Deep Science Publishing
https://doi.org/10.70593/978-93-49307-44-5_10

Chapter 10: Combining human expertise and artificial intelligence to improve strategic business decision-making

10.1. Introduction

Businesses around the world are aiming to become data-driven organizations, bringing together human and artificial intelligence to provide individually tailored services in an efficient way. Artificial intelligence and machine learning have enormous potential to transform businesses and disrupt entire industry sectors. Many companies are already using data analysis, algorithms, and AI to collect, store, and analyze their data. Machine learning algorithms enable the automatic detection of complex relations in data, which is then used to predict future events. When referring to artificial intelligence, the distinction between general and narrow AI is generally made. General AI systems exhibit intelligent behavior on par or even surpassing human intelligence. Narrow AI systems aim to solve a particular problem and specialize in the execution of a specific task. Current AI systems are still far from general intelligence and act as systems that perform specific tasks. Still, efforts to achieve general AI continue.

Overall, businesses need to address the question of how to generate value for their customers and stakeholders. Alongside knowledge, information, and resources, algorithms are a new source of competitive advantage. Algorithms allow creating value and can be tied to decisions. The output of an algorithm is typically a prediction, which can then be translated into operational decisions, for example, how much of a product to produce or purchase, how to price a product, or whom to send targeted advertisements. Which kind of decision a data-driven algorithm can optimize? Integrating artificial intelligence into a business requires more consideration than traditional analytics. The knowledge worker needs to define which decisions concerning which data should be taken by which algorithm and under what conditions. Additionally, integrating decisions taken by artificial intelligence also needs to address how human and artificial intelligence work together and how decisions are taken.

For the foreseeable future, AI systems are not suitable for all kinds of decisions. Deciding which category a particular business idea falls into and which requirements must be addressed to build an appropriate algorithm requires extensive technical expertise. The Enterprise AI canvas is designed to tightly engage Data Scientists, AI specialists, and business experts to ideate together, identify the most promising, data-driven, AI-supported use-cases that bring value to the company and its customers, prioritize them, and evaluate and assess their feasibility. It also makes the engagement process productive and efficient by guiding participants through key issues and providing suggestions on how to implement them.

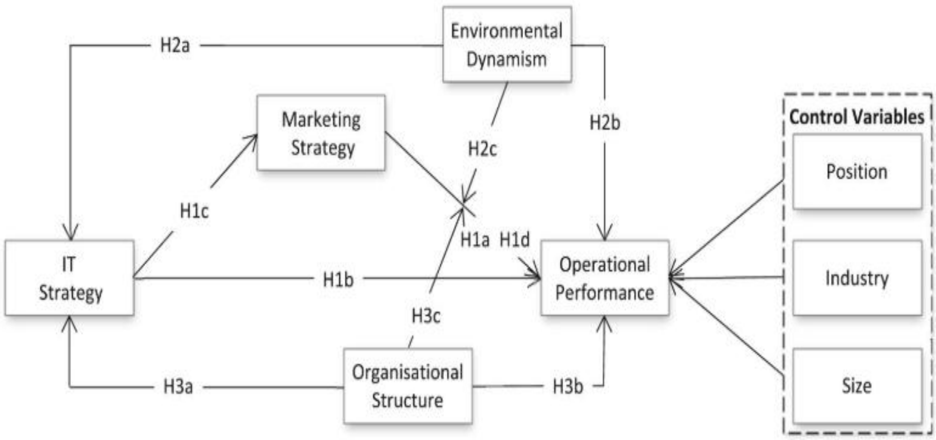

Fig 10.1: AI based decision making combining strategies to improve operational performance

10.1.1. Research design

This section describes the hierarchical modeling framework for understanding human decisions in deliberation processes. The models are fit to public judgments from an experimental study. This study provides insights into how AI can assist humans in collective decision-making.

Group-lived deliberation problems are often characterized by social comparison processes. In these deliberation problems, beliefs and influences can be categorized as parsimonious summary statistics. This section presents the findings of the public judgment study that demonstrates how humans form beliefs and influence over multiple candidates in complex deliberation issues. This section also addresses the limitations of the model and concludes with discussions.

