

WHERE ARE THE PROFESSORS IN THIS SYSTEMATIC STUDY OF AI'S POTENTIAL USES IN UNIVERSITIES?

Vinay Chowdary Manduva^{1*}

¹Department of Computer Science, Missouri State University, Springfield, MO, UNITED STATES

ABSTRACT

A number of recent studies have identified Artificial Intelligence in Education (AIED) as a promising new area of educational technology. Although it has been available for over 30 years, educators still don't completely understand how to use it for pedagogical purposes and how it might significantly affect higher education teaching and learning. This paper's overarching goal is to provide a thorough evaluation of the literature on artificial intelligence (AI) and its potential uses in academic settings. The final synthesis includes 146 articles out of 2656 papers initially found for the period between 2007 and 2018, based on specific inclusion and exclusion criteria. According to the descriptive statistics, the majority of the fields represented in AIED publications are STEM (science, technology, engineering, and mathematics), and quantitative approaches were most commonly employed in empirical investigations. In terms of academic support services and administrative and institutional services, the findings synthesis identifies four areas of AIED applications: 1. learning, 2. evaluation and assessment, 3. personalization and adaptive systems, and 4. AI-powered instructional platforms. The findings highlight the following issues: the dearth of critical analysis of AIED's hazards and difficulties; the tenuous relationship to theoretical pedagogical viewpoints; and the necessity for more investigation into educational and ethical methods pertaining to AIED's implementation in universities.

KEYWORDS: Mobile Applications; Securing Date; Cybersecurity Protection Data

INTRODUCTION

Recently, there has been a lot of focus on the potential of artificial intelligence (AI) in the classroom. The 2018 Horizon study highlights artificial intelligence (AI) and adaptive learning (AL) as significant educational technology advances. The research estimates that these technologies will take two or three years to be widely used. Although the Horizon research 2019 Higher Education Edition projects that AI applications connected to teaching and learning are expected to develop even more dramatically than this, experts foresee a 43% growth in AI in education from 2018 to 2022, according to the research. "There is little doubt that the [AI] technology is inexorably linked to the future of higher education," says Contact North, a prominent Canadian non-profit online learning group. Thanks to private firms' huge

investments—like Google, which bought out European AI—funding for non-profit public-private partnerships like the German Research Centre for Artificial Intelligence¹ (DFKI) and for-profit start-up Deep Mind at \$400 million, this influx of capital is likely to have far-reaching effects on universities. The Technical University of Eindhoven in the Netherlands, for instance, has just announced the establishment of an Artificial Intelligence Systems Institute, complete with fifty new professorships dedicated to AI education and research [1–5].

Researchers have been studying AI education (AIEd) for about 30 years. This year marks the 20th annual AIEd conference, and the International AI Education Society (IAIED) has been around since 1997. They publish the International Journal of AI in Education (IJAIED). On a larger scale, however, educators have just recently begun to investigate the educational possibilities presented by AI applications in terms of assisting students at various points in their learning journey [6–10]. Developing AI applications in higher education brings new ethical concerns and hazards, despite the vast benefits that AI may provide to assist teaching and learning. For instance, when faced with budget shortages, administrators may feel tempted to substitute teaching with more lucrative automated AI solutions. Intelligent tutors, expert systems, and chatbots may instill panic among faculty members, teaching assistants, student counsellors, and administrative staff who worry about job security. While artificial intelligence (AI) has the ability to improve learning analytics, there are significant privacy and data protection concerns because of the massive volumes of data that these systems need, including sensitive information about students and teachers. In an effort to establish a framework for ethical governance of AI in education, several institutions have been recently set up. For example, in April 2019, the Analysis & Policy Observatory released a discussion paper with the goal of developing an AI ethics framework for Australia [13–26]. Another example is the Institute for Ethical AI in Education in the UK.

