizing and supporting key contributors at all parties. So, it may not be surprising that numerous major companies have implemented formal measurement systems for some or all of their strategic alliances. After all, alliances are risky endeavors, and they require careful attention and rigorous assessment if they are to produce the desired level of success.

But measuring the performance of strategic alliances is not easy. It would seem that a variety of contexts would yield different standards for success, based upon the reason for forming the alliance in the first place. Each participant in an alliance will have different goals and objectives. The partner's perspective is always important but must not be a substitute for alliance considerations. For example, an early-stage biotech company that has just licensed a drug candidate to a large pharmaceutical company, with the prospect of earning royalties for the next seven to ten years, may be unsuccessful from the perspective of a large pharma company that must pump millions into fees and development costs in the hopes of creating a major blockbuster.

10.1. Key Performance Indicators

In this chapter, we explore how organization and collaboration success are measured in co-creation projects. We have primarily focused on three collaborative projects involving leading organizations in the fields of technology, consumer electronics and fashion. In retail, for example, there are many strategic and successful co-creation projects; all those famous brands have chosen to synchronize with extraordinary co-creation models with creative individuals, part of their sewing and production. Each collaboration model ensures brand awareness and crosses market barriers.

While discussing the success of collaborations, we focus on key performance indicators established by partners. KPIs act as tangible goals to achieve for both partners; the introduction of KPIs helps deter people from giving up and provides a clear focus. Well-established KPIs have been recognized as a helpful mechanism in past marketing alliance, co-branding and co-sponsorship success. Co-creating partners tend to have fewer previous relationships and firm-specific enactment alternations can result in poor performance evaluation. Others argue that in-depth prior collaborations minimize relational uncertainty and thus enhance performance. Prior relationships also reduce performance differences through the establishment of routine patterns in monitoring task execution and team management. Quality control has been shown to lead to better performance in prior internal new product launches. In terms of experience, we believe that company-leading teams have established various performance evaluation guidelines thus empowering companies.

10.2. Feedback Mechanisms

In contrast to KPIs – which typically apply to entire collaborations or to logical groupings within them – feedback mechanisms are generally applied to specific activities within collaborations. Feedback mechanisms are conceptionally similar to KPIs, in that doubts regarding their implementation need to be tackled at the start of the collaboration. As such, less experienced collaborators often initially see them only as an obligation that brings more complexity. However, once applied in a spirit of continuous improvement, feedback mechanisms can create significant value in terms of accelerating achieving collaboration objectives or even broadening those objectives. In order to achieve this positive effect, it is essential that collaborators state up front that the feedback mechanisms along specific activities are not intended to penalize specific collaborators, but rather that the function of the feedback mechanisms is to improve collaboration quality in these activities together, in a spirit of learning together.

Feedback mechanisms can either be frequent and light-weight, concentrated at the end part of collaboration activities, or less frequent, but more comprehensive. Their lightweight nature means that frequent feedback mechanisms are effective at someone involved in the relevant collaboration activity, who is not necessarily a high-level decision maker regarding the collaboration. This decision has great implications for choosing the right collaborators, as quality people may be stretched too thinly if they need to provide top-down feedback regarding many different kinds of collaboration activities for many different collaborations in parallel. A different implication is that the more limited the selection of best-suited collaborators among the different collaborator types, the more limited also the number of different types of the activities.

11. Policy Implications and Recommendations

The empirical findings of the preceding sections provide important lessons for the design of policies that support and enable cross-industry collaboration. This policy-friendly discussion is, in part, motivated by the growing prominence of the cross-industry business agenda, in particular the calls for agreements between clusters and industries within specific developed countries, and between countries around the world. Moreover, developing a more understanding-centered research agenda towards the role of diversity in innovative endeavors is called for. Our study highlights three key areas where science and technology policy can build on and contribute to the developing cross-industry research agenda.

