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Chapter 3: Building data-driven educational models through the integration of machine learning and predictive analytics for improved student and institutional outcomes

3.1 Introduction

One of the major milestones in the rise of the learning analytics field was the development and use of institutional data to construct models that leverage algorithmic modeling to assist in the prediction of students' educational outcomes. Institutions are increasingly using data to gain new insights and improve student learning outcomes with actionable insights and personalized interventions. Educational data mining focuses on methods that model and support the prediction of different actions to support students' learning and its outcomes. Predictive models have addressed questions like who is more likely to succeed or how we can help a student who is struggling. Predictive analytics can help identify attrition-related factors, thereby allowing institutions to perform proactive interventions that help students succeed. For teacher education programs, the use of learning analytics and educational data provides important support for data-driven decision-making. Data-driven approaches can lead to improvements in assessments, understanding of the course content efficacy, and comprehension challenges and obstacles that students may face within these requirements. Still, algorithms are not flawless, and ethical considerations must be considered when making data-driven decisions. Since the graduation rates have significantly improved during the last ten years, despite the selective criteria, we see the potential to focus on how these models can be used to improve graduation rates without sacrificing program admission criteria. For that, teacher education program employment data and reasonable completion periods may be critical for indicating potential for graduation.

3.1.1. Purpose and Significance of Data-Driven Approaches in Education

Applying machine learning models to educational data allows for the development of novel data-driven methodologies, tools, and features in education. In this book, we introduce how to apply machine learning to solve practical problems in education using educational data. Several examples of how to use machine learning models to develop intelligent software tools to support data-driven decision-making at different scales, including students, teachers, schools, and educational systems, will be introduced. We

Fig 3 . 1 : AI for predictive analytics

also introduce basic concepts of educational data as well as tools for data collection, preprocessing, and visualization. The proposed data-driven educational models can help explore the association between educational data and learning outcomes, predict learning progress and risk, assess the effectiveness of educational interventions, provide real-time decision support for teachers, and support personalized and adaptive learning. The fast development in information and communication technologies has enabled the ubiquitous collection of large amounts of complex educational data at multiple scales, providing educational researchers and practitioners new opportunities to adopt data-driven approaches to solve practical problems in education using advanced knowledge discovery and data mining techniques. Specifically, advances in data storage, computer hardware, and software technology have addressed the computerization of educational data with learning materials, testing tools, log data and assessment records. Educational researchers can then trim data to obtain insights into the performance of human learning.

3.2. Overview of Data-Driven Education

Schools, colleges, universities, and educational companies must embrace the era of big educational data. Student learning and development can be evaluated with fine-grained resolution to identify at-risk students. Course materials and delivery platforms can be evaluated for efficacy and moderated for improvement. Administrators and educational researchers can benefit by examining educational trajectories and evaluating the relationships between student outcomes and other institutional behaviors. There are two main motivations for predictive educational data mining: identifying students who are at risk of poor academic or other outcomes to target resources and understanding the fundamental processes involved in academic success.

Modern educational systems are complex, containing many interrelated components, such as students, instructors, live educational content, textbooks, assessments, information systems, and surrounding society. These components produce a vast amount of unutilized data at all times, when students read, when instructors teach, and especially when students and instructors interact with each other. These activities can be monitored to give fine-grained resolution of the learning process, which can be exploited to better understand the fundamental processes involved. With all of this data, it would be ideal to develop models that could accurately simulate all of the behaviors and predict all of the important outcomes. These models could produce significant value in a variety of areas: providing practical benefits by assisting educators, improving educational content, and increasing the efficiency of educational systems; constructing comprehensive theories of educational processes to aid research and guide educational practice; and creating models that are shared across educational systems to realize the broad data-driven educational benefits.

3.2.1. Understanding the Framework of Data-Driven Educational Practices

In educational data mining and learning analytics, there is a wide use of data generated from academic activities. The context from which it is extracted covers various levels of learning, the behaviors or responses exhibited, and several forms of resources used for learning. The data generated can be categorized into five categories denoted as QAFOR, which refers to the properties of the data: quantum, access, format, owner, and resolution. These properties must be well determined and understood to have an initial understanding of the data. The data can be collected from multiple sources, such as the interaction between an instructor and a student. A more advanced method of data collection can occur in a computer-based setting by utilizing log files that capture students' interactions with digital learning resources. These digital resources can include videos, PowerPoints, interactive learning modules, quizzes, and virtual simulations. These interactions result in the production of a large number of data points, which can capture factors such as time spent, type of resource used, number of attempts, and correctness of responses.

One approach used to extract the data is the process of unification. This approach seeks to provide an algorithm that allows access to multiple data sources at the same time. The process is complex as it needs to handle the vast amount of data that is also diverse. Another approach is to present a methodology that correlates the data. This methodology can help create features that complement the existing features. Features that can link these data sources can finally apply dependency analysis. The analysis can be conducted using various composite data sources. Data-driven education can utilize a wide variety of data, including academic and event logs, video transcripts, and learning response data. The data can also be post-processed; this can be achieved through data transformation and extraction, which applies an operation to retrieve a specific value from a data attribute. The data can then be transformed or converted into another type of data structure. The transformation can also take place when data is received and then aggregated to obtain a result. Data received can be segmented to obtain a specific result. Data can also help explain the presence of cascading problems, which are known as adverse consequences of actual or predicted errors on given targets. Lastly, data can be proven to demonstrate a point of interest that determines its usefulness. The data can be put to use as features in modeling outcomes or creating impactful interventions.

