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Artificial Intelligence in Education: A Panoramic Review

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Abstract Motivated by the importance of education in an individual's and a society's development, researchers have been exploring the use of Artificial Intelligence (AI) in the domain and have come up with myriad potential applications. This paper pays particular attention to this issue by highlighting the future scope and market opportunities for AI in education, the existing tools and applications deployed in several applications of AI in education, research trends, current limitations and pitfalls of AI in education. In particular, the paper reviews the various applications of AI in education including student grading and evaluations, students' retention and drop out prediction, sentiment analysis, intelligent tutoring, classrooms' monitoring and recommendation systems. The paper also provides a detailed bibliometric analysis to highlight the research trends in the domain over six years (2014–2019). For this study, we analyze research publications in various related sub-domains such as learning analytics, educational data mining (EDM), and big data in

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education. The paper analyzes educational applications from different perspectives. On the one hand, it provides a detailed description of the tools and platforms developed as the outcome of the research work achieved in these applications. On the other side, it identifies the potential challenges, current limitations and hints for further improvement. We also provide important insights into the use and pitfalls of AI in education. We believe such rigorous analysis will provide a baseline for future research in the domain.

Keywords Artificial Intelligence · Education · E-learning · Personalized Learning · Machine Learning · Sentiment Analysis · ITS · EDM

1 Introduction

Artificial Intelligence (AI) is revolutionizing the way humans live their life. The research methodology taken by AI is the use of data acquired from a system to develop models, understand its complexity, and solve pertinent problems through these models. The field of education is going through a paradigm shift through the use of AI which can be used to unleash insights about understanding how students learn, how to personalize the learning experience of students, how to get more information to help in the decision-making process, how to model the complex interaction between student learning, the knowledge domain, and the tools that enable students to interact with the domain. Indeed, AI is relevant to addressing education-related challenges that are rooted in both the inadequacy of the traditional way of teaching the current generation and the complexity of the educational system itself. In particular, e-learning is making a huge amount of data available that will enable AI to address complex challenges in education and adopt smarter educational technology solutions. Over the past decade, the role of AI in learning has been on the radar of education institutions, government agencies, funding agencies, and industry [1]. It is expected to grow by more than 47% from 2018 to 2022 in the US Education Sector based on AI Market [2].

At the same time, different research communities have taken different approaches in addressing educational research problems through the use of data driven methodologies. This is because data mining research community addresses research problems using big data approach while AI communities address research problem focusing on algorithms. Although these fields are overlapping, these communities tend to develop distinct research areas as they have had different research histories. Knowledge Discovery and Data mining (KDD) research community aims to discover patterns and extract knowledge through data mining in general including AI. The Educational Data Mining Community (EDM) attracts inter-disciplinary scientists from computer science, education, psychometrics, and other fields to analyze data acquired from the educational environment and apply data mining techniques to solve educational challenges [3–8]. On the other hand, the Society for Learning Analytics Research (SoLAR) community is an “inter-disciplinary network of leading international researchers who are exploring the role and impact of analytics on teaching, learning, training and development" [9,10]. Many other research activities are being developed by different research groups around the world to explore how machine learning can be utilized to solve educational problems.

We note that we use the term AI broadly as an umbrella term that subsumes methods, algorithms, and systems that learn from data (data science, statistical learning, machine learning, deep learning) or aim to create machine intelligence that can perform tasks such as perception, reasoning, inference (such as expert systems, probabilistic graphical models, Bayesian networks). These terms are largely used in current convention synonymously [11], and our use of the term AI will ease exposition and reduce clutter. We make the distinction between AI and other subsumed techniques where it is important.

Given all the diverse amount of research endeavors in the application of AI in education, it has become therefore more conceivable to address grand challenges facing the education of our society [12]: How will technology support learning in fundamentally new ways across lifespan? How far can scientific advances take us towards highly adaptive learning? How will new data and methods of analysis reveal pathways to success? What innovations join research and practice to enable continuous improvement? How technology can be utilized to develop a cost effective personalized learning experience?

These questions point to the challenge brought by the interplay of adopting a cost-effective traditional mass education system that has a one system fits all and the current trend of developing a personalized education system that is expensive to adopt. Besides, different constituents see the problems from different perspectives and they have objectives that are sometimes competing. These decade-old research challenges are now exemplified with multiple projects being investigated using machine learning, and there is a big hope that solutions are forthcoming.

1.1 Market Trends and opportunities

A lot of data is generated by a learning management system (LMS) in several ways. These data can be collected at different time scales and levels; keystroke, answer, session, student, classroom, teacher, and school providing a hierarchical view to the model [3,5]. It then can be used to "sense" student engagement and learning and their cognitive activities, to do fine-grain formative assessment, and harness the power of technology using these data generated. Other important structures are time, sequence, and context. Parameters extracted from data can be represented as time-series data that can give an idea about sequencing. The activities have meaning within a certain context which is important in evaluating the results and giving recommendations for the next step. The time and scope of hierarchical data will create opportunities to address following challenges:

– *User/Learner Modeling:* Modeling knowledge, difficulties, and misconception of a learner is important to provide intelligent support for the learner

[13]. Open Learning Model (OLM) is being investigated by multiple researchers [14] and is adopted by the NEXT-TELL [15] project funded by the 7th framework program of the European Commission. Online learning systems provide the data to explore how to model learner's behavior? How to infer learner's motivation? How to develop a positive learning experience? The Massive Open Online Courses (MOOCs) provide a platform to collect a massive amount of data to improve the quality of education.
- *Personalized Learning:* One-on-one tutoring is a better personalized learning paradigm where the tutor (expert) gives direction to the learner based on their specified need and abilities. However, personalization becomes a challenge when a teacher is dealing with a high number of students. AI will bring a differentiated service that will help the teacher harness the power of AI to personalize the experience of students. Students don't have to all go through the same lectures presented in traditional learning environments. AI will promote personalized learning through the design of formative assessment embedded in the system [1]. To achieve the learning objective of a course, students will be able to learn a topic by going through a set of learning material by their pace meeting the student's abilities and needs. Several companies such as VALAMIS [16], content technologies and Carnegie learning [17] are developing solutions for personalized learning.
- *Teacher and AI Collaboration:* AI will never replace the role of the teacher, the question addressed by researchers is how to best support the job of the teacher using AI. AI will be utilized to fill the needs gap in terms of personalized learning and tutoring and allow teachers to be efficient saving them time and make the "guidance" decision easier to make. People need time to grasp concepts, but they also need to be given feedback on the right steps to take and they need to be evaluated on the right background they need to learn; therefore, AI will promote efficiency, personalization, streamlining of admin decisions to provide understanding and adaptability. AI will enable the development of an efficient teaching system with the best outcome for students.
- *Tools for Policy Makers, Administrators, Teachers, and Product Developers:* Tools to support administration processes such as grading, mentoring and tutoring, and advising using available data will enable administration decisions to be made with appropriate knowledge about the student.
- *Translation Tools*: Tools for translation will make learning available globally with real-time translation.

These challenges open up the following research directions [3]:

1. Model student's knowledge, motivation, metacognition, and attitude to predict their learning behavior;
2. Optimize the content sequence that needs to be explored by students given a domain of knowledge useful for a certain context
3. Understanding the impact of a pedagogy on the different types of learner
4. Developing computational models that can implement student learning style models, the knowledge domain model, and pedagogy.

The methodologies for the potential solutions of the above mentioned challenges could be:

- *Prediction*: Prediction of different behavior such as off-task, failing to answer questions; whether students will fail the class; student educational outcome.
- *Clustering*: Grouping of students depending or their levels, purpose and interaction patterns [18]. Working with unstructured data such as text, discussion boards and posting etc.
- *Association*: Involve discovering the relationship among variables in a dataset similar to online shopping relationship identification [19].
- *Distillation for human judgment*: Involves data visualization for humans to extract the features of interest easily. These features can be used to improve AI as a human can understand patterns related to human behavior and other patterns such as collaborations among students.

1.2 Scope of the Survey

The paper revolves around the key applications of AI in education, and covers different aspects of AI in education. The paper starts with delineating future scopes and market opportunities in the application of AI in today's education landscape. The paper also describes the most commonly used AI techniques used in different applications of education. It also describes the tools and platforms developed in the market as outcomes of the research work achieved in different applications of AI in education including (i) student's grading and evaluations, (ii) students' retention and drop out prediction, (iii) personalized learning (iv) students' performance analysis and prediction, (v) sentiment analysis, (vi) recommendation systems in education, (vii) classrooms' monitoring and visual analysis, and (viii) intelligent tutoring. We also analyze research trends in AI applications in education by providing a detailed bibliometric analysis of the domain. The paper also advises on the current limitations, pitfalls and future directions of AI for Education and how it can fill the current gaps and create new business opportunities.

1.3 Related Surveys

Due to interesting applications of AI in education, it has always been an area of keen interest for researchers. In literature, several interesting articles analyzing different aspects of AI applications in education have been proposed. There are also some surveys targeting specific application areas of AI in education. To the best of our knowledge, there is no recent detailed survey covering the domain from different perspectives. In previous works, Romero et al. [7] provides a general review of existing literature to analyze how EDM and LA have been applied over educational data. Romero et al. [20] surveyed the educational data mining literature for a decade (i.e., 1995 to 2005). Baker et al. [3] reported a detailed survey of data mining techniques used in the education sector. More recently, Fischer et al. [21] surveyed the existing data mining techniques in education with a particular focus on highlighting challenges in mining big data. Mduma et al. [22] focused on students' retention and dropout prediction techniques. Almasri et al. [23] provides a detailed survey of Intelligent Tutoring Systems (ITS), another attractive application of AI in education, proposed from 2000 to 2018. Al-Emran et al. [24] surveyed the Internet of Things (IoT)-based educational solutions. In contrast to the existing surveys, this paper provides a complete picture of the domain by covering most of the application areas of AI in education, such as student's grading and evaluations, students' retention and drop out prediction, students' performance, e-learning, sentiment analysis, education data mining, education quality support recommendation systems, classrooms' monitoring and ITS. The paper also highlights the key market players, tools and platforms along with key challenges, potential market opportunities, future research directions and pitfalls of AI in education. More importantly, we analyze the trends of the research in the domain from a different perspective by providing a detailed bibliometric analysis of the domain. Table 1 provides summary of existing surveys on the topic.

Table 1: Comparison of our paper against existing surveys

Survey	**Application Domains**	**Tools & Platforms**	**Bibliometric Analysis**	**Pitfalls of AI**
[5]	*Covered 2 applications.* (i) Students' Performance Prediction and (ii) Recommendation Systems	✓	Yes (2005-2010)	X
[3]	*Not Covered.*	X	Yes (2000-2008)	X
[21]	*Covered 4 applications.* (i) Students' Grading and Evaluation, (ii) Students' Retention and Dropout, (iii) Sentiment Analysis in Education and (iv) Recommendation Systems in Education	X	X	X
[22]	*Covered 1 application.* (i) Students' Retention and Dropout	X	X	X
[23]	*Covered 2 applications.* (i) Students' Performance Prediction and (ii) Intelligent Tutoring Systems	✓	X	X
This Work	*Covered 9 applications.* (i) Students' Grading and Evaluation, (ii) Students' Retention and Dropout, (iii) Personalized Learning, (iv) Students' Performance Prediction, (v) Sentiment Analysis in Education, (vi) Recommendation Systems in Education, (vii) Classroom Monitoring & Visual Analysis and (viii) Intelligent Tutoring Systems	✓	Yes (2014-2019)	✓

1.4 Contributions

This paper is intended for researchers interested to explore the potential applications of AI in education by providing a detailed overview of the existing work in the domain, most commonly used learning strategies, key market players and platforms as well as the potential future research directions. The main contributions of the work are summarized as follows:

- We provide a detailed overview of the existing literature in nine different application domains in which AI is deployed for education.
- The paper also describes and highlights recent papers on the most commonly used learning strategies adopted in literature over the years for these applications.
- We also explore and identify the future scope and market opportunities for AI researchers and developers in the education sector.
- We analyze the publication trends of the research literature taking into account a total of 2929 papers published in various top subject venues through a detailed bibliometric analysis in terms of research productivity by authors, institution, and country, and knowledge flow across various research venues.
- To introduce the readers to the key market players, tools and platforms, we identify the research and development companies and corporations working in the domain along with the tools and platforms available for both educational institutes and researchers.
- We also identify the limitations, pitfalls and open research challenges in the domain.