The following questions motivate this research: How do teams of humans and imperfect AI reach agreement on important strategic questions? In particular, how do they aggregate subjective beliefs about a large number of candidates? In modern organizations, teams of humans and AIs increasingly deliberate about difficult strategic questions, such as making hiring decisions, evaluating promotion candidates, or determining product features. Each agent in these deliberations begins with a distinct set of uncertain beliefs about the candidates. Beyond the individual's initial beliefs, deliberations begin when agents exchange their beliefs, and they publicly respond to one another’s arguments and counterarguments. This elaborated reasoning process influences both beliefs and the impact of these beliefs on decision-making. Over time, the group aims to reach a shared conclusion.

The study on human-AI joint deliberation includes the individual-level models of human deliberative reasoning presented in this chapter, along with the team-level models of AI transformation of evidence and task decomposition models. Future directions include investigating within-agent dynamics, preferential treatment in decision-making activity, how feedback affects behavior in real-world settings, how humans reason with AI, and modeling the internal machinery of AIs. Understanding the unknowns of AI black boxes can shed light on human-AI accountability and trust.

10.2. The Role of Human Expertise in Decision-Making

The research proposed and tested computational models of deliberative group decision making, using a group choice problem from the field of natural hazard mitigation. This setting encompasses both intellective and risk elements, making it well-suited to explore new human-AI teams. An empirical study was conducted using this task and data were collected from 816 human participants. Modeling human-AI teams was particularly challenging, because the AI agents and human groups interacted in complex but semi observable ways via over 38 different message types, and because consensus achievement did not equate to correct group choices.

The research also proposed and statistically validated models at two levels of granularity. The individual-level models directly predicted the probability that a human group or AI agent would send one of the different message types given the other’s messages and the ongoing discussion history. The group-level models encoded societal learning processes over the sequence of deliberation rounds and further predicted group choice and consensus achievement outcomes. Both levels of models were applied to investigate processes and implications of six different human-AI team arrangements (four types of human groups and two types of AI agents) for group choices (best action, worst action, abort action, and false active choice), team consensus, and deliberation behaviors. All models were found to fit and make predictions consistent with observation.

The research opens up a new direction for interactive human AI team decision-making modeling and potential applications under a rich and interdisciplinary human and AI interaction design scenario. The proposed models could be further extended to cover a wider range of tasks, leader-follower group structures, and human-AI system arrangements. Furthermore, the research conducted a set of representative experiments embedding these models into an actual human-AI team decision support system and tested their effectiveness in assisting decision-makers with reliable insights.

10.2.1. Understanding Human Intuition

Human decision-making in strategic contexts often blends both rational consideration and intuitive judgment. Intuitive judgment is particularly relevant in high-stakes managerial situations where uncertainty abounds and time is limited. Human intuition, the expertise that the managerial decision-maker has developed over their life, allows for effective performance in complex strategic situations. Nevertheless, it is difficult to specify the rules behind intuitive outputs. There is increasing interest in how to utilise artificial intelligence (AI) to improve business decisions. AI primarily enhances the first component of the dual process: it can gather all the relevant data, rationally process it, and ultimately provide the most satisfactory output (or advice) under the assumption that a rigid specification of desired outcomes exists. However, AI architectures capable of autonomously executing human-like intuitive processes have yet to be developed.

Bridging the gap between intuition and AI design is critical. This task is twofold: (1) Since human expertise is conceived as an emergent phenomenon, it is imperative to understand the conditions under which it resembles intuition; when it does, its underlying processes must be understood. In complex domains, i.e. where human expertise emerges as intuition, effective performance cannot be formally defined. Nevertheless, it is to be determined how business decision-makers might successfully operate in a complex domain. (2) If the specifications of intuition (in terms of complex schemata) are identified, artificial architectures that replicate it must be devised. AI can thus be made to resemble human performance in complex domains. Progress advances the analysis of the phenomenon.

Intuitive judgment is thought to be fast, automatic, effortless, associative, and skillful. The reliance on intuition in strategic decision-making may indicate a fear of using rules or algorithms that, while producing the best outputs, are challenging to comprehensively understand. For a decision-maker with the expertise to perceive a unique pattern, following an algorithm could yield unsatisfactory results. When precise input-output rules cannot be algorithmically specified, they are likely tacit and experience-based.