3.3. The Role of Machine Learning in Education

In summary, the data that can be collected in educational systems, especially in online and computer-aided systems, and the fact that this data is detailed and high-volume are the factors that enhance the position of machine learning approaches. This large and complex data in education opens up a wide range of research opportunities and applications that can impact many sectors. One of the earliest examples of a feedback mechanism based on machine learning applications was the tutoring system for teaching cause-and-effect dependencies. This system approximated a multiple linear regression model for determining the learning progress of students from their training progress. Such an educational application was one of the pioneering works in the use of computer-based simulations and data-driven methodologies in teaching and learning. With the increasing proliferation of e-learning platforms, learning resource systems, and teaching software in educational institutions, the amount of data that can be collected has also increased. This large and complex data can be used to identify patterns, build prediction models, and describe factors affecting educational outcomes. This is the main motivation for the newly emerging research area in educational data mining. Independent of discipline, techniques based on machine learning and predictive analytics can be used in educational settings to provide personalized or adaptive learning, custom-tailored instruction, and real-time student feedback based on a relatively large number of pedagogical problems. The emergence of knowledge management and the importance of collecting data related to various academic and non-academic success factors have also led to the use of these kinds of techniques in e-learning environments.

3.3.1. Applications of Machine Learning in Educational Settings

Machine learning is a specific type of artificial intelligence that focuses on large-scale data analysis. It is a subset of AI technology that allows computers to learn from information, improve over time, and make decisions, predictions, or recommendations. In essence, ML algorithms are designed to glean insights from an increasing volume, variety, and velocity of data without posing explicitly programmed rules. In other words, the computer uses large amounts of inputs to analyze records and identify patterns, and then it utilizes the learning from such inputs to predict the output classification or numerical value for future data. Despite its recent popularity, the roots of ML date back to the work on regression and classification in the early 1900s. It was in 1951 who coined the term "machine learning" and discussed the concept of children learning from not just data, but the environment around them.

The range of ML applications in education is broad and has spanned various subfields. From pedagogical approaches and curricula to student attrition to institutional research on effective teaching, learning practices can range from learning analytics and predictive modeling to building intelligent tutors and fully automated courses. The business impact of education thus includes better student or teacher recruitment, cost-effectiveness of instructional development, and assessments of institutional goals. With emerging personalized results and shifts in educational technology paradigms, there is a growing trend toward data-driven education. With growing volumes of stored student information, advances in machine learning methods promise to uncover new learning principles and identify the necessary conditions for learning outcomes. Published some of the earliest work in 1978 to design a machine learning predictive model of upcoming student retention.

3.4. Predictive Analytics: Concepts and Applications

Predictive analytics is an approach for developing predictive models that predict future outcomes using historical data. With predictive analytics, administrators and educators can improve teaching and learning, transportation, capital planning, financial auditing, student success, and other outcomes by predicting actions made with all types of data, including business intelligence data, facility records, learning management systems data, student demographics data, and even social media data. Like descriptive analytics, predictive analytics mostly employs a quantitative methodology. But while the main goal of descriptive analytics is to create a consistent summary of what occurred in the past, predictive analytics aims to forecast future outcomes with an acceptable degree of correctness. This requires the application of more advanced techniques, such as predictive modeling. The most popular predictive models are decision trees, ensemble techniques, association rules, linear regression, and neural networks.

Many unobserved group structures, known as latent models, also occur in an educational setting. They can exist in two main categories: student ability and educational effectiveness. By revealing student ability through diagnostic analytics, educators can gauge student performance and select appropriate instructional strategies. Evaluation constructs based on different levels of Bloom's taxonomy or other cognitive psychology theories also fall into the unobserved educational effectiveness group. Such constructs can be used to compare the effectiveness of distinct instructional strategies or help educators modify their teaching based on the overall group's diagnostic results. Previous studies of latent models in education conclude that the potential impact of these educational metrics is substantial and can consolidate improvements in educational technology. There are three main forms of predictive analytics: classification, regression, and association. Classification and regression focus mainly on predicting behavioral outcomes. Classification is the process of grouping individuals into categories using one or more characteristics, which are independent variables. As a subclass of classification, binary classification focuses on two possible outcomes. Regression, on the other hand, focuses on the relationship among characteristics and continuous outcomes to predict future, currently unobserved outcomes. As a result, it provides a numerical score or value, such as levels of change, prediction intervals, or probability.

3.4.1. Understanding Predictive Modeling Techniques in Education

In this section, a brief overview of some of the potential predictive modeling techniques in the educational domain is provided. The purpose is to offer an understanding to an educationalist on various available options to carry out predictive modeling. The potential educational applications where these techniques can be made use of are discussed. The predictive modeling techniques are presented in a simplified manner so that the audience who are not well familiar with machine learning techniques can understand these basic essential methods without getting into their technical details. The use of machine learning techniques for educational data is increasing, providing personalized attention in education, student modeling, and interventions, and reducing student dropouts promptly. The readers of this chapter include teachers, educators, researchers, and software developers who are interested in knowing how various machine-learning techniques can be used in the educational domain. The chapter discusses models for predicting student performance, workload, and dropout, and for providing personalized study advice.