The rest of the paper is organized as follows. Section 2 describes some key application domains of AI in education. Section 3 details some key AI techniques employed in different applications of education. Section 4 introduces the readers with key market players, tools, and platforms in the domain. Section 5 provides a comprehensive bibliometric analysis of the existing literature in terms of research productivity by authors, institution, country, and the relationship of techniques and applications of AI in education. Section 6 provides basic insights of the domain based on our analysis of the existing literature, and lists the key limitations and pitfalls of AI in education along with some potential directions of future research and open issues in the domain. Finally, Section 7 concludes the paper. (The structure of the paper is also illustrated in Figure 1.)

2 AI Applications in Education

In the modern world, similar to other domains, AI has revolutionized the education by enhancing teaching methods, course content and other materials. Learning is not limited to classrooms anymore. Even in the classrooms, AI has improved the learning experience. In education, AI could be applied in several

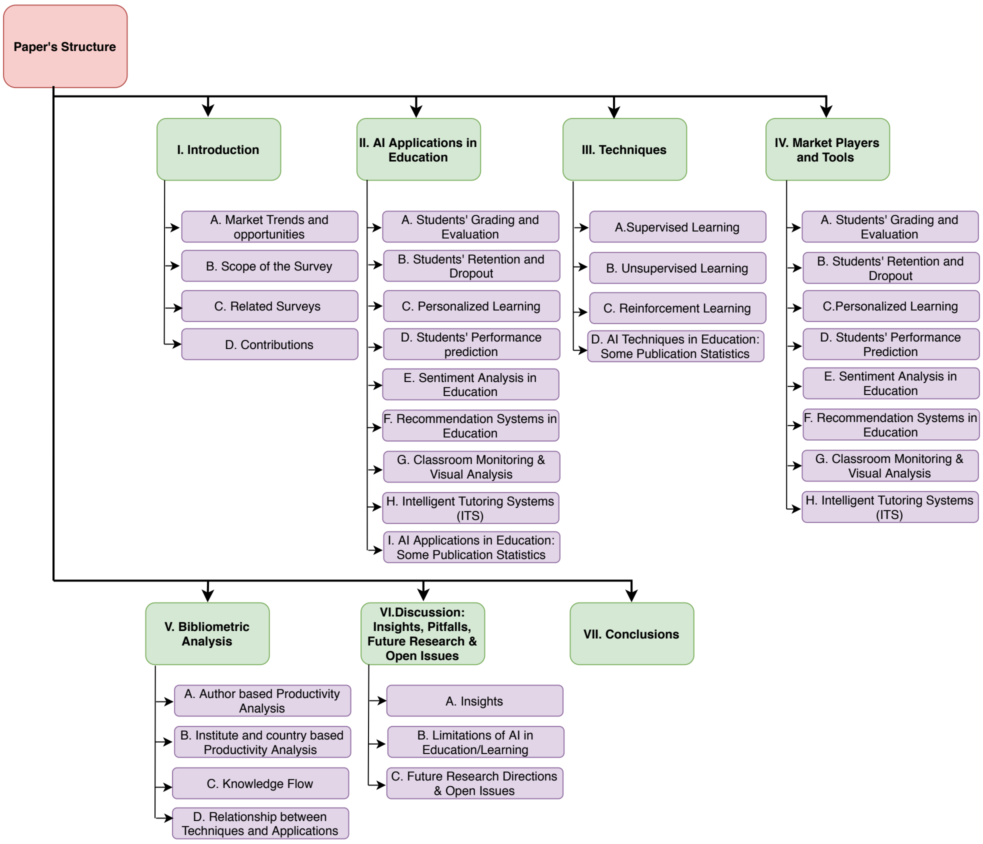

Fig. 1: Structure of the survey

ways. It can support teachers, predict student performance, evaluate and grade students and improve course contents etc. In the next sub-sections, we discuss these applications in detail. We also list some recent key papers on each of the applications in Table 2.

2.1 Students' Grading and Evaluation

In literature, several AI techniques are used to develop accurate models for the prediction of student behavior and in-class performance. For instance, Livers et al. [25] evaluated two wrapper methods for semi-supervised learning algorithms designed to predict the performance of students in their final examination. Their experimental results indicated a higher classification accuracy for semi-supervised methods especially when unlabelled data is utilized in training the models.

Although predicting the performance of students is a very important aspect of modern education supported by AI technologies especially as this helps education administration to put in place measures to preempt and prevent student dropouts before the end of the semester and mark the students who require special support. The performance aspects of students learning that need to be assessed are not always related to grading and marks but also include, very importantly, students learning difficulties. To analyze learning difficulties faced by students, Hussain et al. [26] conduct a study to predict difficulties encountered by students in a digital design course. To this aim, the authors analyzed data logs from a Technology-Enhanced Learning environment (TEL) system using several AI algorithms including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Logistic Regression, Decision Trees as well as naïve Bayes models. The test rig monitors students click behavior while solving digital design exercises of varying difficulty and collects students' total number of activities, average time, average idle time, the average number of keystrokes and total related activity for each exercise; the output/predicted variable is the student grade in each session. AI models were then trained on old sessions to predict student performance in new sessions.

AI and statistical models for the analysis student performance prediction has also been applied by Masci et al. [27], who analyze test scores of students' PISA 2015 in nine countries in order correlate students and schools' characteristics with students' performances. The authors also model interactions between school-level factors affecting results. To estimate school value-added factors, they apply flexible tree-based methods in combination with multilevel regression trees and subsequently use regression trees and boosting models to map the estimated school value-added factors to school level variables. They conclude that although characteristics of student and schools are strongly linked to student achievements, the results vary from one county to another quite significantly which means it is essential to take the structural differences between international education systems into consideration whenever studies are conducted and conclusions are made.

2.2 Students' Retention and Dropout

Student retention and dropout is a universal factor affecting both online and offline learning platforms. Within Baccalaureate programs in the US, billions are lost each year due to dropout rates reaching 30% or more amongst first-year students because of insufficient quantitative analysis of causes and remedies of student attrition. As an initial effort, Aulck et al. [28] have modeled student dropout based on a dataset of 32500 demographics and transcript records at a large public institute. They conclude that early potential dropouts can be detected even with single term transcripts thus opening the door for AI applications to predict and prevent some of the causes of dropouts. The adverse effects of dropouts are manifested even more clearly in MOOCs environments due to the higher rates of dropout with typical enrollments of 10000 entrants and dropout rates reaching 90% [29].

Similar to other application domains, AI has also been proved very effective in students' retention and dropout prediction. In literature, AI modeling techniques have been applied to predict dropout rates to calculate dropout probability as well as identify the ambient, demographic and individual factors related to learning activities such that education administrators can design effective intervention and prevention remedies. For example, Solis et al. [30] analyzed the accuracy of various AI algorithms for the prediction of student retention rates at university levels. They found that Random Forest (RF) algorithm is an optimum method with random sampling. The proposed approach offers hitherto unknown insights although it is a generic view system that does not leverage the interests of education experts in focused/targeted analysis of specific category of learners. The system also handles large amounts of dynamically shifting data including data structures as well as user evaluation metrics.

From a different perspective, Pilkington et al. [31] conducted a qualitative study as part of funded research at a UK university with a sample of 75 researchers, tutors, and professors. They used a combination of "systematic, sequential, explanatory and, thematic" approaches to focus on findings from thematic analysis. They identified engagement, attendance, workload, family pressure and mental health as factors that continue to contribute to dropout issues regardless of university engagement efforts. Apart from these factors, the sense of community, institutional social-environmental contribution and academic integration are other critical factors contributing to students' retention and dropout [32]. It is therefore essential to go beyond basic AI modeling for predicting dropout, and analyze the impact of ambient socio-economic, psychological, demographic and family factors to be able to conduct a determined analysis of the causes of dropout. For example, the temporal and disparate nature of MOOCs data, and the inconsistent learner activities therein such as watching and re-watching a video or posting forum feedback as well as associating learning activities with dropout potential that involves personal reasons is a very difficult task as these reasons are " diverse and highly personalized". Chen et al. [29] applied visualization analytics methods and techniques (DropoutSeer) to analyze large datasets from MOOC systems to correlate (ML) predicted dropout rates with learning activities of MOOC subscribers visually. The aim was to enable content designers to design more suitable, engaging content and AI experts to design better predictive models [33]. This was shown to be more effective, for instance, than the process of feature ideation as a critical step in the model building process [34].

2.3 Personalized Learning

Education has been subject to many simultaneous and fundamental transformations driven by student needs, state needs, internationalization and globalization as well as education management and technology developments. Technology implementation and inclusion notwithstanding, the traditional learning approach with a static, unidirectional model including teacher in front of students, reading text material and written exam based assessments that cover all sections of the classroom uniformly is being eroded. Contemporary learning directions converge to interactive, student-focused, tailored learning models that serve each student or student group much closer with better engagement, closer interaction, improved comprehension and wider scope coverage of learning outcomes. The flipped classroom constitutes one of the important learning methodology shifts that started to feature more prominently recently with a positive impact on learning practices [35]. Other related developments that give rise to personalized learning include, for example, Competency-Based Learning [36, 37], especially in health and medicine education.

The flipped classroom model lends itself well to the concept of adaptive and personalized learning and teaching. For example, Sein et al. [38] illustrate recent advances in educational technology as well as the design of instructional models for facilitating a tailored learning experience for each student. The authors identified several learning advantages to this approach that have a notable positive impact directly affecting final grades as well as attrition and dropout rates through a case-study. Technology plays pivotal roles in the design, operations, feedback analysis of flipped classroom models including analytics which provide insights about time management and commitment from stakeholders. For example, Gašević et al. [39] analyzed the time management aspects of an undergraduate level engineering course that was run according to the flipped model. By analyzing student learning activities, the authors were able to identify specific patterns of time-management strategies using trace data and were also able to identify strong correlations between time management strategies and academic performance. Digital technology plays a major role as a catalyst for the transformation in education. For example, Pedro et al. [40] describe the close relation between technology and pedagogy in support of tailored learning experiences and promote the utilization of data (science) as a platform for the provision of "richer".

Recommender systems in education and in support of personalized learning experiences have been explored since early this century. For instance, Lu et al. [41] provided learning recommendation to students via a personalized learning framework which guides students in identifying learning and reference materials. In [42], the authors applied recommender systems to provide remedial actions for outcome-specific shortcomings of higher education students including additional reference/practice examples, or administrative level recommendations such as changing a course's pre-requisite or location in a study plan. Similarly, the adaptability of the learning model to cater for multiple learning sectors would not have been feasible just a few years ago before the wide availability and accessibility of technology such as Deep and Reinforcement Learning (RL) which leverages the power of cognitive computing is support of education. Shawky & Badawi [43] explore RL as a cognitive computing catalyst to provide adaptive learning materials and paths in support of bespoke, learner-centered requirements.