10.2.2. The Importance of Experience

Aside from AI agents, it is essential to understand how human decision-making is shaped by experience. In the past, more weight may have been given to results from auditors with higher past performance; however, there may be a ceiling effect once the auditors have all developed a base level of experience. Therefore, it may be counterproductive to weight recommendations solely based on oversight ratings and historical accuracy in this environment, as it may result in over-correction. Instead, it may be more beneficial to weight the recommendations to a less extreme extent for higher-experience agents. Each agent has an estimated experience level (mu), which, together with a heavy-tailed distribution, is normalized to seven levels for use in Scheme (b). In comparison to Scheme (b), Scheme (a) uses the agents' posterior means of past performance to determine trust levels (i.e. weight the agents' recommendations to a more extreme extent for higher SRs). Understanding how experience may shape decision-making is essential for a complete understanding of human and AI team performance. Future experimentation assessing how agent past performance and experience may influence weight transfer is warranted.

One potential issue with the current experimental design is that the steps taken are considerably complex, making it likely that human agents can revert to helpful heuristics if they know the rules. Two steps in particular may hinder modeling the underlying decision process; for instance, if seven recommendations are received, it may be more useful to consider only the top three or four rather than all groups. Alternatively, inflating the weight of relatively extreme recommendations could result in more favorable outcomes. Because tasks can be completed similarly quickly by all agents, recommending inactivity could also be more straightforward and beneficial than filling in estimations; this change could lead to a better understanding of how the experience may shape averaging during team decision-making.

10.3. Artificial Intelligence in Business

The discussions around "what is AI" and "what do using AI in business scenarios mean" usually highlight what AI can do, but they miss out on addressing the real challenges data scientists face on the path of implementing AI for strategic business decision-making. Basically, the goal is to transform business decision-making into a data-driven process prominently supported by AI.

The path from Business and Data Science candidate identifying use-case to deploying those in production involves multiple steps. Those steps can require very divergent skills and types of knowledge. This often leads to Timelines getting used up, so project deadlines are missed. Or AI-solutions get tailored up and work on data one expert team knows how to provide, but those solutions are a burden in daily operational business. From a broader view point there is also the question, if already established solutions should be used in the first place, as they will be far more complex to manage or improve in the future.

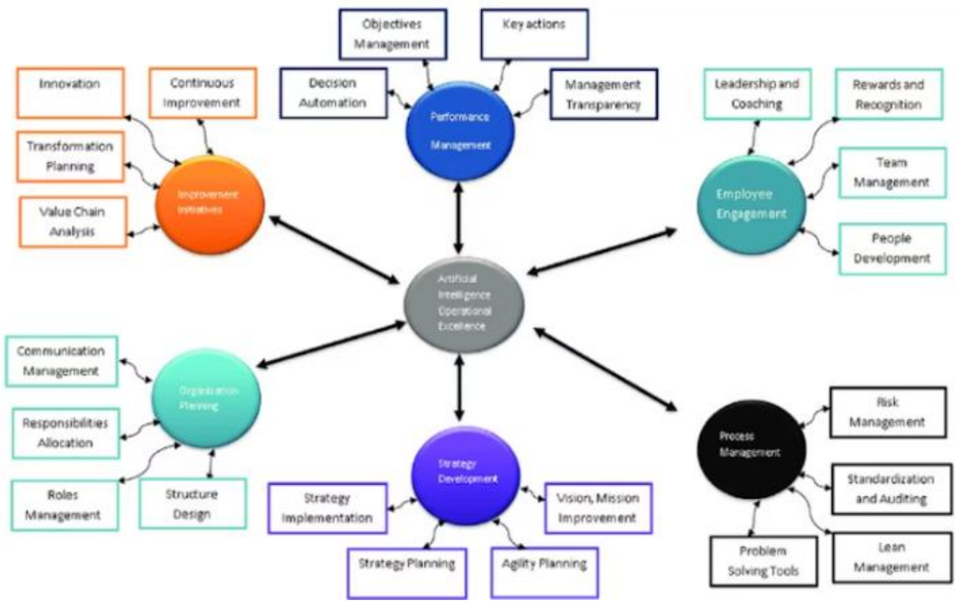

Fig 10.2: AI in Business Operation

10.3.1. Overview of AI Technologies

Artificial Intelligence (AI) technologies such as machine learning, natural language understanding, processing and generation as well as computer vision have enormous potential to transform businesses, industries, economy and society. Recently published reports estimate a staggering economic impact of AI for the global economy in the order of several trillion dollars in the coming years. Companies who recognize and act on this opportunity are expected to gain substantial competitive advantage in contrast to those who don't. Since AI algorithms gain knowledge from data, while "traditional" software systems are explicitly engineered by human programmers, an entrepreneurial focus on data and development of AI expertise is crucial to account for this paradigm shift.