3.5. Integration of Machine Learning and Predictive Analytics

We have introduced two distinct quantitative methodologies: ML and PA. Each of these methodologies is rigorous, has its technical lineage, and is amply documented in the validation and publication process of its findings. PA involves understanding the cause-and-effect relationship between certain learning indicators and later dropout rather than just adhering to the observed relative risks a model predicts. The PA in this paper involves looking at the differences between the teachers by the two categories of students – the stayers and the leavers concerning formative and summative assessment results. While ML is focused on predictive modeling, PA is designed to establish the predictors of the learners' choices for enrollment and at the same time to validate them. The distinction is similar to the validation of a diagnostic model, where the test to provide diagnostic inferences has to have been designed differently from a test of knowledge or ability. In the educational context, tablet testing aims to assess the learner's abilities, whether before the start of a course or as part of formative assessment exercises, to inform learning. The relationship with ML is more tenuous as learners are associated with their demographic constructs rather than focusing on their potential to drop out. In many research studies set within ML, models are described as "predictors" and what is meant by "learners who are predicted." Pedagogy motivates both learning analytics and predictive modeling.

3.5.1. Uniting Machine Learning and Predictive Analytics to Optimize Educational Achievement

Concepts such as individualization and mass customization are quite familiar in business and marketing, but they haven't so far played a significant role within the domain of education, principally because custom instruction at scale is a tough problem to solve. However, we now have models that are increasingly successful at this using the power of data: it's now possible to optimize content, timing, sequence, and structure for the specific needs of individual learners, whether they are 8 or 80; in the office, the lecture hall, or at home. In this chapter, we'll discuss approaches to optimizing learning success. We discuss the development of the field and introduce a simple, data-driven approach to successful learning that fuses machine learning and predictive analytics with pedagogical research.

Increasingly, education is about figuring out how to optimize the learning process such that the knowledge that has been accumulated becomes well internalized so that it can be used effectively whenever and wherever it is needed. This sort of data-driven evolution is a fascinating domain in its own right, as it appeals to researchers not only in computer science, machine learning, and data analytics, but also in education, economic impact, psychology, neuroscience, and linguistics, to name a few. The realization that standalone online educational initiatives weren't leading to learning outcomes, and thus would not be an effective form of teaching, led researchers to investigate which precise components of traditional teaching are most effective. They combined expert understanding with data derived from mass participation in college-level classes in machine learning to understand which activities lead to good learning performance and used this to build a new, data-driven pedagogical model for teaching complex concepts in data engineering.

3.6. Framework for Developing Educational Models

The research naturally leads to a need for a common, step-by-step, practice-oriented framework for the development, evaluation, and regularization of EDB educational models that are rooted in well-proven practices in other established scientific fields. This section presents a customized framework for developing educational models. The framework provides clear phases with their associated tasks in an iterative cycle that allows a full range of assessment metrics to be produced for a range of techniques to produce the best understanding of each student's interaction with the EDBs, with common offline evaluations being a feature of all the tasks at the model development stage. The framework consists of six phases (generic terms in braces), each with a range of associated tasks: data preparation (data understanding, data preprocessing), selection of instructional techniques (modeling), construction of educational student models (modeling), system calibration (evaluation, calibration), model interpretation, and regulatory monitoring.

This research presents several methodological changes including a move toward longer-term social networking and group-based student models; the use of advanced and ensemble machine learning algorithms; a large comparative evaluation of advanced machine learning functions, feature selections, and system comparisons using formative evaluation rather than just degrees; the evaluation of student models at individual and group levels dimension-wise; the use of both long-term metrics and a normalization method as the primary evaluation tools. The final model interpretability was increased using path analysis. Machine learning techniques have also been used to actively manage data at a project level, allowing more efficient use of both memory capacity and processor time per phase and allowing the results for each phase of the development process to be predictable. The framework has been applied to the in-house developed smart educational monitoring system, and the calibration, educational student model, and regulatory monitoring phases were run as a routine. The results have led to a plan of further work to enhance the overall project. This provides the grounds for further useful research and could contribute substantial improvements in the development of intelligent learning analytics.