2.4 Students' Performance Prediction

To be able to predict a student's likely future performance in a course can provide very powerful platforms that facilitate educational interventions and remedial actions promptly. The development of AI models for the prediction of student performance and uncovering hidden insights and patterns are some of the most salient applications and research areas in EDM. Several studies have been conducted in the area of academic performance analysis and prediction, including by Adejo et al. [44], who conducted an empirical investigation and comparison of several data sources, classifiers, and ensembles of classification techniques to predict the academic performance of university students. In detail, they compared and analyzed the performance of ensemble techniques combining information from different data sources against the models trained on data from a single source. To this aim, several algorithms including DT, ANNs and SVM were used and compared individually as well as in ensemble (combination) modes. Livieris et al. [25] also proposed an ensemble-based semi-supervised approach for predicting student performance achieving sufficient accuracy in early prediction of student progress. Khan et al. [45] designed an AI model targeting students in introductory programming modules to notify them about their probable outcomes early on in the academic semester. In total, they employed eleven ML models grouped in five categories, where overall better results have been obtained with Decision Tree (J48) in terms of accuracy and F-Measure.

Deep learning techniques were also employed to tackle the challenging problem of forecasting the future performance of students. For instance, Kim et al. [46], proposed GritNet, a novel deep learning model, for the prediction of students' performance by treating it as a sequential prediction task. GritNet is mainly based on the bidirectional long short term memory (BLSTM). The authors applied the model to a group of Udacity students to predict their graduation predictions and were able to show favorable results of logistic regression models with on-the-ground improvements in the early weeks of the course which are traditionally the most challenging to predict.

2.5 Sentiment Analysis in Education

Sentiment Analysis attempts to improve the learning process in an e-learning environment by analyzing students' feedback to better understand their opinion and make adjustments to the content or delivery of the learning material accordingly [47–49]. Applications of this technology in education and other fields are already established with favorable results in education, healthcare, social media, and natural language processing domains [50–52]. Often referred to as Opinion Mining, it is a challenging task generally involves different phases, such as collection and storage of data as well as analysis of the data using a combination of knowledge-based and machine-learning techniques [53].

There is a significant amount of literature on the topic generally involving analysis of students generated text or their social media posts about curriculum, teaching methodology and materials [54–57]. For instance, Munezero et al. [56] analyzed students' learning diaries to predict students' sentiments, emotions and opinions about their learning experience. According to Kechaou et al. [58], knowledge and evaluation of user opinions is an essential prerequisite for the effective development of e-learning systems. To this end, an opinion mining method has been applied in their research to support e-Learning content developers to enhance the quality of provided services using three feature selection methods, namely Mutual Information (MI), Information Gain (IG) and CHI statistics (CHI) in conjunction with HMM and SVM-based hybrid learning methods. Experimental results indicating that opinion mining is more challenging in e-learning blogs. More recently, Mostafa et al. [59] reviewed work in sentiment analysis related to Gamification in learning, the author proposed a Classifier that will analyze the sentiments of students while using Gamification tools for learning in Egypt.

Liu et al. [60] argue that the "temporal nature" of student feedback in MOOCs environments stipulates that students' emotions and learning activities be tracked for understanding learning requirements. To classify emotional aspects of students, the authors propose a Temporal Emotion-Aspect Model (TEAM) which tracks emotions over time with two main outputs: a) aspect probabilistic distributions that are emotion-specific and b) their time-based evolution, which uncovered emotional salient student emotions as well as their evolutionary trends. The results indicated that: (i) content-related aspects were the main emphasis with higher likelihood to confused or negative emotions; (ii) there were higher likelihoods of emotional expressions at the start and end of a semester; (iii) under-achieving students were less active in emotional engagement and tended to express more confusion towards the end of a semester when compared to high-achieving and medium-achieving students.

2.6 Recommendation Systems in Education

With the advances in design and accessibility of AI packages and tools, it has become quite attainable to incorporate AI services with Learning Management Systems (LMS) that store and collate student assessment results and provide basic analytics and reports to academic managers either for daily operations processes or for local, regional or international quality assurance and accreditation aims [61]. The branch of LMS evolution that goes in connection with AI is an intelligent tutoring system (ITS), which has demonstrated greater achievement when compared to traditional classroom instruction and studies from printed materials [62].

Applying data mining and AI algorithms to recommend remedial actions in support of learning quality is an obvious choice in support of the operational side of academic teaching [63]. In this environment, assessment data collected over several academic semesters are grouped by learning outcomes at the course and program levels. Historical student attainment shortcomings that are typically remedied with domain experts and course coordinators are gathered for learning, wherein a pool of remedial actions (recommendations) is gathered over 3 to 5 years [42]. Training data/features, such as course domain, course level, section size and lab option, are sufficient to guide experts to choose a remedial action that is recommended for subsequent assessments; formative or summative. A multi-label classification algorithm is then used to select appropriate actions for each rubric line (performance per group of students) from the master pool. AI provides obvious strengths in this application domain and are manifested with efficiency, consistency and fairness in the application of remedial actions. Although to achieve optimum performance such a setup is most appropriate for massive colleges with thousands of students and availability of archives of structured, outcome-based, assessment data for several years, nonetheless the approach was sound and successful with reasonable accuracy even with a few thousand learning instances.

2.7 Classroom Monitoring and Visual Analysis

Classroom utilization and occupancy calculations are part of budgetary planning and strategic planning of higher education institutes, especially where real estate is a premium asset [64]. Students in modern offline or online degrees have many technology-driven advantages at their fingertips but equally suffer excessive demands which often cause dropouts and classroom under-utilization. Although predicting room occupancy/utilization is an age-old problem [65], the use of modern AI technology as instruments in measuring or increasing the efficiency of room utilization is a new topic. Sutjaritthamet et al. [66] used on-campus sensor instruments to monitor classroom attendance while respecting student privacy. Several measurement approaches were evaluated in a lab experiment to identify best sensor technology in terms of cost, accuracy and convenience.

Technology Enhanced Learning (TEL) lends itself well to AI applications in many sub-domains. One such area is to aid in the understanding of the difficult task of understanding the various dimensions of TEL in schools. One reason for this difficulty is the limitation of monitoring classrooms for a longer period to analyze teachers' teaching methods and students' learning experience. Howard et al. [67] explored the area of observing, analyzing and visualizing TEL classrooms over time and used sensors to collect observation data over two months. This data is presented as insights to academic administrators and teachers for reflection and corrective action to enhance student learning. AI and EDM approaches are deployed to handle the complex learning aspects in a TEL environment at a higher level of precision.

Other applications of EDM and AI for the transformation of the traditional classroom include the analysis of student facial expressions to assess their level of engagement in the classroom. Soloviev et al. [68] proposed a system that analyzes (in real-time) the data feeds from video cameras that are installed in the classroom and apply AI and facial recognition technology to recognize student emotions to determine their level of enjoyment. Although the bulk of research focus tends to be on MOOCs, digital and online learning environments because of the massive data they generate, nonetheless the physical classroom has been the focus of much research recently as well. Chua et al. [69] reviewed case studies and technologies developed to collect and analyze educational data. Several aspects of the learning environment, which is a combination of physical and digital classroom setting, are studied. Moreover, different aspects of the learning process are assessed and analyzed to quantify teaching and learning processes, student assessments are also analyzed automatically. The authors introduce data pipelines that leverage data and information collected from both physical spaces as well as digital spaces.

2.8 Intelligent Tutoring Systems (ITS)

ITS systems play a major role to plug the growing gap between the increasing number of learners and the shortages in qualified specialist teachers globally. Many ITS systems are in active use supporting and enhancing traditional school curricula in thousands of schools in the US and beyond [70–72]. ITS systems were designed based on knowledge-based domain. Meanwhile the 21st century started with a tremendous growth and strength in resources, research and tools relating to data science, big data (see MOOCs) and AI [73]. Combined with an educational domain shift towards more complex, tailored, interactive learning approaches, such as learning by teaching [74] or example [75] or even by games [76], meant that ITS systems limitations are becoming more apparent with their knowledge-based approach.

AI and data science technologies are ideally suited for dynamic problems that require constant learning. This is not least because these technologies extract new, hitherto unseen insights and knowledge from high-dimension, non-structured data in a much more effective way than extracting expertise or knowledge from human teachers. AI is also very effective in predicting student cognitive needs, results, mental states and skills and subsequently recommending the right course of action. For example, ITS systems with AI enhancements are applicable in modelling student emotions [77], efficacy [78], ability to perform scientific enquiry within a virtual environment [79] and then generate recommendations automatically [80].

Although ITS research is yet to refine the mapping between the what, how explanations of Intelligent Pedagogical Agent system (IPAS) decisions and actions on the one hand and students or teachers on the other, the role of AI technique and model interpretability is even more essential within these contexts of modern learning. This is because it enables an IPA to justify actions and inferences. This, in turn improves IPAS' effectiveness (providing "why" analysis rather than merely "what"). Furthermore, this fosters user trust and confidence in the correctness and integrity of the learning system [81]. The

Table 2: Some key papers from each application of AI discussed in this section.

Grad Pred.	Dropout Pred.	Personalize Learning	Performance Pred.	Sentiment Analysis	Recommendation Sys.	Intelligent Tutorial Sys.
[86–90]	[91–95]	[96–100]	[101–105]	[30, 59, 106–108]	[109–113]	[114–117]

branch of ITS research pertaining to interpretable student and learning models is Open Learner Models [82].

Open Learner Models (OLM) which stem from ITS systems aim to open up AI learner models in terms of human cognition, learning and teaching. While ITS systems research focuses on how AI can be used in education effectively, OLM research focuses on the essential components needed to make AI models interpretable and explainable in the context of learning. Interpretable AI as such can provide a framework for the implementation of knowledge-based and AI systems in education and beyond. Interactive and personalized learning [83, 84] models require IPAs that predict and respond to learner backgrounds, skills and attitudes [85].

2.9 AI Applications in Education: Some Publication Statistics

Figure 2 provides the statistics of some interesting applications of AI in education in terms of the number of papers published on each in the leading venues of the domain, including International Conference on Educational Data Mining (EDM) [9], International Conference on Learning & Knowledge (ILAK) [118], Journal of Educational Data Mining (JEDM) [119], and the society of Learning at Scale (L@S) [120], International Conference on Artificial Intelligence in Education (AIED) [121], International Conference on Intelligent Tutoring Systems (ITS) [122], Journal of Learning Analytics (LAK) [123], and British Journal of Educational Technology (BJET) [124]. These venues share a significant portion of the literature and provide a reasonable generalization of the overall research trend in the domain. Moreover, the statistics are based on a six-year window (i.e., 2014-2019) wherein a total of 2929 articles are considered from these venues. Table 3 provides the details of the articles analyzed from each of the venues. The most popular application of AI in education is in developing intelligent tutoring systems followed by its use for evaluation and personalized learning. A more comprehensive bibiometric analysis covering various facets of the use of AI in the field of education will follow in Section 5.

3 Techniques

The literature on AI in education based on the nature of the AI algorithms can be roughly divided into three main categories, namely (i) Supervised ML, (ii) Unsupervised ML and (iii) Reinforcement learning. In the next sub-sections, we provide a brief description of each of the ML algorithms category. Moreover, detailed statistics of techniques in each application are provided in Section 5.