As with any new technology, successful integration of AI into a business is complex and comes with massive challenges. On the one hand, companies who recognize the opportunity for value creation must identify potential use-cases in which artificial intelligence can create value and how decision-making or execution can be supported or even taken in an automated way. On the other hand, the organization will need to be transformed to be able to integrate AI based systems into their human work-force.

An AI system per definition creates system effects as defined by: An AI system can gather market data, use transaction logic to identify situations of interest and check prevailing conditions, while at the same time generating alternative scenarios for unrealized business opportunities. It can make decisions and interact directly with market participants. In the extreme case AI systems can even create synthetic data for training/learning. Since AI can potentially create system effects, quantum leap value creation and higher order paradigm shifts, this fear is justified, not least due to the effects of opacity, lack of accountability and undermining trust in human society.

10.3.2. Data-Driven Decision Making

As the volume of data available for strategic decision-making increases, many consider that AI/ML could be a useful tool to improve decision-making processes through automation. An increasing number of articles on the topic focuses on discussing the opportunities of data-driven decision-making (DDDM) and addressing some barriers to its application, with most research focusing on ongoing projects. However, some concerns around over-automation of decision-making processes could undermine many opportunities. This section outlines the opportunities of DDDM alongside barriers considering a holistic view.

The volume of data that can inform decisions expands almost exponentially, due to numerous social changes. The challenge lies in turning the data into actionable information that can directly inform relevant decisions. Yet, with the growth in data and processing capabilities, it is far too late to rethink mechanisms of strategy formation to be entirely data-driven. This may lead to inevitable decision errors. The over-automation of decision rules could lose sight of the original organizational objectives.

Due to recent advances in ML algorithms, some organizations have adopted AI-based analytics horizontally, attempting to use the same techniques independently of the domain. There are concerns around whether the adoption of improper information processing techniques could shape biases with potentially disastrous consequences. A physician must increase the width of the time window used to detect a heart abnormality and adjust for patient feedback; likewise, a bank must factor in educational and geographic variables to evaluate credit worthiness. A decision model that leads to unintended and damaging actions cannot be practically augmented by search or observability guarantees. AI possesses formidable social benefits; however, poorly performed models could cause havoc.

10.4. Integrating Human Expertise with AI

To make trustier decisions in uncertain environments, companies have been integrating artificial intelligence (AI) systems into their decision-making processes, which raise new opportunities and challenges for the collaborative efforts between human experts and AI systems (Brown & Zhang, 2023; Lee et al., 2023; Patel & Kumar, 2024). Individuals express their decisions (e.g., a recommended business action) in either verbal or mathematical forms. Human-AI teams typically struggle to communicate and reason about these recommendations due to heterogeneous representations and the need for accurate and efficient decision integrations.

With the co-existence of multiple human experts and AI systems, the proposed framework models the evolution of the overall recommended opinions across the human-AI team through a consensus-reaching process that combines diverse expert opinions and outputs the team's final recommendation (Smith & Lee, 2024; Wills & Yang, 2024). Decision makers are individuals who possess a certain depth of knowledge in the target domain, professionally analyze the environments based on the data, and express decisions (recommendations) in a mathematical form. The validity of AI systems learned from data relies upon the assumption that given the same input data, they could output stable decisions (recommendations) in the same way.

Some of them are fundamentally uniform in representation level but personalized in the solving ways, which endow the human-AI team with explainable heterogeneities. Outputs of the decision makers are interpretable unlike mathematical models, which makes it more difficult for the human-AI team to reach a consensus since a valid consensus must make sense at the interpretable level. Interaction between human experts and AI systems are modeled as decision-making agents that are heterogeneous in decision-making representation? However, some AI systems employ advanced models and lack interpretable rules to output decisions.

10.4.1. Collaborative Decision-Making Frameworks

Various collaborative decision-making frameworks that allow humans and AI agents to work jointly on decision-making processes have been proposed in recent years. Such frameworks can be either a pivotal technology or a backdrop in which researchers investigate the effect of a specific aspect of collaboration between humans and AI agents. Frameworks explicitly used or proposed for frameworks are reviewed in detail in this section, focusing on how they structured collaboration and decision-making between the agents involved.