Russel and Norvig, in their seminal work on artificial intelligence, AI, "The ethical implications of their work should concern all AI researchers". Therefore, we are interested in delving into the new ethical implications and concerns that the authors have identified within the domain of AI-enhanced education. Research on artificial intelligence applications in higher education is the focus of this article, which aims to offer educators with an overview of the topic. A literature analysis on artificial intelligence (AI) in higher education is necessary due to the field's rapid growth and educators' increasing interest in it [27–38]. In particular, this work uses a systematic review to answer the following research issues across three domains: The interest in knowing the evolution of AI-related publications in higher education, the journals that publish them, the geographical distribution of the authors, and the fields to which they belong.

What are the conceptualizations of AI in education, and what are the ethical implications, problems, and dangers that are taken into account? In the context of universities, how broadly are artificial intelligence applications used? While AI has its roots in engineering and computer science, it has also drawn heavily from fields like economics, philosophy, cognitive psychology, and neuroscience. The lack of consensus on a shared definition and understanding of AI and intelligence among AI researchers is a result of the field's interdisciplinary character. In relation to the use of AI-based tools and services in higher education, Hinojo-Lucena, Aznar-

Díaz, Cáceres-Reche, and Romero-Rodríguez state that "this technology [AI] is already being introduced in the field of higher education, although many teachers are unaware of its scope and, above all, of what it consists of" (p. 1). It would be helpful to define key terms before diving into our examination of AI in universities. Following this, we will conduct a systematic evaluation of the literature [39–59] after defining AI in education and discussing the potential components and methodologies of AI applications in higher education.

Artificial Intelligence in Education (AIED)

Artificial intelligence (AI) was born in the 1950s during a two-month workshop that John McCarthy organized at Dartmouth College in the United States. The phrase "artificial intelligence" was initially used by McCarthy in 1965 in the workshop proposal. The premise upon which AI research will be based is the idea that, in theory, it should be possible to construct a system that can mimic every facet of intelligence, including learning. We will look into ways to teach computers to understand human language, build abstract ideas, solve issues traditionally handled by people, and even develop themselves [60–88]. In their expansive definition of artificial intelligence, Baker and Smith state: "Computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving" (p. 10). As they point out, artificial intelligence does not define a certain technology. It encompasses a wide variety of tools and approaches, including algorithms, machine learning, data mining, neural networks, and natural language processing. Machine learning and artificial intelligence are frequently brought up together. Machine learning is an artificial intelligence technique for supervised and unsupervised categorization and profiling. It may be used to do things like identify subjects in written assignments, forecast if a student would drop out of a course or get admitted to a program, and more. Machine learning is defined by Popenici and Kerr as "a subfield of artificial intelligence that includes software able to recognise patterns, make predictions, and apply newly discovered patterns to situations that were not included or covered by their initial design" (p. 2) [89–104].

"An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators." While the vacuum-cleaner robot exemplifies a very basic type of intelligent agent, the concept becomes extremely complex and open-ended when we consider an automated taxi.

Artificial intelligence (AI) specialists differentiate between weak and strong AI, sometimes called narrow and general AI. The philosophical question of whether computers will be able to do more than mimic human thought processes and exhibit logical behavior persists. We should not expect to see such powerful or widespread AI very soon. Agents and information systems that behave intelligently are what we're talking about here in the context of higher education [105–115]. With this background in AI, what are some possible uses of AI in the classroom, especially at the university level? Personal tutors, intelligent assistance for collaborative learning, and intelligent virtual reality are the three types of artificial intelligence software applications in education that are now accessible, according to Luckin, Holmes, Griffiths, and Forcier.

By simulating one-on-one personal tutoring, intelligent tutoring systems (ITS) can use learner

models, algorithms, and neural networks to decide on a student's learning path and which content to select, as well as to engage the student in dialogue, provide cognitive scaffolding, and offer assistance. When compared to human one-on-one tutoring, ITS show tremendous promise, particularly in massive online education institutions that teach courses to thousands of students at once. Despite the importance of online collaboration, which requires facilitation and moderation, a large body of evidence indicates that learning is fundamentally a social activity. By assisting with learner-model-based adaptive group building, encouraging online group interaction, or summarizing conversations that may be utilized by a human tutor to lead students towards course goals, AIED can help to collaborative learning. Lastly, intelligent virtual reality (IVR) relies on ITS as well to immerse and direct students in realistic VR and game-based educational settings. In online or distant laboratories, for instance, virtual agents might play the role of student peers, instructors, or facilitators.