First, while many firms across different industries are already sharing R&D activities, sharing R&D resources, such as R&D infrastructure, labor, and knowledge resources with other, likely foreign industries is still a relatively rare practice. This is partly due to barriers to sharing inherent in the nature of R&D management. However, it is also a question of incentives. Governments may support firms not only through traditional subsidies or tax incentives for R&D, but also by establishing and building infrastructure that facilitate collaboration, such as joint laboratories, digital R&D platforms, and industry R&D clusters that cover industries that do not usually collaborate within a specific country.

Second, traditional funding mechanisms are needed to divert more resources towards emerging clusters of cross-industry-relatedness. For instance, the research and innovation activities need to increasingly look at cross-industry different designs for potential policy measures supporting cross-industry-relatedness and diversity. A Framework Program in the digital and green transition industries; the creation of adverse cross-national regulatory disincentives; and possibly the use of existing taxation measures favoring R&D activities in individual countries.

11.1. Government Support for Collaboration

What determines whether companies in different industries will retain a certain degree of distance in their competitive activities, or will develop close relationships for sharing knowledge? The actual relationships are the outcome of both external incentives and internal motivations. For activities which are valuable but too risky or difficult to execute within a firm, the alternative to take on mutual collaborative risks is to remain external to one another, facing the uncertainties of competing for market share. And, the greatest barriers to collaboration between companies in different industries lie in mutual knowledge. At the very beginnings of an exchange and relationships become of increasing value to the companies involved, there is no special knowledge specific to that collaboration.

Companies are then developing their own forecasts about the potential added value collaboration could create, relative to the costs and risks involved, and there is nothing unique to assist in the analysis. As long as competition prevails, external companies have little reliable information on which to base an initial decision to begin exchange. And the first steps in collaboration should be made in small areas. During this period, the companies involved are trying to manufacture information about the competence and integrity of their partners: is a partner able to fulfill the commitments made, and does it really want to? Companies facing these costs of information can benefit from some help. Proper action could reward choices which are investment at risk into a collaboration, but that, alone, lack sufficient advantages to justify the cost of information. For companies which have more downstream orientation, action could perform a signalling function, for example through the publication of research on entire set of parameters which describe fundamental tendencies.

11.2. Incentives for Cross-Industry Partnerships

In a rapidly growing world, companies have limited resources and may benefit from combining complementary assets in order to remain competitive in an economic downturn without draining their funds. Research has substantiated that collaborative partnerships are generally a reply to the need to access critical complementary resources and capabilities that are not wholly owned. For survival in an uncertain external environment, MNEs from all over the world would be advised to invest in the development and enhancement of absorptive capacity, internal company capability development, and the sense of urgency or motivation to combine or develop sufficient new capabilities to meet the challenges of a very competitive marketplace. However, it is also important to cultivate an open approach to building ties with partners and the local host countries without any specific ulterior motives to exploit that particular market, but rather with an aim to enter co-creating value space with another partner. Since new knowledge is often acquired through networks, or general partnerships with non-existing perspectives, it is also important to maintain a diverse tie-mix to different partners to multiply learning opportunities.

Given the opportunities from cross-industry collaboration, it is worth understanding how and when these cross-industry partnerships are formed. The traditional company context — in other words, industry focus — would argue against cross-industry partnerships. Short of government or some other third-party interference whether in the form of grants or tax relief or perhaps even publicly funded seed ventures, companies would be unlikely to benefit from pioneering efforts toward cross-industry collaboration without greater reward and lower risk.

12. Ethical Considerations in Collaborations

As the commercial world changes, partnerships among businesses are changing as well. Recent decades have brought increased scrutiny of the ethics and, more specifically, the social responsibility of businesses. As a result, businesses are looking beyond their own corporate social responsibility policies to consider the larger ramifications of the goods and services produced by business collaboratives or conglomerates, as well as the operational interactivity that must be managed between business partners. Issues such as executive pay, accounting practices, labor policies, and the environmental impact of goods and services are considered as salient business partner variables because a collaborator's bad behavior can trigger disapproval of a large number of consumers, regulatory agencies, shareholders, and tax authorities.