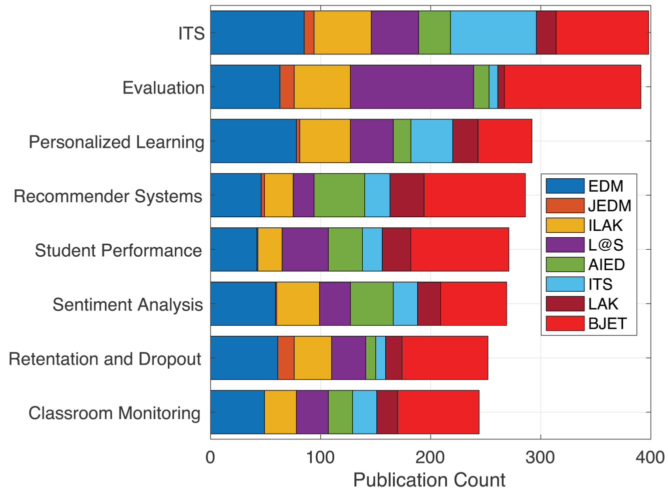

Fig. 2: Statistics of AI papers at top venues in terms of applications.

Table 3: Statistics of the dataset used for the bibliometric analysis

Venue	# Articles
JEDM	87
EDM	663
L@S	393
ILAK	406
AIED	225
ITS	235
LAK	180
BJET	740

Besides a list of some recent key papers from each of the categories is provided in Table 4.

3.1 Supervised Learning

As can be observed in Figure 3, the majority of the works on AI in education rely on supervised learning. Supervised learning aims at function approximation or cure fitting by finding a relation/function $f : x \rightarrow y$ using a training set $\{x, y\}$. Though the efficiency of supervised learning largely depends on the availability and quality of training data, it is far more accurate learning strategy compared to its counterparts [125, 126]. Supervised ML algorithms can further be divided into several categories at different hierarchies. A complete taxonomy of supervised learning techniques can be found in [125]. Some well-known techniques include Random Forests (RF), Conditional Random Forests (CRFs), SVMs, Decision Trees, Neural Networks (NNs), Logistics and Linear

Regressions, Belief Networks, Naive Bayes and Markov Random Fields and Markov models.

In education, supervised learning is mostly used in predictive analysis, such as grade, retention, and dropout prediction [127–132]. For instance, Majeed et al. [127] proposed several supervised learning techniques for students' grade prediction. In details, around 2500 students' records were collected from a degree awarding institution to train different supervised learning algorithms including Naive Bayes and K-nearest Neighbour classifiers. Similarly, in [129], several supervised learning algorithms including Decision Tree-based algorithms, Naive Bayes, k-NN, Linear Models and Deep Learning, are employed for identification of students at risk using around 15,825 samples from from Budapest University of Technology and Economics.

One of the main limitations of supervised learning based strategy in education sector is the availability of large number of quality training samples as detailed in Section 6. In order to overcome these limitations, a modified form of supervised learning, namely semi-supervised learning aiming to exploit partially labelled train sets for the classification tasks, has been introduced. For instance, Livieris et al. [25] proposed a semi-supervised learning based framework for secondary school students' performances. Similarly, Kostopoulos et al. [133] proposed a semi-supervised regression algorithm for prediction of students' grades in distance learning courses. Table 4 provides a list of some key papers based on supervised and semi-supervised learning techniques.

3.2 Unsupervised Learning

Unsupervised learning, which aims to discover or extract patterns of regularities and irregularities in a set of observations, has also been widely exploited in educational data analysis. Unsupervised algorithms process and discover hidden patterns in input samples without needing any training samples, and thus are easy to implement and deploy in an application. Unsupervised ML algorithms can be mainly divided into two categories, namely (i) clustering and (ii) dimensionality reduction techniques, which are further divided into subgroups. A detailed taxonomy of unsupervised ML algorithms has been provided in [125]. Clustering algorithms aim to divide a collection of samples into clusters or segments while dimensionality reduction algorithms are used to extract a smaller but more relevant set of features for building a more reliable model.

In literature, unsupervised learning especially clustering algorithms have been mostly used in educational data mining to extract useful information for a diverse set of applications from raw data [134–136]. Some of the applications of educational data mining in which clustering has been proved very effective include students' performance prediction [137], students' profiling and modeling [138], recommendation systems for students and instructors [110], enrollment management [139], constructing course contents [140] and analyzing students' behaviour [141]. Similarly, dimensionality reduction algorithms, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), have also been employed in educational data analysis. For instance, Borges et al. [142] employed PCA for students' performance prediction and data analysis. Similarly, LDA has also been employed in several works aiming to improve the quality of education [143, 144].

3.3 Reinforcement learning

At the beginning, reinforcement learning was mostly restricted to robotics and game theory, however, more recently it has been deployed in other application domains as well [125]. As can be noticed in Figure 3, a significant portion of literature, especially the work presented in top venues, is based on reinforcement learning. Reinforcement learning provides a set of recommended actions to maximize reward in a particular situation/application. Reinforcement learning differs from supervised learning in several ways. For instance, supervised learning algorithms are trained on class labels to predict a class while reinforcement learning algorithms are trained on a reward signal and predict/recommend an action to solve a particular problem. Moreover, reinforcement learning performs a task in a sequential way where the input depends on the previous decision.

Similar to supervised and unsupervised learning, reinforcement learning algorithms can be divided into different categories. Reinforcement learning algorithms can mainly be categorized as Markovian or evolutionary. A complete taxonomy of reinforcement learning can be found in [125].

In education, reinforcement learning has been mainly used for generating feedback for students on time series data [145], modeling students' learning style [146], personalized learning [147], adaptive tutorial modeling [148] and improving students' problem solving capabilities [149]. Table 4 lists some recent key papers employing reinforcement learning in different applications of AI in education.

Table 4: Some key papers from each category of AI discussed in this section.

Supervised Learning	**Unsupervised Learning**	**Reinforcement Learning**
[127–129, 147, 150, 151]	[110, 138, 142, 152–154]	[147, 148, 155–157]

3.4 AI Techniques in Education: Some Publication Statistics

As shown in Figure 3, algorithms from each of the three categories have been deployed in educational data analysis works presented in top four venues of the domain. It is important to mention that for this particular study, we analyze and categorize more than 1500 papers from these venues into the three categories of ML, namely supervised, unsupervised and reinforcement learning, to show the trend of research in ML-based education. The most common technique type by far is supervised learning followed by unsupervised learning and then reinforcement learning.

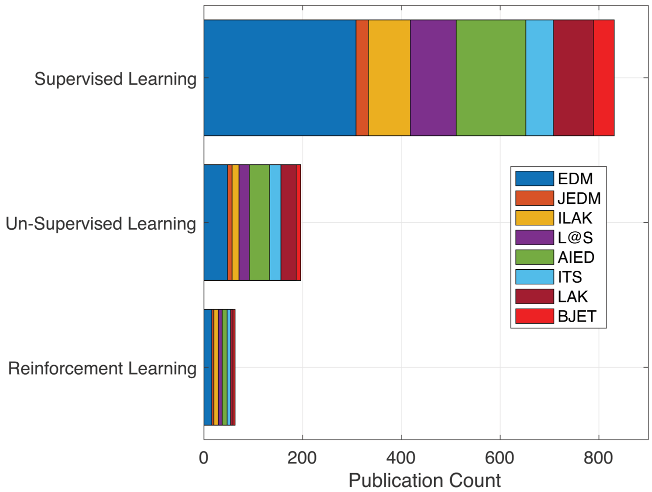

Fig. 3: Statistics of AI papers at different venues and techniques.

4 Market Players and Tools

There are numerous AI applications in education. The key market players are Pearson, IBM, Amazon, Nuance Communications, Cognizant, Quantum Adaptive Learning, Google, Microsoft, Third Space Learning, and Blackboard. Several tools and platforms have been developed by these organizations helping learners and teachers in different areas. In this section, we categorize these tools and platforms based on the application domains/areas of the education sector and describe key features of these tools. A taxonomy of these tools and platforms based on the application they aim to cover is provided in Figure 4.

4.1 Students' Grading and Evaluation

Automatic grading tools analyze, assess and score students' assignments and tests. Several tools are available to mark students' assignments and tests (including both yes-no and open-ended questions) at large scale. Some of the available tools are:

– *WriteToLearn [158]*: WriteToLearn's team believes in writing for learning, and the ultimate goal is to develop students' ability to summarize what

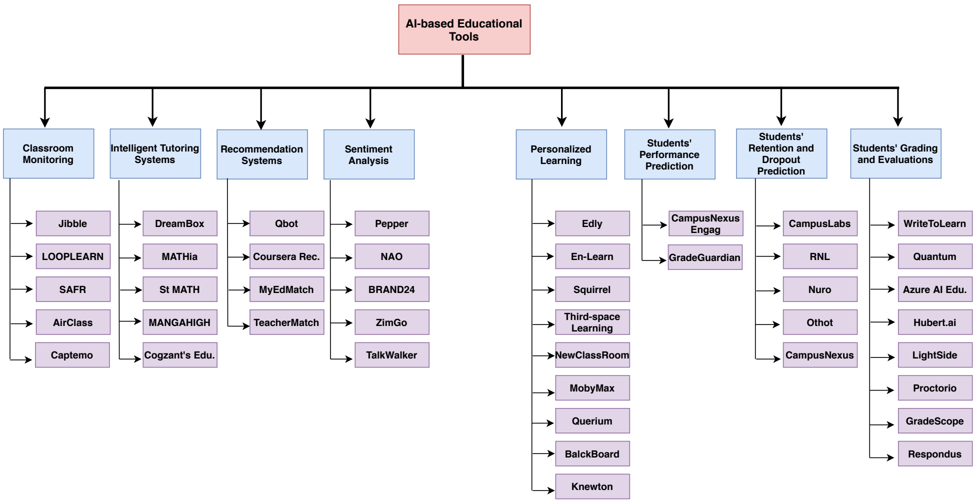

Fig. 4: A taxonomy of AI based educational tools and platforms

they learn. To this aim, a web-based tool has been provided for the evaluations of students' writing skills not only in terms of grammar and spelling but also in their understanding of the text.

– *Quantum Adaptive Learning and Assessment [159]*: Quantum uses artificial intelligence technology to interpret individual student work (not multiple choice answers) and explain why student answers are right or wrong with personal step-by-step feedback.
– *Microsoft's Azure Cloud AI Tools for Education [160]*: Office Graph API, Cognitive Services and Media Analytics can be combined with AI to provide deep analytical insights into student performances and then be visually displayed using Microsoft PowerBI dashboards.
– *Hubert.ai [161]*: offers a cognitive computing assistant takes test-taking a step further. The cognitive assistant effectively turns surveys into speaking tests by asking students follow-up questions. This in turn effectively personalizes assessment. Every response of the student is subjected to a deep learning-based text analytics model that automatically categorizes and analyzes feedback. It can evaluate important student skills and abilities such as creativity, imagination, ethical reflection, background reasoning and so on.
– *Turnitin's Lightside [162]*: The objectives of the tool are manifold. On one side, it helps students in developing their writing skills by providing them feedback and suggestions on their drafts. To this aim, it provides more than a spell checker by facilitating them to check and evaluate their writing skills not just to cross the t's and dot the i's, but also ensure their arguments and prose are logical and sound. On the other hand, it facilitates teachers to evaluate and mark their students' work.