A "[r] enaissance in assessment" has been declared by Luckin et al. (p. 35) due to the development of AIED and the accessibility of (large) student data and learning analytics. AI has the capability to offer timely evaluation and feedback. An alternative to stop-and-test methods is to include AIED into learning sessions so that student achievement may be continuously assessed. The likelihood of a student failing an assignment or dropping out of a course may be accurately predicted using algorithms [116-124].

Baker and Smith consider three vantage points in their recent study on educational AI tools: a) learner-facing, b) teacher-facing, and c) system-facing AIED. Software designed with the needs of students in mind is known as "learner-facing AI tools."

In other words, ITS, which stands for "learning management systems," may be either adaptive or personalized. Systems aimed at teachers automate administrative, grading, feedback, and plagiarism detection processes, thus reducing teachers' workloads. The use of AIED technologies also allows teachers to see how their pupils are doing in class, which allows them to proactively help those who need it. For example, system-facing AIED can help keep tabs on faculty or college attrition rates by providing data to administrators and managers at the institutional level.

We outline the numerous AI-based services on the larger scale within the framework of the student life-cycle in the context of higher education on an institutional and administrative level, and to a lesser extent, to bolster academic instruction and student learning.

Methodology

Based on an explicit, systematic, and replicable search strategy, studies are included or excluded in a systematic review. Data is then extracted and coded from included studies to synthesise findings and shed light on their application in practice, as well as any contradictions or gaps. The purpose of the review is to answer specific questions. This contribution compiles 146 papers on the use of AI in academic settings.

Methodology for the Search

This systematic review used three international databases—EBSCO Education Source, Web of Science, and Scopus—to index peer-reviewed articles written in English that reported on the

use of artificial intelligence in education at any level. The search string and criteria for this review are presented in Tables 1 and 2, respectively. Articles in this review were only accepted for inclusion if they had been published in a peer-reviewed journal. This was done in November 2018 after a thorough search yielded 2656 records; however, there are valid concerns about the scientific community's reliance on peer-review processes. Following the elimination of duplicates, it was determined to restrict articles to those published in 2007 or later. This was done because that was the year when the algorithm-based personal assistant Siri was introduced in the iPhone. Siri had its origins as an artificial intelligence project funded by the US Defense Advanced Research Projects Agency (DARPA) in 2001, but it evolved into its own company after being acquired by Apple Inc. Another decision was to restrict the corpus to papers that only cover AI in higher education.

Preliminary Evaluation and Consistency Among Raters

A team of three coders screened 1549 titles and abstracts. During this first screening, sensitivity was more important than specificity; in other words, publications were included rather than discarded. Regular meetings were held to debate the grounds for including or excluding the first 80 items in order to obtain a consensus gather together. The coding judgments of three coders (A, B, and C) were evaluated in twenty articles chosen at random. To establish inter-rater reliability, Cohen's kappa (κ) was used, which is a coefficient for the degree of consistency across raters, depending on the number of codes in the coding scheme. There was a coding consistency of $\kappa = .79$ between raters A and B, $\kappa = .89$ between raters A and C, and $\kappa = .69$ between raters B and C, with a median of .79, for the inclusion or exclusion of articles. Kappa values between .40 and .60 are considered fair, .60 to .75 are acceptable, and values over .75 are excellent. Consequently, the coding of inclusion and exclusion criteria may be regarded as having great inter-rater reliability.

There were 332 articles that made it beyond the first round of screening and into the full-text stage (see Fig. 1). Unfortunately, neither the library's order system nor contacting the authors yielded 41 articles. As a result, 291 publications were collected, evaluated, and categorized; after 149 papers were removed, 146 articles were left for synthesis.