Business activity has a significant impact on society. Organizations do not exist in a vacuum, with no regard for the people and communities surrounding them. When businesses have viable partnerships, communities claim or reject co-branding partners as being “with us” or “against us.” As a result, brands that want to be welcomed into a partnership need to do due diligence. Although addressing cumulative effects—worries of unfair and disproportionate impacts from several governmental entities regulating zoning, infrastructure, clientele, labor, and environmental factors of a business partner—is certainly part of good partner choice practice, it is a partner-specific investigation. Each business's policies and practices affect relationships with other brands and other stakeholders, including customers, investors, and employees. Stakeholders from these groups broadly support responsible partners. Therefore, unlike traditional business-to-consumer strategy, which focuses entirely on synergy for the participating brands, the business-to-business-to-consumer value conversation increasingly includes attention to how brand partnership behavior affects these outside stakeholders.

13. Conclusion

"Cross-industry synergy creates value by eliminating the costs of differentiation, the costs of integration and transaction, and the costs of learning. The companies which exploit the muses of enterprise synergy today will be the large conglomerates of an emerging world economy. They will combine the activities which share know-how. They will dominate your product line the way the music companies and the art companies now dominate your world of entertainment. You listened to one hero in one act. You listened to another as he stood beneath his artist-ceiling staring up at the birth of man. You are channeled through the doors of a giant sport building by robot guides to your seat as a world of color and sound opens before you. You close your eyes as the computer channels you through your neighborhood to an electric shock that sets you dancing to the beat played just for you. The sport celebrates lightning speed and incredible skill. Tomorrow's world will be equally impressive in the construction from borrowed programs of artful stupendous complex creations, in the synthesis of diverse fields of music and image or in the combination of different domains of knowledge into the music of intellectual wonder. Change is certain in all of specialization. You will buy and sell what others have produced not as haphazardly as today nor for a time longer, through a stranglehold monopoly. And everything we believe is beautiful, and all that experience means in inner warmth and letting go is implanted directly into the computer. With love, intelligence, skill, artistry."

References:

Chantry, M., Christensen, H., Dueben, P., & Palmer, T. (2021). Opportunities and challenges for machine learning in weather and climate modelling: hard, medium and soft AI. *Philosophical Transactions of the Royal Society A*, *379*(2194), 20200083.

Deser, C., Lehner, F., Rodgers, K. B., Ault, T., Delworth, T. L., DiNezio, P. N., ... & Ting, M. (2020). Insights from Earth system model initial-condition large ensembles and future prospects. *Nature Climate Change*, *10*(4), 277-286.

Kadow, C., Hall, D. M., & Ulbrich, U. (2020). Artificial intelligence reconstructs missing climate information. *Nature Geoscience*, *13*(6), 408-413.

Deser, C., Phillips, A. S., Simpson, I. R., Rosenbloom, N., Coleman, D., Lehner, F., ... & Stevenson, S. (2020). Isolating the evolving contributions of anthropogenic aerosols and greenhouse gases: A new CESM1 large ensemble community resource. *Journal of climate*, *33*(18), 7835-7858.

Barnes, E. A., Toms, B., Hurrell, J. W., Ebert-Uphoff, I., Anderson, C., & Anderson, D. (2020). Indicator patterns of forced change learned by an artificial neural network. *Journal of Advances in Modeling Earth Systems*, *12*(9), e2020MS002195.

Irrgang, C., Boers, N., Sonnewald, M., Barnes, E. A., Kadow, C., Staneva, J., & Saynisch-Wagner, J. (2021). Towards neural Earth system modelling by integrating artificial intelligence in Earth system science. *Nature Machine Intelligence*, *3*(8), 667-674.

Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, *9*(1), 381-386.

Zhou, Z. H. (2021). *Machine learning*. Springer nature.

Alpaydin, E. (2021). *Machine learning*. MIT press.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260.