The decision support system, termed "ADAM," blends human and AI reasoning processes for decision-making in three modes: (1) from the human perspective, making the human user face the choice and allowing explanation-based, interactive help; (2) the AI alone, in which the AI agent devises a plan and acts on it without the user's cooperation; and (3) expert-controlled, in which the AI may offer suggestions for consideration but the plan rests with the user. In SDM, models were developed to determine how human-AI collaboration enhances strategic decision-making for companies with competing subsidiaries. In DECIDE, one of the earliest decision-support systems, probabilistic inference was used to help doctors identify possible diseases. The Cognitive Assistant that Learns and Organizes (CALO) project was based on machine learning techniques that helped the user with simple predictive decision-making tasks. HyperContext was presented as a purpose-oriented, interactive tool that assists in focused information discovery and visualization.

KA begins with knowledge acquisition and gradually progresses through model generation and selection, simulation and "what if" generation, evaluation and decision making, action, and refinement of model and tactics. Viewed as a normal human reasoning process, case-based reasoning must first recognize a new case type and then create a generalization from the previous case type to the new one. However, to help build a well-structured CBT actor model, it is important to provide guides or hints for the construction of a recognizer to a novice programmer. To create a commonly used terminology for language and learning that is adjustable across cultures and time zones, a co-design process was developed to enable teams of business stakeholders to estimate the economic value of natural language processing AI technology. This multi-stakeholder process is based on a conceptual framework that decomposes NLP technologies into a multi-faceted hierarchy, which is mapped to metrics that stakeholders can use in qualitative and quantitative predictions, analysis, and comparison.

10.4.2. Case Studies of Successful Integration

The business world is in the early days of adopting artificial intelligence, machine learning, and generative AI. Progress in this area is akin to the emergence of the web. Many early efforts will fail, while some will lead to transformative success. Innovators will build tools to run businesses better. This is not AI because human expertise is still required for synthesizing information and making strategic decisions. More successful will be use cases where AI is combined with human expertise. Very few companies apply AI-supported analysis as the basis for C-level strategic decision-making. The 'Success Prediction for Early Stage Startups' (SPESS), a systems-supported process integrating machine learning and collective intelligence, is one such business case. The success of startups is not only based on the technology: business models, market environment, and personality traits of the founders play an important role. Many companies that have invested in a startup in the early stage use an expert-based process to analyze their chances of success, which are subjective and time-consuming. The SPESS approach utilizes a blended intelligence method under the design science research paradigm. An analysis model is derived from a user-centered design process and built in an interactive application. The SPESS, a software tool to systematically analyze early-stage startups, is suggested for practical use. To make every day decision under risk, an AI-supported quick and reputation-preserving decision was developed to assist a Usability Office. Analyses of the future Usability Office decisions are based on or contain a tradeoff between soft, subjective knowledge and hard, quantifiable data. Decision support based on a historic model to reduce the amount of time required to make larger decisions. Two strengths of different information types needed to make decisions under uncertainty are combined: collective intelligence's ability to assess unknowable risk and machine learning's accurate predictions based on prior distribution instances. A hybrid intelligence-based multi-method support defines the best analysts to investigate the prediction along with expert ranking is suggested to tackle the resistance to reveal too much historical information. The applicability of the prediction, the analyst ranking, and modularized design allow for further enhancement.

10.5. Ethical Considerations

AI technologies unquestionably represent a strategic advantage for organizations that can harness them properly, particularly regarding data provision and algorithm development. Thus, AI must be aligned with an organization's strategic objectives, and therefore, organizations must be both prepared to mold their strategies around new opportunities provided by AI and grasp challenges posed by the emergence of AI capabilities at rivals. To this end, organizations must assess whether AI will affect their main business and the value-proposition components it entails comprehensively. Once a diagnosis is made, organizations must thoroughly analyze specific gaps where AI can intervene to improve their functioning. It is also essential to treat AI as long-term initiatives that can exceed once-an-entry investments and ensure AI initiatives are perceived by employees as opportunities rather than threats. The bridge between AI and outcomes in the public domain must be investigated, and the opportunity for academics and practitioners to share research, experiences, and best practices must be allowed.