- *Proctorio [163]*: Proctorio is a fully automated examination proctoring tool, which facilitates educators in several aspects of examinations, such as identification and verification of candidates' IDs, content protection and content analytics.
- *Gradescope [164]*: Gradescope makes use of AI algorithms to evaluate and grade exams as well as course work including assignment, quizzes, projects and technical reports. The tool is able to evaluate both: fixed templates and variable length assignments.
- *Respondus [165]*: Respondus is an online testing and evaluation tool specifically developed to facilitate creation of online exams questions and preventing cheating in online exams. To this aim, the platform provides a large collection of online exam questions via its exam tutoring tool. Respondus's technology can also be found in third party learning and assessment platforms.

A summary of some of the existing AI based grading and evaluation tools and platforms has been provided in Table 5.

4.2 Students' Retention and Dropout

Students' retention and dropout prediction tools facilitate educational interventions and remedial actions promptly. Some of such existing tools are:

- *Campuslabs [166]*: The tool employs state-of-the-art AI algorithms to provide actionable insights from campus-wide data for an early alert on students' retention. The tool can identify students at the risk as well as the potential reasons for students' retention, and supports them by identifying the most effective programs and best resources for the students.
- *RNL Student Retention Predictor [167]*: This tool helps administration in students' retention prediction and the students at the risk by allocating a score from 0 to 1 (.01 = very likely to persist and .99 = unlikely to persist) to each new student. The scoring mechanism allows the school administration to keep an eye on students and help them to allocate resources whenever and wherever needed to have an impact on retention. The tool also identifies the potential causes and the variables impacting student retention directly or indirectly on a campus.
- *Nuro Retention [168]*: In contrast to other retention predictors, Nuro retention team claims to cover different aspects of a student life-cycle with real-time data analytics capabilities to cope with different scenarios. The tool makes use of data from several datasets, such as CSI, MYSA, SYSA, SRP, which are combined and analyzed via state-of-the-art AI algorithms for students' retention prediction.
- *Othot [169]*: Othot makes use of data from different sources and employs advanced data analytics to facilitate different stakeholders in education throughout student life-cycle. The predictive analytics module of the tool employs state-of-the-art AI algorithms to provide actionable insights from

Table 5: Summary of tools/platforms for students' grading, retention and performance prediction.

Tool/platform	**Provider**	**Domain**	**Key Features**
WriteToLearn	Pearson	Generic (text only)	– Automated assessments, scoring system, and reporting to teachers – An immediate feedback to students to better practice – Focuses on summary and essay writing – Teacher as well as student reporting capabilities
Quantum Adaptive Learning and Assessment	Quantum	Generic	– Provides a question answer facilities where students can put their inquiry – Acts as a cognitive coach observing the thinking and questioning expertise of the students
Azure Cloud AI Tools for Education	Microsoft	Computer Science	– Facilitates all stakeholders in the education sector including students, teachers and administration – Provide deep analytical insights into student performances and then be visually displayed using Microsoft PowerBI dashboards – Coding courses and tutorials – Helps students to pursue careers in technology or other fields
Hubert.ai	Hubert	Generic	– Makes use of chat-bot technology and AI to engage and extract actionable insights from students' personalized conversations – Provides an attractive user interface – Able to extract qualitative insights from its personalized conversations with students – Posses the ability of intelligent follow-up questions
Lightside	Turnitin and Carnegie Mellon	Text only	– Evaluates of students' writing – Provides feedback on the use of language, focus of the document, organization and evidence – Specially customized for students in grades six through 12
Proctorio	Proctorio	Generic	– Fully automated exam proctoring without scheduling 24 hours a day, 7 days a week – Supports automatic ID verification – Provides admin dashboard and aggregates exam data – Ensures content protection with copy/print/download restrictions
Gradescope	Turnitin	Multiple subjects	– Supports grading of paper-based, digital, and code assignments – Also provides insights on students' performances – Covers multiple subjects
Respondus	Respondus	Generic	– Supports both K-12 and higher education – Uses LockDown Browser to prevent cheating – Creates exams questions

data, which facilitates all stakeholders in decision making regarding enrollment and students' retention. The tool also identifies the potential areas to be focused on and to allocate more resources for a greater impact.
- *CampusNexus Succeed [170]*: CampusNexus Succeed is an institution-wide engagement platform with specialized students' retention functionality using state-of-the-art AI algorithms. The fusion of AI and advanced predictive analytics makes it a preferable choice for educators to monitor and identify students at the risk, and modify the policies and re-allocate the resources accordingly.

A summary of some of the existing AI-based tools and platforms for students' retention, drop out and performance prediction has been provided in Table 6.

4.3 Personalized Learning

Personalized learning tools and platforms use AI algorithms to scaffold instruction based on the student's previous knowledge and level of understanding. Some of the existing AI-based educational tools and platforms that support personalized learning are:

- *Edly*: Edly is equally useful for both teachers and students providing them actionable insights via learning analytics. The tool makes the learning process smoother and better than ever by employing AI algorithms in different aspects of the learning analytics. On one side, it allows teachers to keep track of students' progress throughout the course. On the other side, it helps learners by designing the course contents according to the learner's capacity.
- *EnLearn [171]*: Provides a complete adaptive learning ecosystem by involving all stakeholders, such as students, teachers and curriculum, in creating personalized content. Moreover, the platform can extend the content for targeted students instead of just shuffling the content.
- *Squirrel [172]*: Powered by its proprietary AI-driven adaptive engine and custom-built courseware, the Squirrel AI Learning platform provides students with a supervised adaptive learning experience.
- *Third Space Learning [173]*: Aims to help students in mathematics with personalized content and premium maths resources. The tool is also able to pay more attention to target students, and provides weekly reports on their progress. The tool assess all the registered students and develops personalized materials for each of them before proceeding with the training.
- *NewClassrooms [174]*: Uses learning analytics to schedule personalized math learning experiences.
- *MobyMax [175]*: MobyMax uses AI to pinpoint and fix learning gaps with adaptive and differentiated learning materials for all K-8 subjects. Students can learn at their own pace with lesson plans and practice sheets that are automatically generated for them.

Table 6: Summary of tools/platforms for students' retention, drop out and performance prediction.

Tool/platform	Provider	Key Features
CampusLabs	CampusLabs	– Integrates data from different sources to cultivate campus intelligence and make better decisions. – Identifies students at risk – Special supports for targeted students – Strengthen educators' ability to guide students on their pathways for success.
RNL Student Retention Predictor	RNL	– Poses accurate assessment capabilities and extracts actionable insights from data obtained from different sources a – Its predictive analytics identifies students who need special attention and help – Helps in developing strategies that increase efficiency and the impact of retention efforts – Helps administration to recruit and retain the right students
Nuro Retention	Nuro	– Efficient predictive analytics helps educators in engaging each student – Identifies students at the risk and also provides insights on the reasons for it – Helps educators in devising strategies and acquiring tools and other resources that will have a positive impact on students' graduation and retention results – Can be customized to an institution's needs
Othot Retention Predictor	Othot	– Real time and dynamic predictions – Identifies the individuals who needs more attention – Recommends actions and devise strategies that will have the greatest impact on an individual's performance – Affordable tool showing educators where to focus resources
CampusNexus Succeed	Campus Management	– Tracks each students engagement and progress – Identifies and prioritizes students based on the risk level – Flags and allows a teacher to respond to alerts from other teachers

- *Querium [176]*: Querium uses AI in their company to help students with STEM skills so they can be ready for further studies. The platform delivers personalized, bite-sized lessons and step-by-step tutoring assistance.
- *Knewton's Alta [177]*: Alta is an adaptive learning tool/platform providing personalized content to students in the fields of science, technology, engineering and mathematics. The tool makes use of AI to create personalized learning content from openly available high quality content, leading to high quality affordable and world-wide accessible personalized learning materials.
- *IBM Watson Content Analytic [178]*: Watson's cognitive capabilities are available to millions of college students and professors, which makes use of

AI to improve learning outcomes. It helps all the students to succeed by ensuring personalized content for students based on mastery.

Table 7 provides a summary of the existing personalized learning tools in terms of provider, the domain/subject they cover as well as their key features.

4.4 Students' Performance Prediction

Students' performance prediction tools help to analyze and predict a student's potential performance in examinations.

- *CampusNexus Engage [179]:* It makes use of advance AI and business analytics to enhance engagement and drive students' and institutional success. CampusNexus engage provides several services including predictive analysis to predict students' performance.
- *GradeGuardian [180]:* GradeGuardian provides a complete solution for modern education challenges, and supports different stakeholders including policymakers, educators, advisors and students. It makes use of advance AI algorithms to predict schools' and students' performance in both short and long term along with other services critical for the modern education.

4.5 Sentiment Analysis in Education

Sentiment analysis tools can help to improve the learning process in an e-learning environment and a classroom by analyzing the opinions and facial expressions of the students in order to better understand their opinion and emotions, and make adjustments to the content or delivery of the learning material accordingly [47]. Some of the existing sentiment analysis tools developed or customized for education are:

- *SoftBank Robotics's Pepper [181]*: It is mainly developed for interaction with human and personalized recommendations. Pepper posses face and basic human emotions/expressions recognition capabilities and engages human in an interactive conversation. Pepper could be optimized for any business domain including education.
- *SoftBank Robotics's NAO [182]*: Similar to Pepper, NAO is intended to help businesses in dealing with their customers/visitors'. Though it is adopted by other businesses and health care centers, NAO is widely used in education and research. NAO is equipped with several touch sensors, microphones and speech and object recognition capabilities.
- *BRAND24-AI-Driven Sentiment Analysis [183]*: Brand24 is a general purpose sentiment analysis tool, which can be deployed in different application domains including education. The tool can help the educators in several ways. For instance, it could be used to detect students' negative feelings about the learning process, and the teaching process can be adjusted before these feelings overwhelm students' attitude towards learning.

Table 7: Summary of AI based tools/platforms for personalized learning.

Tool/platform	Provider	Domain	Key Features
Third Space Learning	Third Space Learning	Math	– Special attention to target students based on their weaknesses – Provides weekly online lessons – Personalized learning by adapting the tutor to a student's needs with weekly reporting – Provides access to premium maths resources
Alta	Knewton	Math, statistics, economics and chemistry	– Available for multiple courses including mathematics, statistics, economics and chemistry. – Provides personalized content in terms of text, visual and audio – Affordable and world-wide accessible – Provides secure and turnkey integration with any learning management system and comply using WCAG 2.0 ADA standards for accessibility
EnLearn	EnLearn	Generic	– Personalized content via an adaptive learning ecosystem involving students, teachers and curriculum – Can increase content for target students – Able to identify misconception and remedies in the learning process
IBM Watson Content Analytic	IBM	Generic	– Provides personalized content for students – Vocabulary learning applications – Helps teachers to track students' progress – Conducts real time assessments and provides insights to instructors – Addresses the high-tech skills gap
Querium	Querium	Generic	– Uses AI to help students with STEM skills so they can be ready for further studies – A personalized program is called Step-Wise and it works on smartphones and computers – Delivers personalized, bite-sized lessons and step-by-step tutoring assistance
Edly	ArbitSoft	Generic	– Supports students of all ages including K-12 and Higher education – Provides training management of different stack-holders of the education
Squirrel	Squirrel	Chinese, Math, English, Physics, and Chemistry	– Squirrel AI Learning offers the high-quality after-school courses in subjects such as Chinese, Math, English, Physics, and Chemistry. – Provides students with a supervised adaptive learning experience
MobyMax	MobyMax	all K-8 subjects	– MobyMax platform is widely adopted in the U.S. – Uses AI to pinpoint and fix learning gaps with adaptive, differentiated learning materials for all K-8 subjects. – Students can learn at their own pace with lesson plans and practice sheets that are automatically generated for them.