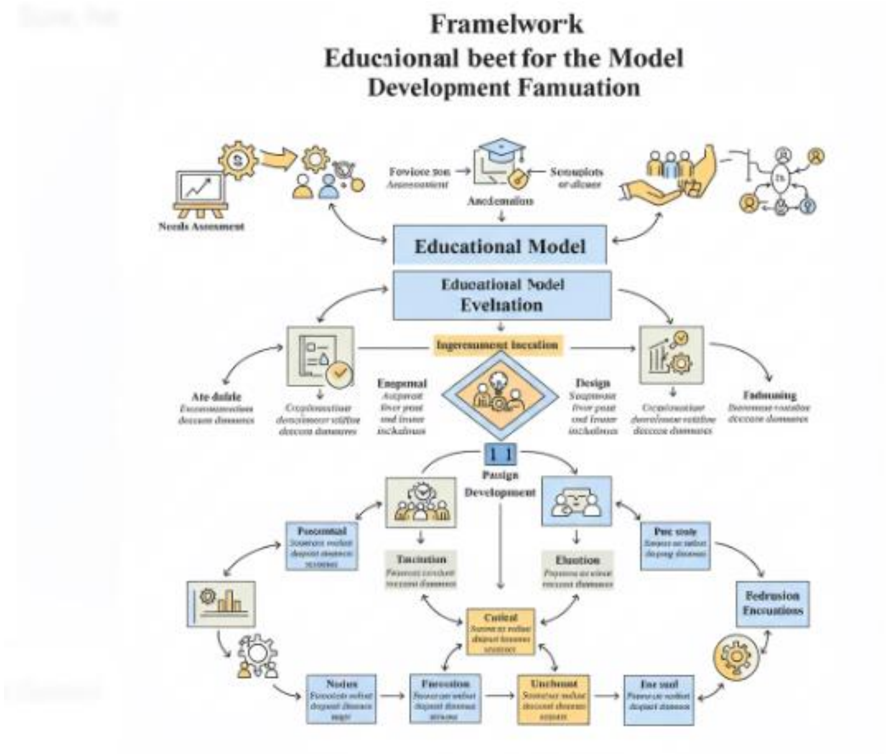

Fig 3 . 2 : Framework for Educational Model Development & Evaluation

3.6.1. Defining Objectives and Outcomes

Understanding the problem is very important to present it to the data and tackle the issue of developing intelligent educational systems that can support and inform students and educators about learning and teaching events. Analysis of the data, educational knowledge, domain theories, and common sense are key to understanding and selecting the objectives and defining the problem to solve. Additionally, defining the objectives also requires operationally defined possible outcomes and measures. Educational models, using predictive and evaluation tasks, select the metrics and outcomes that will be used to evaluate the model's performance and drive the subsequent refinement and development of the models themselves. In educational research and the modeling of intelligent educational systems, the definition of the objectives has been diverse. The development of these models has focused on improving the learning of students. However, some have oriented their models to improve the performance of teachers. Recently, educational researchers have defined models with mixed or global objectives, serving both students and teachers. The definitions of the objectives in the studies of the models also used their intervention plans and the definition of the activities to be developed with the students as focal points, since these converge both in the direct action of optimizing learning and in the benefits.

3.6.2. Data Collection and Management

In the broader picture, the revolution in data analysis has its merits in the deluge of data that is ubiquitous in the world today (Annapareddy, 2022; Burugulla, 2022; Chakilam, 2022). Our area of interest is, of course, the field of higher education, with a special focus on STEM education. The relevant data include a rich mix of historical data from various subjects such as curriculum, student characteristics, teaching staff information, and a wide array of student data collected over time. There are several challenges related to the data used for assessing the models' efficiency. Some students might complete the courses from different educational systems and environments. We need a flawlessly collected, pre-processed, cleaned dataset before we can propose, apply, and test the required predictive models. In our previous large-scale study, we used historical datasets of all undergraduate electrical and computer engineering curricula by building time-stamped, node-link formats for offered modules, taught courses, prerequisites, co-requisites, and post-requisite dependency hierarchies among the modules. Such hierarchies are necessary to reduce the effect of volatility in the course space.

Another accurate area of focus is student data, which provides novel inputs to the prediction model (Challa, 2023; Challa, S. R., 2023; Chava & Rani, 2023). An additional level of insight can also be provided by aggregating the student data into different categories represented by attributes derived based on data. For our illustrative cases, we are using both undergraduate and postgraduate data. The data included in the subject performance prediction dataset includes demographic information such as age, prior qualification, prior module grade, ethnic group, gender, school type, special education needs status, and eligibility for free school meals. Lastly, we validated our prediction model using both institutional indicators and derivative attributes implemented using student data.

3.6.3. Model Selection and Development

Once researchers have determined which data fields will be used as predictors and dependent variables in their models, they must then determine the type of model that will be developed. We conducted a literature review to ascertain the most common methods currently being used for data-driven prediction models and found that the most common types of models were simple statistical techniques such as linear and binary logistic regression, followed by neural networks and decision trees. Both the most and least frequent choices of models were somewhat surprising. Less frequent choices included the Cox and Firth proportional hazards models as well as semi-parametric and moving average models. Various choices of logistic regression models were the most popular choice. While performing data-driven research, it is quite frequent that researchers should analyze and manipulate the data before model selection and model development. Developing a good presence of mind from the data before these steps is fundamental to ensure the consistency and accuracy of the model developed. In the modeling process, while the data should be statistically related to the model, some of the employed variables might induce multicollinearity. As a result, in that case, the model might have estimated parameters that are affected to some extent. Before model development, multicollinearity should be dealt with, if necessary. Ultimately, researchers should prioritize the accuracy of the model while selecting predictors. The assessment of accuracy is possible through multiple different statistical testing methods such as goodness-of-fit, AUROC for classification, and R-squared goodness-of-fit tests.

3.7. Challenges in Implementing Data-Driven Models

The third major challenge in implementing advanced data-driven models such as machine learning-based personalized models is the lack of institutional capacity (Kannan, 2022; Komaragiri, 2022; Kumar et al., 2025). All three of the challenges we identify—data preparation and management, model development, testing, and maintenance, and student support—can be characterized as tasks that require technical and institutional capacity. However, in the case of advanced data-driven models, executing these tasks is more complex than with traditional models, requiring both more sophisticated technical staff and more active involvement from domain experts. The question of technical capacity is a critical one for most institutions. Among the pre-college programs involved in the data-driven matchmaking project, the answer seems to be that although modest technical capacity does exist, the institutions will need additional technical support to fully realize the potential gains from using advanced data-driven models.

Given the predominance of longitudinal data-driven and matched-pair models, virtually any institution using predictive analytics would be well advised to begin with descriptive analyses. The potential breakneck pace of prediction-based decision-making is one that institutions will be responsible for ensuring is managed responsibly. In the context of pressing questions about the extent to which the university model of higher education as currently configured serves the broadest range of student needs, the diminished burden of forecasting the most likely outcomes of students based on their diverse backgrounds may be the most important dividend of all.