Data Extraction, Coding, and Analysis

A coding system was devised and all papers were submitted into the systematic review program EPPI Reviewer6 for data extraction. Year of publication, journal name, countries of authorship, and discipline of first author were some of the codes included in the articles. Other codes included study design and execution, whether empirical or descriptive, educational setting, and the use of artificial intelligence (applications in the student life cycle, specific applications, and methods). Additionally, articles were categorized based on the presence or absence of a definition of AI, as well as the obstacles and benefits of AI. The tidyr package in R, a statistical program, was used to do descriptive data analysis.

Limitations

Although great care was taken in conducting this systematic review, it is important to remember that the search technique of each study introduces some limitations. Despite the extensive worldwide breadth of the three selected educational research databases, this study did not cover

research on AI published in languages other than English or Spanish due to the inclusion requirements of peer-reviewed papers. Articles not included in journals indexed by the three databases surveyed are also considered to be part of the grey literature, conference proceedings, or book chapters. Furthermore, none of the Spanish peer-reviewed publications met the inclusion requirements, and no particular search phrase was used in the inclusion of language reduced the likelihood of including Spanish documents that were not indexed with the selected keywords. To broaden the scope of the review, future research should think about employing more databases, publication categories, and languages. Review manageability and project resources must therefore be carefully considered (see Authors, in press).

Final Product

Publications, conventions of authorship, and methodologies Annual articles the number of papers published increased significantly beginning in 2007. There were six items included in 2007, but by 2018 there were twenty-three.

Journals

A total of 104 journals published the papers that made up the sample. Computers G Education had the second-highest number of papers published ($n = 8$), followed by the International Journal of Emerging Technologies in Learning ($n = 5$), and the International Journal of Artificial Intelligence in Education ($n = 11$). covers the years 2007–2018 and the 19 journals that published at least two papers on artificial intelligence in higher education.

Nation States

The country of origin of the initial author was considered for the geographical distribution study of publications ($n = 38$ nations). reveals that nineteen nations

Methodology

Theoretical or descriptive research accounted for thirty of the papers (20.5%). Of the investigations that were conducted, 73.3% used quantitative methods, 0.7% were qualitative, and 5.5% used a mixed-methods approach. Interviews with English as a Second Language (ESL) students served as the basis for this qualitative study's examination of the differences between human and automated essay scoring systems. Several of the authors used quasi-experimental designs, with the experimental group receiving feedback from an AI application (such as an intelligent tutoring system) and the control group receiving no such intervention; both groups were then tested before and after the intervention.

Acquiring Knowledge About AI and Thoughtful Consideration of its potential hazards

Five articles out of 146 that were considered (3.4%) define the word "Artificial Intelligence" explicitly, despite the fact that there are numerous references to AI at various levels and types in the articles. The five research all agree that AI is primarily characterized by similarities to the human brain. The objective of artificial intelligence (AI) research is to understand how the human mind functions and to apply those principles to the construction of technology in a way that mimics intelligent humans' behavior. AI is an interdisciplinary field of study. Artificial intelligence (AI) has the potential to mimic human performance in language acquisition and instruction Dodigovic, who hails from the Arts, Humanities, and Social Science department and

considers AI and intelligent tutors in second language acquisition, is the sole author to offer a definition of AI. Out of 146 publications, a pitiful two (1.4% of the total) address the ethical concerns, difficulties, and dangers of using AI in the classroom. In his essay about AI-supported online learning, Li addresses privacy concerns:

When using agent-based personalized education, privacy is also a major consideration. Several pieces of personal information about students, such as their learning style and capacity, may be learned independently by agents, as mentioned before. True, one-on-one details are confidential. Personal information, such as a student's learning style and/or talents, is something that many students would rather have hidden. Because of their unique educational requirements, students may express anxiety about the possibility of prejudice from teachers over their academic progress. Consequently, you can't apply until the privacy problem is fixed personalized learning and instruction systems based on agents.

Welham also brings out an additional difficulty with AI implementations: the time and money needed to create and implement AI-based approaches, which are out of reach for many public schools.