Table 8: Summary of tools/platforms for sentiment analysis in education.

Tool/platform	Provider	Key Features
Pepper	SoftBank Robotics	– Can answer visitors'/costumers' queries – Helps administrative staff to performing routine tasks – Engages visitors in an effective conversations and provides personalize responses
NAO	SoftBank Robotics	– Informs and entertain visitors – Provides an optimized teaching-aid tool – Effective tool for special education ("students with disabilities such as autism, emotional and behavioural disorders" [187])
ZimGo Emotional Intelligence	ZimGo	– Recognizes and differentiates in human emotions from text – Employs state-of-the-art AI and NLP techniques – Poses Contextual Analysis capabilities – Can be customized for any application
Talkwalker	Talkwalker	– An effective social listening and analytics tool – Helps educators to promote their college and university – Poses user-generated content detection capabilities – An influencer identification tool

– *ZimGo [184]*: ZimGo is another sentiment analysis platform, which could be used in education for different purposes. The tool employs state-of-the-art AI and Natural Language Processing (NLP) tools to extract and analyze people's response, attitude and feelings towards a service. More recently, the tool has been customized to continually monitor students for signs of stress and depression based on the information obtained from social networks of students from low income backgrounds.
– *Talkwalker [185]*: Talkwalker is another sentiment analysis tool that has been employed in education. The tool in general monitors social networks and extracts meaningful information. The tool can help educators in social analytics to promote their institutions in a better way [186].

In Table 8 we summarize key features of some of the existing tools for sentiment analysis in education.

4.6 Recommendation Systems in Education

Some existing recommendation systems in education are:

– *Qbot [188]*; Qbot, which a joint venture of Antares Solutions, Microsoft and the University of New South Wales, Sydney, is an AI-based chatbot that helps students in several ways. It engages students in an interactive conversation and answers their questions. QBot uses AI to build a learning platform accessible to students 24 hours a day. The tool also recommends students different learning online sources and materials to benefit from.

Table 9: Summary of AI based tools/platforms for recommendation systems in education.

Tool/platform	**Provider**	**Key Features**
Qbot	Antaras (in collaboration with Microsoft and UNSW, Sydney)	– Tags tutors and classmates to answer students' questions – Recommends contents individual students based on their current level of knowledge – Provides students' analytics
MyEdMatch	MyEdMatch	– Connects schools and teachers having shared beliefs and goals – Helps schools to recruit best talent – Helps teachers in searching jobs
TeacherMatch	Power School	– Uses AI for real time analysis of the candidates in the pool maintained by the platform – Assess teachers on four factors including teachers' qualification, teaching skills, cognitive abilities and attitudinal factors

- *Coursera-Recommendation Tools for Courses*: Though it is very challenging to find details on what exactly they use, Coursera seems to have an AI-based recommendation system to recommend courses to students based on the initial information provided in terms of students interests. In the recommendation process, the system also considers the current level of students' knowledge as well as the current courses registered by the students.
- *MyEdMatch [189]*: MyEdMath helps educators to find their perfect match by connecting schools and teachers with common goals, beliefs and interests. The tool is equally useful for administrators and teachers, and makes the recruitment process smoother and faster.
- *TeacherMatch [190, 191]*: TeacherMatch relies on AI for real-time analysis of the candidates in the pool maintained by the platform. The assessments are mainly based on four factors, namely teachers' qualifications, teaching skills, cognitive abilities and attitudinal factors. To this aim, the platform maintains an inventory namely Educator's Professional Inventory (EPI) for the prediction of teachers' impact on students' achievement. Using AI techniques, the platform pinpoints useful insights in knowledge, skills, abilities, experiences and other characteristics crucial for teachers' effectiveness in a certain context.

Table 9 summarizes some existing recommendation systems in education for both students and teachers.

4.7 Classroom Monitoring and Visual Analysis

- *Jiblle Attendance Platform [192]*: Jibble is an AI-based attendance platform that utilizes data from several sources, such as students' photos and GPS data. The tool employs state-of-the-art facial recognition algorithms along with the GPS data to ensure a reliable and cheat-free attendance

system. The tool also retrieves and generates time-sheets and reports with actionable insights on students' attendance.
- *LOOPLEARN: Automated Attendance Keeping [193]*: LoopLearn employs AI and Computer Vision (CV) techniques to automate the school attendance relieving the school administration from the tedious job of marking students manually. The tool also generates insightful reports on students' attendance.
- *Secure Accurate Facial Recognition (SAFR)*: SAFR is a general-purpose AI and AI-based facial recognition tool for different applications, such as security, convenience, and analytics. It is also customized for schools to ensure the security of school kids by allowing authorized people to pick students from schools. To this aim, the photos of students' parents or guardians have been added to a database, and the doors of the school are opened only if the tool recognizes an individual.
- *AirClass*: Airclass is a facial expression and emotion recognition system that aims to automatically analyze students' responses to a lecture. The tool makes use of state-of-the-art facial expression recognition algorithms and can detect whether students' eyes are opened or closed during a lecture. Moreover, it analyzes students' interests and commitment in learning through facial emotion recognition and analysis.
- *Captemo: Emotion Recognition [194]*: Captemo is another AI based emotion and expression recognition tool used for emotion recognition in a classroom for different purposes. For instance, the tool can help teachers and tutors by providing feedback on the effectiveness of their teaching and lecture materials. It also helps educators to monitor the behavior of their students in classrooms.

Table 10 summarizes the classrooms monitoring systems presented in this section.

4.8 Intelligent Tutoring Systems

- *DreamBox [195]*: Relies on AI techniques to track and improve students' analytical skills and decision-making capabilities. It is mainly developed to help learners in mathematics in a systematic way promoting learners' growth and deeper conceptual understanding by allowing them to solve a problem in different ways.
- *Carnegie Learning's MATHia [196]*: MATHia is named the best AI solution in 2019 (EdTECH Awards [197]). AI-powered MATHia is the closest to a human coach. It uses AI and cognitive science to mirror a human tutor. MATHiaU was intentionally designed by a team of cognitive and learning scientists with one goal: delivering a better math learning experience to every development in Math student.
- *ST Math [198]*: A game-based Pre K-8 visual instructional program leveraging brain's innate spatial-temporal reasoning ability to solve mathematical problems. The tool provides students with a unique experience of learn-

Table 10: Summary of AI based tools/platforms for Classrooms' Monitoring.

Tool/platform	**Provider**	**Key Features**
Jibble Attendance Platform	Jibble	– Provides an accurate attendance mechanism with bio-metric verification – Tracks tttendance with Phones and Tablets – Prevents cheating with the use photos, facial recognition and GPS – Generates automatic attendance sheets and reports with actionable insights
LoopLearn	LoopLearn	– Provides secure and efficient roll marking facilities by allowing designated school staff only to access the tool – Generates automatic attendance sheets and reports with actionable insights – Can be customized to the needs of other departments of a school, such as sports, peripatetic and excursions by adding additional features
Secure Accurate Facial Recognition (SAFR)	SAFR	– A general purpose AI based facial recognition – The tool is customized for K-12 schools with facial recognition of students' parents to allow them to enter the school
AirClass	AirClass	– Analyze students' response to a lecture automatically – Detects whether students' eyes are opened or closed during a lecture – Also analyzes students' interests and commitment in learning through facial emotion recognition and analysis.
Captemo: Emotion Recognition	Captemo	– A general purpose tool that analyzes customers' experience through emotional intelligence – Embedded with state-of-the-art facial and emotion recognition algorithms – Supports both: a continuous and on-demand monitoring capabilities

ing through solving challenging puzzles and non-routine problems and informative feedback on their approaches.

- *MANGAHIGH [199]*: Another game-based tool/platform for students to excel at mathematics excitedly by involving them in puzzles, interactive games and social competitions.
- *Cognizant's tools for Education [200]*: Aims at learning and better students experience across all aspects of students' journey, including admissions, onboarding, learning, assessments, e-credentialing, and reporting. To this aim, it relies on a fusion of modern technologies, such as Virtual Reality (VR) and AI.

Table 11 provides a summary of the intelligent tutoring systems presented in this work.

Table 11: Summary of AI based tools/platforms for Intelligent Tutoring Systems.

Tool/platform	Provider	Domain	Key Features
DreamBox	DreamBox Learning	Math	– Available in two languages namely English and Spanish – Provides a game-like environment engaging students in analytical problems – Pinpoints real time data and academic insights – Customized professional development aligned with curriculum
MATHia	Carnegie Learning	Math	– Delivers a successful math experience to each individual student – Provides teachers with a real-time feedback and assessments of their students
STMath	MIND Research Institute	Math	– Can be used by the administrators, teachers and parents to track students' knowledge – An attractive user interface involving students in learning through solving puzzles and challenging problems – Provides valuable feedback to learners on their approaches
MANGAHIGH	MANGAHIGH Westerman	Math	– An attractive user interface – Involves students in challenging puzzles, interactive games and social competitions – Can be aligned to any curriculum – AI-based real-time analytics and feedback
Cognizant	Cognizant	Generic	– Make use of AI to improve students' access to education (admissions), experience and success – Provides testing and assessments services – Personalized content

5 Bibliometric Analysis

AI application in education is rapidly transforming the research and education sector. These applications are redefining the roles of teachers as well as students. The sheer importance of this domain in the development of the education sector makes it timely to analyze the research trends in AI applications in education.

To analyze the research trends in AI in education, we used 2929 articles from the top venues including five conferences and three journals in the domain. The choice of the these venues for the study is motivated by significant portion of the literature covered in these venues. The data used in the analysis include 663 articles from International Conference of Educational Data Mining (EDM) [9], 87 article from the Journal of Educational Data Mining (JEDM) [119], 393 articles from the ACM Conference on Learning at Scale

(L@S) [120], 406 articles from the International Conference on Learning Analytics & Knowledge (ILAK) [118], 225 articles from International Conference on Artificial Intelligence in Education (AIED) [121], 235 articles from International Conference on Intelligent Tutoring Systems (ITS) [122], 180 articles from Journal of Learning Analytics (LAK) [123], and 740 articles from British Journal of Educational Technology (BJET) [124]. These numbers from the top venues are expected to provide a reasonable generalization of the research trends in the domain. The data was obtained from various sources, including ACM Digital Library [201], Scopus [202] and CrossRef [203]. Data from the CrossRef repository were scraped using Harzing's Publish or Perish' utility [204]. In detail, we analyze four factors namely (i) authors based productivity analysis, (ii) institution and country-wise productivity analysis, (iii) knowledge flow by highlighting the cross-references of different venues, and the (iv) relationship between the applications and techniques.

5.1 Authors based Productivity Analysis

Author productivity is one of the common methods to evaluate the significant entities. By consulting the work of top authors in a domain, the directions of a research domain can be easily determined. In this subsection, we analyze the top publishing authors in the domain of educational data mining (EDM). We also analyze the trend of co-authorship among EDM researchers.

Figure 5 shows the most publishing authors in the field of educational data mining. We observe that authors from USA based organizations are significantly contributing to the field of Educational Data Mining. Neil Heffernan from Worcester Polytechnic Institute, Ryan S.J.D. Baker from the University of Pennsylvania, and Kenneth Koedinger from Carnegie Mellon University are collectively ranked as top three authors in the field of Education Data Mining. Most of the subsequent authors on the list also belong to USA based institutes.

With advancements in Information and Communication Technologies (ICTs), distances are virtually eliminated around the globe. These advancements encourage researchers from different geographical, economic, cultural backgrounds to work with each other collaboratively.