Assessment of orderly ways of ameliorating outcomes in advanced economies could benefit from AI applications, as this assessment must include how they function. There is an opportunity to analyze how AI affects the paradigm of public decision-making, whose expectations about a second upgrade by the Digital Mind and machine learning algorithms capable of producing predictions. Collectively interpreting incoming percepts is essential for decision-making but a daunting task in modern democracies due to increased complexity and operationalization. After reviewing early experience with AI applications in European cities, it reflects on why governments demand public visibility on the logic behind AI decision systems and the nature of the data used.

10.5.1. AI Transparency and Accountability

While Artificial Intelligence (AI) continues to be the buzz word across various domains, understanding its principles of workings are becoming harder day by day. As a result, there are growing interests in promoting AI transparency through well-defined research endeavors on the explanation of how AI works. The end-users of AI systems are beginning to take cognizance of the biases and email deception which can exist there. Causality offers one way to resist such deceptions and introduces a richer type of explanation than the description-based ones that are prevalent in traditional XAI. Eventually, stakeholders are anxious to ferret out, to the extent possible, the real mechanisms that produced the results displayed by the manipulative agents represented in AI technologies.

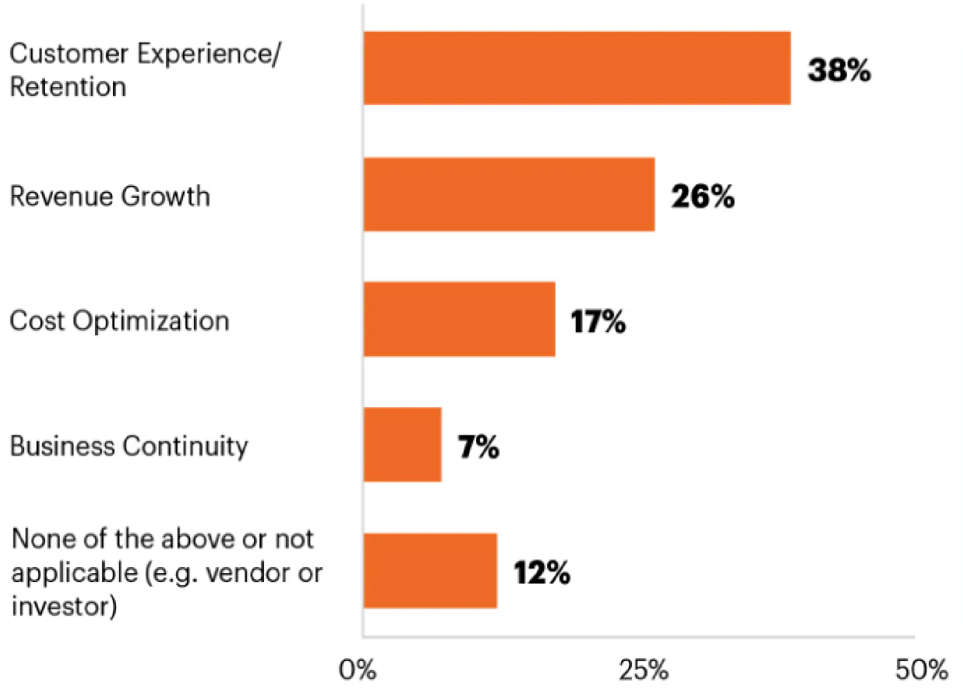

Fig : AI for Business Strategy

On the other hand, industries are struggling with the question of AI accountability. Probably this dilemma is even more troubling than explainability, as it weighs in on the reasonable boundaries of a trade long considered a sacred privilege. Architects and developers of AI systems are becoming increasingly concerned, as there is a real threat of crippling censure, heavy fines, and legal proceedings against the companies that allow unfettered use of AI technologies, if accidents keep occurring. The main argument of this section is that to be able to make claims about accountability both for the AI systems themselves and for the people and organizations that maintain and operate them, a well-defined complex system-level model of AI systems and their relevant environment is necessary. Whether or not "AI" systems can be made to understand nuances of social norms and ethics is one of the pending questions of contemporary debates.