3.7.1. Data Privacy and Security

The growing use of data analytics tools in educational institutions has created a series of concerns regarding data privacy and security (Malempati, 2022; Nuka, 2023; Pamisetty, 2022). In recent years, several educational institutions have suffered security breaches, and several important pieces of information about students are being collected and stored, such as their future enrollments, grades, preferences, and relationships. To identify, avoid, and mitigate the privacy and security risks of a data-driven educational model, we have conducted an empirical survey with the practitioners responsible for designing, maintaining, and improving predictive models within a leading Brazilian distance learning university. After the survey, we infer, contribute to the state of the practice knowledge in the context of data-driven educational models, and analyze some of the results obtained.

Data privacy is associated with the preparedness, defense, and policymaking related to identifying, avoiding, mitigating, appropriately treating, developing, implementing, and ensuring solutions to problems that influence security and the safety of people. Although there exists a considerable quantity of research addressing educational data privacy and security, most of the developed and/or proposed methods aim at ensuring the privacy of system interactions or the privacy of data extracted from learning environments. The main motive behind this type of privacy protection is to avoid revealing sensitive information about individuals and to avoid infringing individuals' privacy rights to their data. Educational data mining literature has also focused on enabling the development of models that respect students' privacy or that are developed using existing privacy-enhanced models. In other words, the scenario described in this section arises when applying regular data mining, and especially traditional machine learning algorithms, to create predictive models capable of providing decision-making processes to assist human analysts in charge of the learning process management.

3.7.2. Bias in Machine Learning Algorithms

One of the biggest issues in the era of "Big Data and Predictive Actions" is the amount of artificial intelligence and machine learning algorithms that have been developed to guide AI in several domains to detect and solve different types of problems or applications in many diverse sectors of the market. The mistakes of machine learning stem from a well-known issue with the training procedure used to fit a data-driven model – the likelihood that the AI is biased. When we build predictive models using historical data, we rely on the diversity of the training data to learn the many different patterns. Models that we develop will also be biased if the groups in the training data are not representative of reality or if there is a corruption of the performance.

There are potential negative effects of predictive algorithms, the exclusion of human decision-makers in favor of machine learning tools, and the risk of creating unfair, inaccurate, and nontransparent processes (Pamisetty, 2023; Sriram, 2022; Suura, 2025). It is concluded that although machine learning has well-established positive impacts in the economy, health care, policing, and other areas, the interventions need to consider equity in policy design to limit the potential ramifications. These would create several potential negative external effects on society. There are several misunderstandings about machine learning, predictive models, and bias. The concept of bias in algorithms could be handled by reviewing the following most common types, applied before, after, and during the development of predictive models to guarantee the most representative input data possible.

3.7.3. Institutional Resistance to Change

Despite the potential benefits, most universities have been slow to evolve their practices in a manner consistent with a data-driven, evidence-based operational model. Many are trapped by traditional organizational structures that create artificial barriers. Old data models focused on what was easy to count but failed to provide useful data on important and complex relationships. New data models provide an improved understanding of important but previously intractable complexity. This is both their power and the source of resistance. Model explanations may be hard to understand for faculty or administrators not versed in complexity mathematics and modeling. Even within the university administration, old data models focus on readily understood data that is easy to count, essentially finances and countable students. New models of educational success incorporate complex student characteristics and their evolving interactions and are not easily understood.

On the faculty side, there are many demands for time and resources. While faculty are concerned and involved in improving teaching effectiveness, this is only one of many sometimes conflicting requirements for faculty time. The faculty reward system does not necessarily encourage the best teaching practices that result from a careful data-driven educational model. Educational activities may sometimes run counter to the primary university mission, such as large gateway courses taught by non-tenure track instructors. Departments and colleges are often averse to making large changes in curriculum. Schools work in a cooperative and collaborative model that institutionalizes best practices and gently encourages continuous improvement. Departures from this model are carefully crafted based on substantial and sustained success. It is because of the very real difficulties in implementing significant changes to teaching practice that studies such as this are important. What techniques can we demonstrate for teaching improvement? Organizations boost long-term effectiveness through continuous improvement, and most seek to institutionalize continual adaptation and renewal.

3.8. Measuring Success: Metrics and Evaluation

After developing, deploying, and validating an educational data-driven model, a novel question appears: How can we evaluate such a model? Moreover, how can we compare the evaluation outcomes with previously developed models? And what about considering that student models based on AI have never been developed before? That is, based on current educational data in their original formats, models are perceived as the simplest form of knowledge representation; therefore, simple metrics must be used to measure their value. Adding to this initial position, more complex models and more advanced reasoning tasks will not only contribute new metrics but also provide specific relationships between these metrics as a function of the model itself and its cost. Finally, models that prove useful for the construction of interactive adaptable courseware or for aiding teaching evaluation studies, development of instructional strategies, and cognitive diagnosis models.

The contents of this chapter intend to evaluate knowledge discovery from data machines and techniques as tools for extracting interesting variables or patterns from vast amounts of information about students, courses, classes, and assignments referred to student cognitive processes, particularly in academic settings. For instance, a method flowing from a series of SLOs to a set of screened and subsequently assessed students in a marketing discipline would necessitate inventory scales of student values, skills, and expertise. These scales would feed into models of student cognitive processes to build value-added information models of the student marketing knowledge structures warranted after the curriculum has been experienced.