Artificial Intelligence for use in Universities

As previously stated, the student life-cycle concept served as a framework for describing the various AI-based services offered at both the administrative and academic levels. These services include admissions, counseling, library services, and academic support for teaching and learning, including assessment, feedback, and tutoring. There were a total of 102 studies that dealt with academic support services (63.1%), 48 research that dealt with administrative and institutional services (32.8%), and 6 studies that dealt with both levels (4.1%). Of the studies that were conducted, 92.3% were on undergraduates, 7.5% were on graduate students, and 30.1% were on students of some other level. The papers address four areas of AI applications that emerged from the iterative coding process: adaptive systems and personalization (a), assessment and evaluation (b), profiling and prediction (c), and intelligent tutoring systems (d). Each of these topics has seventeen subcategories. Research in a few areas covered several uses of AI.

In the following synthesis, we will describe the nature and extent of AI applications in higher education along these four application areas.

Analysis and Forecasting

Many AI applications rely on learner profiles or models that can predict things like a student's chances of dropping out of a class or getting into a program, so that they can give timely support, feedback, and guidance on content-related matters as they learn. Educational data mining relies heavily on classification, modeling, and prediction.

Nearly half of the papers (55.2%, $n = 32$) deal with administrative and institutional concerns, nearly a third (36.2%) with course-level academic teaching and learning, and nearly a fifth (8.6%) with challenges at both levels. There were a total of thirty-seven articles that dealt with profile and prediction. Of these, seven were about admissions decisions and course scheduling, twenty-three were about retention and dropouts, and twenty-seven were on student models and

academic success. The project by Ge and Xie, which involves predicting the expenses of a Chinese institution to back management choices with an artificial neural network, does not fit into any of these categories.

The 58 research that have been conducted in this field have all used machine learning techniques to identify and categorize trends, as well as to create prediction models based on student profiles. That is why they are all numerical. A number of studies compared the overall prediction accuracy of various machine learning methods with that of traditional logistic regression. - generated logistic regression for every study according to their percentage of correct classifications. Classifier performance can also be assessed using the F1-score, which is a numeric value between 0 and 1 with 1 being the optimal score (i.e., perfect precision and recall). It accounts for the number of positive instances correctly classified as positive, the number of negative instances incorrectly classified as positive, and the number of positive instances incorrectly classified as negative. The study by Yoo and Kim to predict students' group project success from online discussion participation yielded strong F1-scores of 0.848, 0.911, and 0.914 for J48, NB, and SVM, respectively.

Chen and Do note that "the accurate prediction of students' academic performance is of importance for making admission decisions as well as providing better educational services" (p. 18), which pertains to both course scheduling and admission decisions. The goal of these four research was to find out what factors influence a university's admissions decisions. Take Acikkar and Akay as an example. They used a combination of physical ability testing, National Selection and Placement Examination results, and graduation grade point average (GPA) to choose students for a physical education and sports school in Turkey. They classified students using the support vector machine (SVM) method and had an accuracy of 97.17% in 2006 and 90.51% in 2007 for predicting admission decisions. Andris, Cowen, and Wittenbach also used support vector machines to identify geographic patterns that may benefit prospective students from certain geographic locations in the United States. Researchers Feng, Zhou, and Liu used ANN model training data from 25 Chinese provinces to forecast registration rates in other regions. In order to aid with course design, machine learning techniques like ANN are also employed to forecast how students would choose their classes. In two Master's programs in computer engineering and information technology, Kardan, Sadeghi, Ghidary, and Sani developed a model to predict course selection using an artificial neural network (ANN). The factors influencing student course selection included course and instructor characteristics, workload, mode of delivery, and examination time. The same author group also suggested a decision-support system for course offerings in another publication. In sum, the findings demonstrate that admission choices may be forecast with a high degree of accuracy; hence, an AI solution might free up administrative personnel to concentrate on more challenging instances.