10.5.2. Bias in AI Algorithms

Despite the increasing use of AI to analyze data and gain insights to aid in business decisions, biases of discrimination, transparency, and accountability are widely known in AI algorithms, especially when based on machine learning. For decisions guarding privacy or where it is insufficiently clear how they were derived, like hiring or mortgage lending, companies using algorithms incur reputational and regulatory risk. Discriminatory or biased algorithms, which trigger security questions or poorly explainable decisions, also lead to ethical concerns and transparency or accountability gaps. Hiring processes have a long tradition of explicit human biases or differences on the basis of sex, race or ethnicity, age, looks, and weight. Human bias is evidenced in hiring decision making on the basis of a first impression: recruiters make an initial assessment, and look for reasons supporting the first impression. AI or algorithmic solutions are offered to solve human problems, such as eliminating bias in hiring. One solution is algorithms or automated strategies to filter the job applications, with the promise of minimizing human bias and discrimination while increasing diversity, cost-efficiency, and speed.

10.6. Conclusion

Good business decision-making usually requires information and analysis from a range of human experts who have domain-specific skills and knowledge relevant to the decision being made. Business decisions become more complicated when there are a wide variety of unfiltered knowledge sources available to humans, as occurs with modern artificial intelligence (AI) tools such as generative AI chatbots. These tools can be both human partners and bilateral experts, and human agents can be required to assess the relative capabilities, expertise, and impartiality of these tools, which can be a complicated process with risks.

Understanding AI-human business decision-making in settings with uncertainty and observation of risk is new territory for research. A business goal is to combine human expertise and AI such that the relative strengths of each type of agent are maximized and leveraged. What feedback information about knowledge sources do humans need? How does this information affect behavior, learning, and decision-making? How can the best policies be learned? This chapter has laid the groundwork for addressing these questions, including searching for outcomes that assist with business question evaluation through a tree search.

The modelling and empirical work presented here is expected to be valuable for scholars, practitioners, and software engineers working on business decision-making with AI partners or opponents. It has been developed by applied mathematicians working in game theory and economics, utilizing a range of research methodologies from human experimentation, to game theory, to empirical testing using real-world data, which should grow increasingly accessible in this era of data science. This chapter describes how this toolkit can be translated to the problem of discovering how AI may impact strategy formulation and strategy enactment in business.

10.6.1. Future Trends

Business Intelligence (BI) has been around for some time now, and there are many well-known BI vendors. However, a platform definition for BI is emerging that is broader than "simple query and reporting" offered by many organizations. Instead it incorporates some rather complex algorithms to perform what is known as Advanced Analytics, covering areas such as traditional statistics, data mining, artificial intelligence, and operations research. For companies wanting to utilize this new BI definition, it will not be just a matter of adding additional hardware, software, databases, or algorithms. An entirely different understanding of BI is needed. Combining information reporting and the addition of these analytics, such a BI will no longer represent a "mere" intelligence tool as is currently offered externally to companies, as organizations will not know what is happening. Instead BI will act as a business partner, covering the caveats as much as the attributions.

Technological advancement may allow some intelligence to be available "on the fly" instead of pre-calculated between "intelligence" cycles. These solutions bring the additional on-the-spot data integration and prediction capability (data at rest and data in motion). With other hand the very complementary concept of Social Intelligence leverages Organizations Collective Intelligence – knowledge represented by group history and the competency of the group as a whole. From an executive perspective, such Collective Intelligence would reside in a Social Network Map that represents the organization's expertise. This view upon a further enhancement on the BI industry, but far from either the market maturity or technical industry readiness for it.

References

Smith, J., & Lee, K. (2024). Agentic Intelligence in Supply Chain Management: Harnessing the Power of Cloud Computing and AI. International Journal of Supply Chain Innovation, 14(2), 67-85.

Brown, T., & Zhang, Y. (2023). AI-Driven Transformation in Wholesale Distribution: A Case Study of Cloud-Based Solutions. Journal of Business Technology, 29(1), 102-118.

Lee, M., & Garcia, R. (2023). Cloud-Powered Supply Chains: Advancing Big Data and AI in Insurance and Banking. AI & Financial Services Review, 15(4), 89-110.

Patel, A., & Kumar, S. (2024). Revolutionizing Banking with Cloud-Based AI and Big Data: An Agentic Intelligence Perspective. Journal of Financial Technologies, 18(3), 45-60.

Wills, L., & Yang, D. (2024). AI and Big Data in Wholesale: Improving Supply Chain Efficiency through Cloud Integration. International Journal of Retail & Supply Chain Management, 23(2), 98-112.