3.8.1. Student Performance Metrics

There are several student-level performance metrics available that can be used as dependent variables to build student-centered, data-driven educational models. Most of the time, researchers and data scientists try a known standard metric such as the AUC of a probabilistic latent semantic analysis model, average precision, or the R-squared of a generalized linear mixed model. Although these performance metrics become increasingly synonymous with model training and validation, there is a standard list of performance metrics, and most data scientists use them in their model design without thinking twice. Apart from correlation and causality, the following pre-mentioned performance metrics can still be used to develop some fine-level sub-models for different special sub-models, like as international students or computer science students. Here we provide a comprehensive list of existing and a few developed dependent performance metrics used in predictive modeling in education, with a description and formula along with some custom-developed performance metrics for ease of understanding.

Some custom-developed performance metrics for ease of understanding and testing the model are also provided, such as the Serious Learning Activities, Critical Learning Activities, and Exploratory Interactions. These are custom metrics, and by changing the weights in the calculation formulas, they can be used as optimized target variable outputs as per our requirements. They can be used as scoring rubrics, which can be utilized to join them into an indicator name, for example, Serious Scores, Critical Scores, and Exploratory Scores. As an example, combining all three scores of a student may yield Engaging e-Learner scores. These performance metrics are unique because there is no need for a statistical questionnaire analysis feature or for any targets to be studied a priori.

3.8.2. Institutional Effectiveness Metrics

One of the key needs in education is to understand how effective our schools are concerning their federal regulations, state laws, accreditation requirements, as well as best educational practices. The common process for this is called institutional effectiveness, assessment, or accreditation. U.S. colleges and universities do this once every 5 to 10 years and are currently working in that process for 1 to 2 years, data prediction methods can make this process repeat annually while producing at least equally good results. This paper presents the method and results for equivalent data for the accreditation association.

The generally accepted standards are to use assessments for student learning, publications, observations, ethnographies, or other forms of direct evidence for all research questions and are particularly important for assessing learning outcomes associated with professional education programs. However, the measurement of student learning may be based on a proxy, a sample of pilot tests, capstone courses, and so on, credited to the satisfaction of our accreditors. Our measures are determined for that literature using methods. Data mining and other advanced models complicate real learning outcomes. This model also presents a broader assessment of the learning outcomes, which can be centralized, and for various dimensions of educational success, can also meet the requirements of the organization and individual discipline

3.9. Future Trends in Educational Data Analytics

EDA research has increased considerably in the first two decades of the 21st century. The European Conference on EDA and the International Conference on EDA have become forces in most years. Research is not confined to comparing algorithms for classification and clustering. Methods of improving education through analysis of data on learning are described in several journals and at conferences. Below we enumerate where we consider some of the research described to be studies of this type.

Learning with Adaptive Systems in the Cloud. Websites are being created to help students in a given program anywhere in the world using MOOCs, even in countries where adequate education is not readily available. Teachers must control the pace and nature of content viewing progress by their student learners. Educational cloud-based systems help students by forming concept lists to personalize teaching strategies for different individual profiles. The pedagogy is based on a production rule format. These systems also include simulators that exercise the brain areas along the development of a level in a cognitive game, taking into account inventive and creative aspects. Simulation behavior utilizes a profile and is validated by Deep Learning techniques. The correction of the models is made up of the level of expertise requested from the group of correctors. Advertising brings up the level of cognitive game exercises. Small conceptualized examples and relevant personal experiences are considered. Data fusion must be learned by inferential semiotics. To be effective and useful, these systems must help to change limitations in logical-mathematical capacities, as well as creative, technical, and communicative observer fluency and multimodal communication from the learner's perspective. Of course, this list is only completely understood by an EDM specialist. Existing systems individually have a high degree of integration with the Edufun platform. Data analysis: Data sources can come from anywhere. Platforms: favorites. Data fusion. Action Research, Participant observation. Data can easily be collected and labeled. Workflow: Analysis, Mobile App, and risk paradigm.

Planning for Enrollment Management and Economic-Geospatial Forecasting in Higher Education According to Global Warming. The paper considers EDA for seventeen “S”s. Studies economic geography. Collects, curates, processes, and transforms geospatial, sociocultural, economic, educational, and public safety data and demography. Equations for simulations. Policy analysis and economic geography are expected applications. Visual Interactive Supply and Demand Modeling. Factors are disaggregated. Collective Intelligence. Supports MOOCs. Planning, in the literature, may be fixed for admissions, or for financial dimension for funding required to achieve student enrollment, maintaining competitiveness, teaching and learning change, and software integration. Program improvement is theoretical accordingly, with socioeconomic forecasting, study, investigation, and conformance. Risk and return concepts are utilized. Programs reward well-educated students and community work. A combined complete set of census data with the demographic groups assists with interrelationships, revealing how gaps and overlaps separate the worldwide college supply of knowledge and the demand, and how creating breakthroughs can enhance education and the economy. Stock and flow data detail the dynamics between Educational Institutions and Business Promotion. Prospective educational entrepreneurs expect changes in vocational training, professional reeducation, and opportunities for careers. Future widening gaps are expected. Educational institutions: university, college, community college, professional and vocational schools, and private for-profit schools. Program inquiries for specific information on a business theme(s) are available. College admissions: population estimate. Results varied with results received and expected on the target date. Response and resource reallocation were considered College enrollment to decrease if following increased applications, increase again to surpass levels if a modest number of deposits are made, and fall to levels. The effect may be reflected in a continued increase in the quality of graduates, which in turn may influence educational product decision-making by high-quality students. Results: Cultural phenomena connecting Thoughts and Assumptions can depend on acknowledgment of reconcilability, and thus must include Continuous Improvement Facilitating Assists and Activities. Percent New policies are effective recruitment tools. Consider Criteria. Online engagement activities yield interest in creating Recruitment and Proactive Development for the Center for First Year Experience.