We also observe the trends of co-authorship in EDM in Figure 6. Median number of authors during 2014–2019 remains consistently 3 authors per paper but the spread of authorship increases in recent years. Some papers have experienced a higher number of co-authorship as well, e.g., in 2014 and 2018 maximum number of authors of a paper is 13 authors.

5.2 Institute and Country based Productivity Analysis

This subsection deals with the varying research trend of EDM in different institutes and countries. Published research is a crucial factor in determining the quality of education and research at any institute. Figure 7 show the

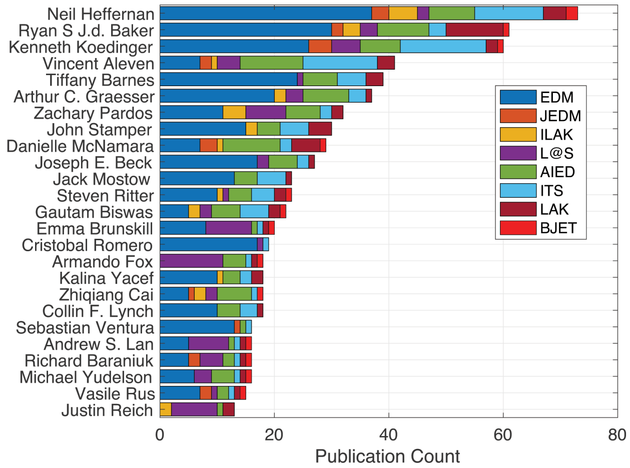

Fig. 5: Authors with the highest publication count during 2014–2019. *USA based authors appear to be prominent in this list.*

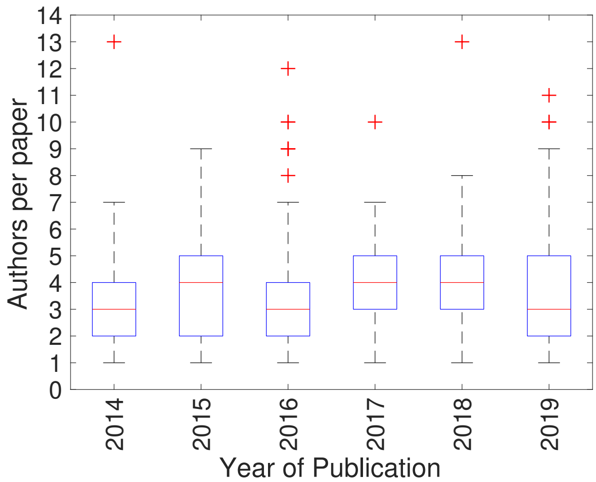

Fig. 6: Distribution of authorship during 2014–2019 in our dataset. *Although median number of authors remained consistent throughout the mentioned time period but spread of co-authorship increases in recent years.*

most publishing institutes in the field of Educational Data Mining. Almost all of the top institutes are from the USA which shows the significant research contributions in this domain by the USA.

In a research domain, some countries play a pivotal role in driving the ongoing advancements in a particular field. Figure 8 shows the rank of a con-

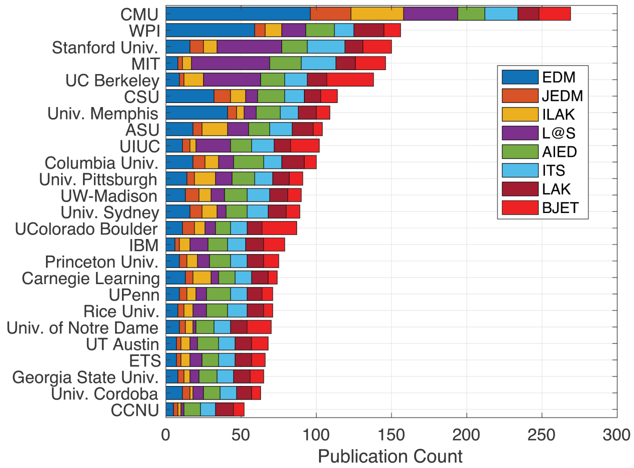

Fig. 7: Institutes with highest number of publications in our dataset during 2014–2019. *Almost all of the top publishing institutes are from USA.*

tributing country in the field of educational data mining using a global heat map. The United States is in the highest position in the field of EDM in terms of publication count. Other top countries include China, Canada, India, and the United Kingdom in educational data mining.

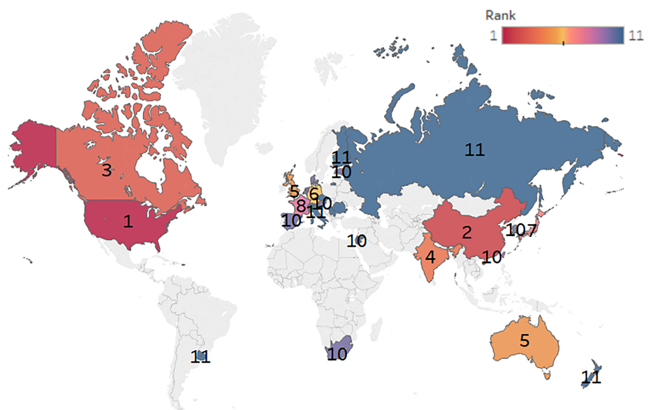

Fig. 8: Rank of countries based on their publication count in our dataset during 2014–2019. *USA emerges as top contributor followed by China, Canada, India, and Australia/UK.*

5.3 Knowledge Flow

First, we extract the references from all papers and create a citation graph, as we are curious to understand how venues in educational data mining cite each other. Figure 9 is a Sankey diagram that shows the fraction of papers that EDM papers reference (left), as well as the other papers that in turn cite the papers in our dataset (right).

Interesting patterns emerge from this analysis. Most noteworthy is the bias for citing papers from the same venue. For example, 26% of references in EDM papers are for other papers previously published in the EDM conference. In contrast, a far more diverse body of papers list publications from our dataset in their references, particularly other conferences (57% of the papers in our dataset which cite EDM venues are journals, rather than conferences). Major citers of papers in our dataset include Computer & Education and LNCS (which subsumes many proceedings) besides their selves.

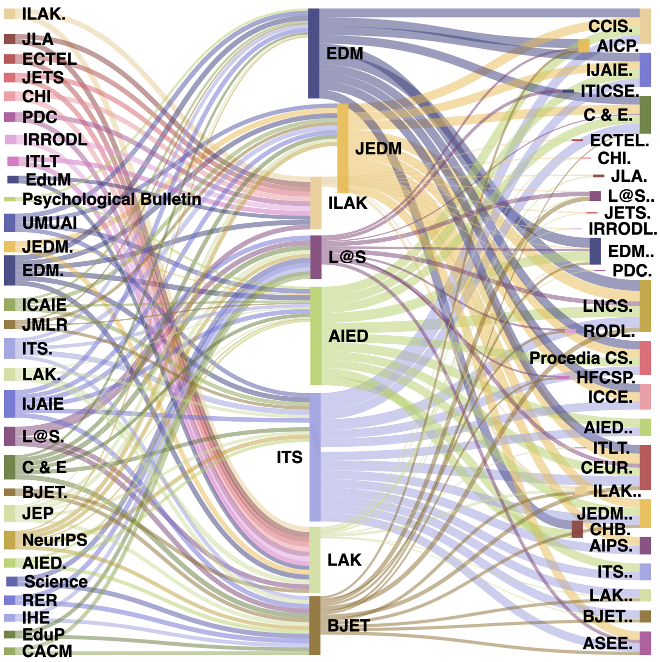

Fig. 9: The distribution of references and citations in educational data mining venues during 2014–2019. The left input shows the conferences that are referenced by our dataset; the right output shows which papers cite publications in our datset. *Major source of references and citations in our dataset are from journals.*

All that said, it is clear that several other publication venues feature heavily in the bibliographies of papers of our dataset, and these are dominated by journals rather than conferences.

5.4 Relationships between Applications and Techniques

It is also important to provide readers with an overview of AI techniques employed in different applications of AI in education. To this aim, in Figure 10 we provide the statistics of three main categories of AI techniques in terms of the number of publications in different applications in top venues. As can be observed, in most of the applications, supervised or semi-supervised techniques learning have been employed suggesting the availability of the annotated data in the majority of the applications. Unsupervised learning techniques have also been widely employed in some of the applications, such as e-learning, students' evaluation, ITS and personalized learning. Similarly, reinforcement learning has also been employed in several works on ITS, students' evaluation and retention and dropout prediction.

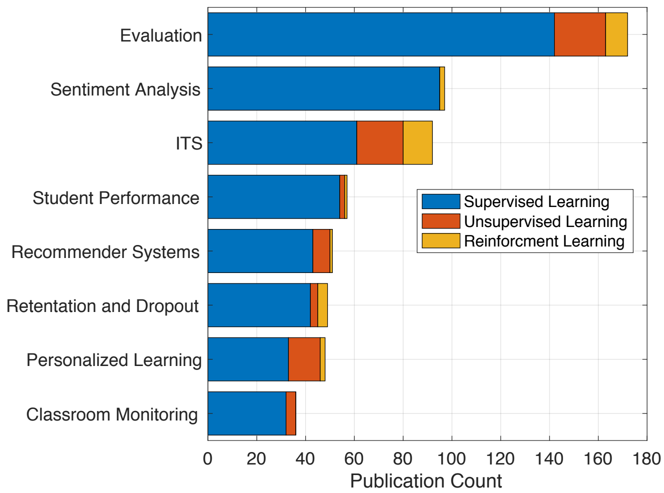

Fig. 10: Relationship between applications and AI techniques.

6 Discussion: Insights, Pitfalls, Future Research and Open Issues

6.1 Insights

The impact of AI on education is expected to continue to rise. In fact, education has become highly dependant on information technologies and the ability of these technologies to integrate diverse information from diverse sources. Integrating AI in education is becoming a necessity rather than a luxury. It is universal rather than local. It is hard to imagine an area in education that can ignore what AI can offer to solve many of the current and future problems in education. For example, safety and security issues in schools are obvious and AI can contribute to solving many of such problems. A safer school, classroom, cyberspace educational environment can be possible by the integration of AI. In the next subsections, we provide some insights from the literature on the use and pitfalls of AI in education.

6.1.1 Changing Roles of Humans and Machines in Education

Authors of [205] argue that, from the perspective of students, AI technology can make their teachers better because they will be better equipped to teach while aware of students' needs. However, technology advancements in AI might eventually change the roles of teachers substantially with their traditional duties of knowledge dissemination changing to becoming coaches focusing on assessment, mentoring, and monitoring. To this aim, they will need to develop new skills, such as an in-depth understanding of the new education system offered by modern technologies and AI.

- *AI is a Learning Catalyst*: In terms of AI as a learning catalyst, it is suggested that AI-powered systems will become smarter in their learning and will contribute greatly to the learning process, especially for children. These systems will focus on individual learning requirements tailored to the needs of each student, for example, writing, reading, social or soft skills with fleets of AI-based instructors serving the education needs of future generations without sick leave, maternity leave or tardiness.
- *An Implementation Example—Robot Teachers*: There are many examples of implementation success for robot teachers including Elias which is a language teacher at a Finnish school, and Jill Watson which is virtual teaching assistant at a US university [206,207]. Elias is patient, considerate and entertaining, Jill Watson's students is quite advanced in her human like responses that most students never realized there questions were being answered by a robotic program.