Research on retention and dropout rates aims to identify students who may struggle to complete their first year of college and provide early warning systems to help them succeed pupils as a whole. Over the course of eight years, Delen analyzed institutional data from 25,224 first-year students at a single American university. The researchers in this study employed logistic regression, artificial neural networks (ANN), and decision trees (DT) to forecast which students

will drop out. Factors such as students' ages, sexes, ethnicities, GPAs, TOEFL scores, financial aid, student loans, and more were included in the data. The ANN model performed the best with an accuracy rate of 81.19%, according to Delen's 10-fold cross validation. The most crucial factors predicting student drop-out, according to Delen, are the student's current and prior academic success, as well as whether or not they get financial support. Using undergraduate engineering students' cognitive and non-cognitive traits as predictors of academic success was a topic of discussion among Sultana, Khan, and Abbas. They went against the grain of previous research by concentrating on non-cognitive factors—such as leadership, community support, self-concept, and self-appraisal in order to increase the reliability of predictions.

More and more research is focusing on student profiles and learning behavior models to forecast students' course-level academic achievements. For a large-scale distance teaching university like Open University UK, where it is not feasible to engage the majority of students in face-to-face sessions, Hussain et al. utilized multiple machine learning algorithms to analyze data on student behavior in the virtual learning environment. This allowed them to predict student engagement, which is crucial. The authors' ultimate goal is to create a smart prediction system that can help teachers see uninterested pupils and intervene before it's too late. In order to gauge the efficacy of project-based learning, Spikol, Ruffaldi, Dabisias, and Cukurova employed face and hand tracking during workshops with engineering students. According to their findings, instructors may learn about important aspects of project-based learning from data collected using many modalities. Using more than 150,000 code transcripts produced by undergraduates in software development projects, Blikstein et al. examined trends in the way students learn computer programming. They discovered that their programming-based model outperformed the midterm results in terms of predictive power.

The work of Babić is another illustration; he created a model to forecast students' academic motivation by observing their actions in a virtual classroom. Intelligent tutoring systems and adaptable learning environments rely heavily on research on student models.

Automated Educational Systems

With the exception of one study that takes an institutional and administrative level of context into account, all of the 29 research that have looked into intelligent tutoring systems (ITS) have only focused on the teaching and learning level. The latter introduces StuA, a smart and conversational student assistant that guides first-years through their college experience by responding to questions about professors, classes, extracurriculars, library resource intelligent tutoring systems, intelligent software agents, and intelligent assistants are among the most popular ways to characterize the ITS that have been studied. Another name for these systems is intelligent online tutors. Launched in 1970, the SCHOLAR system was the first ITS documented by Welham. It allowed for the teacher and student to exchange questions back and forth but did not allow for a continuous discussion.

In their description of the various models typically integrated into ITS, Huang and Chen note the following: the student model, which includes details about the student's knowledge, cognitive ability, learning motivation, and learning styles; the teacher model, which includes analysis of the students' current state, selection of teaching strategies and methods, and

provision of help and guidance; the domain model, which represents both students' and teachers' knowledge; and the diagnosis model, which evaluates errors and defects based on the domain model.

With the exception of Jackson and Cossitt's study, all of the studies that validated and implemented ITSs only lasted a few weeks or months. Moreover, while many of the studies did find some promising early results in terms of the ITSs' performance, they failed to account for the impact that technological innovation could have on students' perceptions of the world around them. The findings of one research were unsatisfactory because the ITS was not tailored to the specific needs of the students, who were advanced in their studies.

In general, the efficacy of ITS requires more investigation. Over five years ago, Steenbergen-Hu and Cooper published a meta-analysis of 39 ITS studies. They found that ITS had a moderate effect on students' learning, were less effective than human tutoring, but performed better than all other methods of instruction.

Course content instruction ($n = 12$), student knowledge assessment and automated feedback ($n = 7$), student-needs-based learning material curation ($n = 3$), and student-to-student collaboration ($n = 2$) were the four main categories into which the research pertaining to ITS functions were categorized.

In the majority of these experiments ($n = 4$), ITS are shown as a somewhat unidirectional flow of information from computer to student with regard to the identification of knowledge gaps and the delivery of feedback. Two of the STEM examples involve virtual laboratories that use ITS to provide tutoring feedback and monitor student behavior; a third is a standalone ITS in computer science; and one study describes an ITS in the context of second language acquisition.