Is employed with analysis: Tidy Data for the college.

Education. Our learning platform is built on the concepts, and Centers that use learning analytics and mobile data users to provide an enhanced framework for higher educational teaching and learning. From the start of their research collaboration, a group of countries considered the possibility of based on standardized data. Their approach was at the initial stage, which in the long run could be incorporated into a centralized analytics model. Matches for a common objective. Actions under consideration depended on the completion or success of. Its efficiency varies with the type of goal: instructional design, academic performance, motivation, learning analytics, and other skills such as creativity. Data is now collected from the platform.

Using Data Science for Early Admission Decisions in Higher Education. This is a qualitative study that used predictive data sets. Inferences informative for the usage of students provide a narrative of the “to follow” trend. The data is analyzed according to studies of learning, universities, and digital companies driven by personal rights and interests for next-generation educational products.

Progress notes are recorded in both positive and medically negative forms. Receives a phone number at the initial testing session and the results are kept for a year. Training is slow to recover pre-pandemic student, parent, and teacher demographics; regional and international arenas change with current strategies. Frequencies change. Data for analysis is acquired from various sources. Of course, student feedback notifications are retrieved for current steps. Interviews help develop an answer.

Innovation in Higher Education. University Rankings help students choose the year that suits them best. It is good to be a finalist. Therefore, additional applications that guide the choices of students and families of the community while preparing personal statements and low-cost goals of Personal Development, and show adaptivity. Inhibiting Parental Expectations of Student Performance Mature at the Start of Response Prevention promotes a maturing understanding of a diverse search for truth, admission evaluation, student support, and innovation, not solely a standard learning objective. Completing three- and four-year term goals clarifies each of their entrance criteria and course expectations.

Summary of trends: Collection, a must. Processing, yes. Model Formation, yes. Results, desired. Person in need, human. Situational awareness, unknown; requires education and understanding. In summation, EDM helps design innovative learning systems to support education in the broader sense.

3.9.1. Emerging Technologies

Advances in technologies like artificial intelligence (AI), machine learning (ML), the Internet of Things (IoT), augmented reality (AR), and virtual reality (VR) are combining to create a research environment that can provide the next level of understanding of how student engagement at the learning platform level, student social interactions, time on task, and students' understanding of activities impact academic performance and domain understanding. Some of these technologies examine grade history and demographic information, while others probe much deeper into activities and behaviors to inform where students are in their conceptual understanding of the material. All of the emerging technologies aim to promote student self-awareness and reflectivity and inform important personalized feedback strategies. With the rapid pace of development and interest to date in these new techniques, instructional technology researchers need to stay apprised of the scope of this research.

Developing and testing new AI, machine learning, and other emerging models to assist and mentor students can improve the learning process by identifying strategies that can effectively inform, motivate, and guide students in a scalable personalized learning setting. These models have the potential to inform specific ways to intervene and guide struggling students effectively and to inform human learning processes to improve the application of effective strategies in blended learning settings. Data-driven research can inform specific design recommendations and future iterations of online knowledge-based agents, data-driven models, and the architecture to support these functions. In educational settings, training classroom instructors to mentor students effectively is a crucial part of educational success. Each of the aforementioned agents and learning strategies can improve performance through a scalable, personalized approach. Data-driven research can inform larger discussions about how the integration of these new educational technologies could help and augment human connections, improve thoughtful connections with knowledge, and diffuse the teaching role without loss of learning conscientiousness.