  Robot teachers are reliable in their ability to cover the list of topics with perfect consistency and without fail; research has shown that they are not disruptive and they can offer positive feedback to human teachers for innovative teaching in the classroom. Some of the challenges associated with using robots as teachers include: Short on the specific human touch which includes real and natural reactions to complex human tendencies; lack of creative sense and ability to exert control or enforce discipline in the classroom; the special teacher-pupil bond constructed over several school years and passed from generation to generation is hitherto, very difficult to incorporate in the algorithms and models that operate within robot teachers.

  Many experts believe machines will be better than humans at most tasks within nine years. AI is rapidly growing in a way that puts human job security in many sectors at a real risk. Reports from Oxford and Yale concluded that AI will outperform humans in several activities soon, for example, language translation within 5 years, essay writing at high-school level within 7 years, driving including passenger bus and truck within 9 years, various retail tasks within 12 years, writing a bestseller novel within 30 years and performing complex surgery autonomously within 35, opening avenues of discussion about new ethics perspectives relating to robot rights [208].

Robots will not, however, be replacing teachers soon because they lack the dynamic, creative ability to inspire students. “In a world where young people are retreating more and more into virtual unreality, the teaching profession has become more important than it ever was. It is human teaching that keeps it real – teaching that keeps young people alive” [209].

As an intermediate stage, AI technology can support human teachers to boost their teaching effectiveness by enabling them to obtain greater insights into student needs and requirements each according to their individual circumstances with minimal human effort overhead. Still, there are known risks associated with moving forward at a pace that is too high in implementing AI solutions for teaching including the loss of the human traits of creativity, diversity, compassion, fun and out-of-the-box thinking, hence the shortages in quality teaching staff in most developed countries.

6.2 Limitations of AI in Education/Learning

Over the last few years, AI has revolutionized the education sector by providing outstanding performances in different application domains. Data analytics and mining techniques developed over the years have contributed to improving the overall quality of the education system to a great extent. For instance, AI-based interactive tutors and personalized learning programs are helping students a lot. Similarly, AI has significantly reduced the administrative tasks in the education sector. However, AI alone is not enough to fulfill the requirements of modern education. There are several aspects of education where AI alone can not contribute much. The limitations and pitfalls of AI in education can be mainly divided in terms of technological and social aspects.

The technological pitfalls of AI in education are either due to conceptual/algorithmic limitations or because of the training data. Some of the pitfalls are listed below.

- *Failure in the extraction of interpretable and actionable insights*: AI alone is not enough to fully understand and extract interpretable and actionable insights from the educational data to improve students’ learning. For instance, in [210], several case studies have been reported where simply AI based predictions are not enough to understand and improve the learning process. The authors, rather propose an explanatory learning model by employing Human-Computer Interaction (HCI) and AI (i.e., model interpretation approaches at the interpretation stage [211]) techniques to derive insights from the students’ learning experiences and suggest how the technology could be made more useful for the learners.

- *Failure in generation of course content*: All AI techniques can do is to recommend a particular chapter/course content to a student at a time stamp (i.e., alter the sequence of the course materials). According to Popovic [212], presenting the same material in a different sequence has little impact on the learner's performances, and the real game changer is the generation of course content on the fly, which is a very challenging task.
- *Lack of clarity and flexibility in teaching of virtual teachers (Robots)*: Though content and learning analytics contributed to a greater extent in creation of personalized content; however, there are concerns about the clarity and flexibility in teaching or the way content are delivered by virtual (robots) tutors/teaching assistants. Moreover, teachers motivate students to learn and master a course. However, robots lack in such capabilities.
- *Lack of training data*: The strength of AI techniques comes from training data, which has significant impact on their prediction capabilities. However, it is very challenging to acquire sufficient amount of training samples for AI algorithms in a sensitive and high-stakes environment, such as education sector, where one can't afford any risk with students [212].
- *High risk due to biased data*: AI algorithms need precise and sound data to be more effective. According to Calhoun Williams [212], a high risk of biases is involved with AI in education, where it is very much probable to reach to false conclusions due to inaccurate predictions.
- *Security concerns*: The increasing dependence on AI will also lead to serious privacy concerns [213]. The institutions would need to focus not only on quality but also on data privacy. According to Calhoun Williams [212], in schools data need to be carefully handled and the administrations need to be ready for AI from a policy standpoint.

There are also some drawbacks of AI in education that are not directly linked with the limitations of the AI algorithms rather their negative impact on the society. Some of such pitfalls of AI are:

- *AI may put students (kids) at risk*: Deploying AI at school level may results in kids' addiction to technology, such as phones and tablets, which may harm their health and personalities. The use of technology in learning also limits interaction with fellows and teachers which may result in isolation. Moreover, the deployment of AI in education may also result in students' dependency on machines to solve every problem that may risk their creativity and problem-solving capabilities.
- *Enlarges the rich versus the poor rift*: Deployment of AI in education will increase dependence on the expensive technology that might deprive the poor of quality education.
- *Increases the cost of power*: Incorporating AI in education results in more consumption of power which will ultimately increase schools' budgets.
- *It causes joblessness*: Similar to other sectors, deployment of AI in education at large scale will reduce the workload significantly, which may result in joblessness. As mentioned earlier, AI could be deployed at different tasks in education, such as administrative tasks, teaching and security.

Deployment of technology in these tasks may significantly reduce human labor.
- *Isolation and Individualization* : AI in education may also lead to isolation and individualization instead of collective learning and teaching.

It is evident from the above discussion that several factors need to be considered while deploying AI in education. Moreover, it is also very important to define the aspects and levels at which AI could be deployed in the education sector.

6.3 Future Research Directions and Open Issues

In this section, we provide some potential directions of future research in the domain. We classify the open directions of research on AI in education into four main areas:

6.3.1 Teaching Methods and Pedagogy

- *Customized Teaching Pedagogy*: Research is still needed to identify the best teaching pedagogy that suits each learner skills and interests. A customized teaching pedagogy which offers effective adjustments could help students in grasping new concepts and course materials effectively [214].
- *Technology Integration in Classroom*: In most cases, technology products (hardware/software) are brought into classrooms using a trial-and-error model. Teachers are asked to integrate technology into curricula and learners are asked to use technology in learning almost all subjects. Developing a model for effective technology integration is critical and challenging due to many reasons. Technology products, learners' skills and interests, and knowledge areas are very diverse. Also, researchers usually focus on the benefits of integrating technology in classrooms and the best ways to achieve the most integration [215]. However, it is intuitive to say that there are possible and sometimes clear negative impacts that can't be ignored when it comes to technology integration [216]. This makes the development of an effective AI model for technology integration a challenging task which requires attention by researchers.
- *Personalized Tutoring*: How to provide personalized tutoring and real-time feedback beyond math topics for diverse levels of learners? A good example is Carnegie Learning's "Mika" software for MathiaU which is designed to deliver a better math learning experience to every developmental Math student [217]. This includes the need to design personalized AI-based tutoring robots [218].

6.3.2 Supporting Educator Effectiveness

- *Minimizing Biased Evaluation*: One of the main challenges that each educator face is how to minimize personal biases when it comes to grading and evaluation. This stems from the fact that human behaviors are hard to predict when it comes to relationships and judgement [219]. Relying on AI can reasonably help in protecting against internal biases by offering an insight on student's performance based on data. However, designing AI techniques that can help in minimizing biased evaluation while keeping teacher's attitudes is mind is not easy and requires careful considerations.

- *Identifying Students at Risk*: Detecting alarming patterns and potential risk of students to drop out is an important area where AI can play a key role.
- *Scheduling Efficiency*: Optimal learning is connected to optimal scheduling of learning lessons and activities [220]. Knowing the best way to design optimal teaching schedules is challenging due to the contributing factors such understanding how people learn (cognitive psychology, knowledge retention, etc.), topic, age, level of learner, availability of qualified teachers, availability of resources such as physical space, etc. AI modeling for an optimized and adaptive teaching policies when it comes to effective scheduling is an area of research. In [221], authors proposed online job scheduling using AI. Such efforts can help in understanding the need for effective scheduling of learning lessons.

6.3.3 Improving Education Systems

- *Predicting Student's Future*: Developing AI solutions to predict the best career paths and specialization areas is challenging due to the diversity of students backgrounds, skills, biological differences, environmental aspects, needs, etc. A comprehensive AI software application is needed to intelligently predict a student's future and the most suitable career path selection. The study in [222] highlights a study that shows the power of AI in predicting employment at graduation.
- *Mistakes Implications*: In education, the consequences of making mistakes can be serious. When AI is used in making decisions, it is critical to identify the potential consequences and risks at different levels. If the AI algorithm recommends the wrong reading or inappropriate clip to students, it can lead to serious social or economic issues. Therefore, AI in education researchers need to integrate a risk factor to quantify potential mistakes and errors implications of implementing any AI technique in education.
- *Generation of Course Contents on the Fly*: AI techniques have been proved very effective in course content recommendations. However, it will be very interesting to investigate how AI can be employed in content generation for a particular learner, which will be a real game-changer in the education sector [212].
- *Favoring AI over Traditional Statistical Methods*: Research is still needed to identify when AI is better than traditional statistical methods when it comes to deciding on education at different levels. Over the years, the usage of traditional statistical analytical methods have been successful (at least

this is what we observed). Nevertheless, it is vital to study if AI analytics can be more successful in deciding on improving our education.
- *Explanatory Learning Model*: To obtain more interpret-able and actionable insights from educational data, explanatory learning models involving all the stack-holders including learners' parents and schools etc., need to be developed [210]. AI along with Human-Computer Interaction (HCI) methods can then be jointly utilized to better analyze the data.

6.3.4 AI Issues and Concerns

- *Identifying Ethical and Privacy Issues*: While AI can offer promising solutions in many fields including education, many ethical considerations can arise and cause limitations. Developing AI algorithms for education with ethical considerations in mind is challenging due primarily to the different definitions of what's and what isn't ethical in education. Also, it is critical to prevent using AI is leading to serious biases when it comes to analyzing data and identifying patterns. In the area of privacy, when our data are left to machines to analyze and detect patterns, this is by itself can lead to serious privacy implications. For example, having access to students' online search behaviors can lead to detecting personal issues which can negatively lead to long term impacts. Therefore, AI researchers need to look for ways to tame their algorithms and analytics when it comes to analyzing data and detecting patterns. Author of [223] discusses ways to address the ethical issues of using AI.
- *Security Implications*: AI is very dependent on data. Data in the education field are miscellaneous. Designing AI algorithms while security is very prominent and in mind is critical. This requires distinguishing between sensitive and insensitive data before jumping to apply AI techniques on educational data. Hence, researchers are in need to develop intelligent AI techniques that are ready to deal with data in classified and careful ways.

7 Conclusions

In this paper, we have reviewed applications of AI in the education sector from different perspectives highlighting the future scope and market opportunities for AI in education, the existing tools and applications developed in several applications of AI in education, research trends in the domain over the last five years as well as the current limitations and pitfalls of AI in education. In particular, we provided a detailed overview of the existing literature in several application domains, such as students' grading and evaluation, students' dropout, e-learning, sentiment analysis, intelligent tutoring systems and classroom monitoring. We also presented and identified the future scope and market opportunities for AI researchers and developers in the education sector. We also provide an overview of the most commonly used AI strategies and techniques in different applications of AI in education. We also provided a detailed bibliometric analysis to highlight the research trends of AI in the education sector over the last few years. The survey also highlighted key market players, tools and platforms in the above-mentioned applications of AI in education, which are expected to provide a good starting point for the beginners in the domain. Based on our analysis of the existing literature and experience in the domain, we also identified the current limitations and the pitfalls of AI in education. We believe such a rigorous analysis of the domain will provide a baseline for future research in the domain.

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