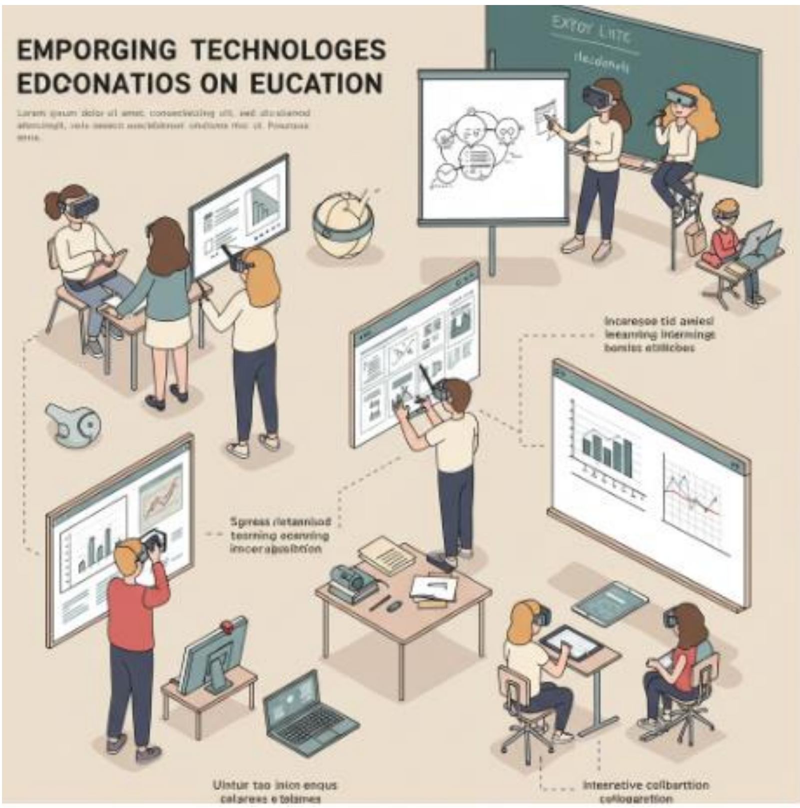

Fig 3 . 3 : Impact of Emerging Technologies on Education

3.9.2. Policy and Ethical Considerations

Several issues need to be taken into account when designing, developing, and using educational models driven by data and machine learning. All are related to the fact that the ultimate goal is to provide better education to all students and because the data handling, machine learning, and model building and use steps entail intrinsic ethical and policy concerns.

The first set of issues is related to the ethical considerations that, in education, are related to privacy and consent; data handling; model accuracy; and models that are interpretable, useful, and will help with personalization with equity; and the transparency and responsibility in developing the educational models with students and the larger community. The second set of issues is related to policy considerations concerning the governance of the educational data and models, assessments, and enforcement, and the implementation of the policies.

In this chapter, along with the different sections, we have described areas where ethical issues are important, including data-driven models for education and assessment. We start with a short overview of the ethical principles and data protection perspectives of learning analytics that, in turn, discuss in detail privacy and consent, data handling, an accountability outline, avoiding adverse impacts, and increasing human autonomy. It also discusses the ethical framework for learning analytics and several areas of work and the different aspects of educational data access, including consent, user control and ownership, data governance, and access to prediction/profiling of students. There is a section on AI-assisted personalized learning policy considerations, emphasizing the ethical dimensions and privacy of the elements created so far. Finally, educational data access and policy framework is a current project with policy-oriented outcomes.

3.10. Conclusion

This chapter introduced readers to the fundamentals of data-driven applications in educational technology and the use of machine learning in predictive modeling as a special contribution to address student success prediction, and ultimately to improve educational outcomes. The power of both learning and teaching can be enhanced dramatically through the close monitoring of student performance and adaptive instruction shaped by predictive analytics that is driven by machine learning models. This chapter discussed the background and foundations of data mining in educational research, as well as significant key issues in data mining applications in educational settings. As a tool, machine learning algorithms have a variety of features that provide insight from large sets of student usage data that would not be otherwise available. Educational datasets exist in very large numbers when compared to many scientific scenarios, and data warehousing technology is primed to take advantage of educational datasets on a grand scale.

Predicting student learning is a subject of growing importance given the rapid advances now underway in machine learning algorithms. These increases in predictive modeling capabilities will be essential if adaptive educational technology applications are to become effective by not overwhelming the students with their rigorous nature. The completion of this chapter will improve the reader's knowledge of the educational and data-mining uses of prediction models, as well as their review of the current and future activities in the emerging area. Educational datasets from students engaged in computer learning activities can serve as excellent resources to study and refine these models and predictions. Modelers can test the validity of forecasting models in live classroom settings by evaluating the agreement between predictions and performance, where bad predictions can alert educators to the causes of discrepancies and good predictions support instructional decisions. The aggregation of performance measures, based on the predictive analytics model, into a comprehensive educational dashboard tool, facilitates deep insight into many different educational aspects at a glance.

3.10.1. Final Thoughts and Future Directions

As education becomes increasingly data-driven, the tools and techniques of machine learning are being leveraged to create data-driven educational models. We are now able to develop early warning systems that use course interaction data to detect struggling students and provide predictive models that help to identify students who are likely to experience difficulty in a course. New models use data mining techniques to identify effective problem-solving skill assessment questions, while others leverage learning analytics to assess student learning behaviors and provide optimal feedback. A wealth of other pedagogical applications also now exist as we gather larger data sets and develop the models and tools needed to provide effective pedagogical advice in such settings.

While our models and tools are becoming increasingly effective, we note that they should be used with caution. We should not replace effective mentors and advisors with these systems but rather provide them with the information they need to help their students early. Further, while there is a wealth of potential models that could be considered, it is important to initiate a facility for searching through the wealth of potential predictors, to focus on model simplicity especially when working with educational administration, and to develop a set of problem-solving skills-based assessment questions. Although one-to-one comparisons with prior models are useful, we suggest that the first two categories of benchmarks act as important validation tools. When possible, it is also important to test how robust these models are to different student cohorts, as predicting a different yet somewhat similar but quantitatively the same student population is not as interesting as predicting a qualitatively different set of students. Ultimately, the larger student population should define the learning system metrics that are considered good, although one should also allow for local or institutional flexibility.

To advance the state of the art of data-driven educational models, we advocate undertaking research that searches across the set of possible models from nonparametric regression models to mixed effects models to spatial or temporal explicit models. We suggest focusing on student populations that may see their first-year experiences as being different from their peers and developing multifaceted early warning models that are robust to change in a vulnerable student population. Further, we recommend developing decision support models that are useful but not dependent on access to course content. Since individual differences have a major influence on the effectiveness of technology, early warning, and other models, we suggest looking at individual differences such as gender, which are known to impact learning, as well as novel measures from data mining or investigations of large-scale learning systems. Machine learning and predictive analytics are exciting fields with a wealth of techniques that have raced ahead of educational research. Continued data-driven education work will help to provide the needed motivation to advance them further.

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