In two cases, the student and the machine have a conversation to diagnose errors and provide each other feedback. One example is the tutoring system, which relies on a tutorial dialogue toolkit for introductory college physics. Another example is the ubiquitous teaching robot that uses question recognition to guide its speech. At its core, the peer dialogue agent proposed by Howard et al. allows an ITS to engage in collaborative problem solving with a student in a one-on-one setting, using verbal, graphical, and process-oriented interactions. It is possible to classify this last work into a new subfield dealing with peer-agent collaboration.

Academically productive talk moves were used in one study to support online collaborative learning discussions, and in the other, automated feedback, generated auto-matic questions, and process analysis were used to facilitate collaborative writing. More research in this area would be desirable given the opportunities described in these studies for supporting student collaboration.

The viewpoint of the educators Baker and Smith differentiate between AI systems that are aimed at students and those aimed at educators. On the other hand, the viewpoint of the educator is the subject of just two of the articles contained in ITS. A study conducted by Casamayor et al. aims to assist teachers in supervising and detecting conflictive cases in collaborative learning. The intelligent assistant in this study gives teachers a summary of each group member's progress and the type of participation they have had in their work groups. It also alerts teachers when conflict situations are detected and provides information about each student's

learning style through logging interactions. This way, teachers can intervene when they find it convenient. In the other research, the focus was on how ITS might share tutoring responsibilities with instructors by automating activities and giving immediate feedback, while still allowing teachers to provide additional clues and the right answers. The goal of ITS is to distribute tutoring responsibilities among educators, as mentioned in the research of Chi et al. Lessening the burden on educators is the primary goal in each of these scenarios. Additionally, the teacher's perspective is under-emphasized in many research that focus on learners, even when many studies also address teacher-facing duties.

Analyzing and Assessing

The majority of evaluation and assessment research (86 percent, $n = 31$) similarly concentrated on the classroom level, with only five studies describing institutional applications. By analyzing student-made remarks on Twitter utilizing Twitter API Twython and system-related phrases, researchers at Anadolu University were able to acquire a sense of the general mood toward online and distant learning at their university. Researchers were able to get insight into student opinion through this study of publicly available data, which has the potential to influence changes to the system. Biletska, Biletskiy, Li, and Vovk utilized semantic web technologies to convert student credentials from different institutions. This could also provide information from course descriptions and topics, making it easier to grant credit. Kalz et al. used ePortfolios and Latent Semantic Analysis to inform personalized learning pathways for students. In order to guarantee that courses were in line with industry demands, the last article at the institutional level utilized an algorithm to match students to professional competences and abilities needed by organizations.

The research concludes that AI applications are capable of efficiently and accurately carrying out evaluation and assessment activities. Supervised machine learning requires calibration and training of the systems, which limits their usefulness to programs or courses with a small number of students.

There were four main groups of articles that dealt with AI in the context of assessment and evaluation in the classroom: automated grading ($n = 13$), feed-back ($n = 8$), evaluation of teaching ($n = 5$), and evaluation of student understanding, engagement, and academic integrity ($n = 5$). The articles that used automated grading, also known as Automated Essay Scoring (AES) systems, came from a variety of fields (e.g., Biology, Medicine, Business Studies, English as a Second Language), but the majority of them concentrated on undergraduate courses ($n = 10$). Among these students, some had low reading and writing abilities. For example, in a study by Gierl, Latifi, Lai, Boulais, and Champlain, they used the open-source Java program LightSIDE to grade the essays of postgraduate medical students. The results showed an agreement between the computer classification and human raters ranging from 94.6% to 98.2%. This could lead to a reduction in the time and money needed to employ multiple human assessors for large-scale assessments.

They did, however, note that AES might not work for all types of writing and that, because of the massive amount of pre-scored assessments needed to calibrate the system, it would be prohibitive to implement in most small classrooms. However, instead of relying solely on

multiple-choice exams to gauge students' knowledge and abilities, utilizing algorithms that detect patterns in text replies has been shown to encourage more modifications by students. Nevertheless, there are still ongoing concerns over the quality of AES feedback. Barker discovered that students were more inclined to doubt their marks when given extensive feedback, and the usefulness of such feedback for first-year language learners was questioned. For instance, the automated feedback system that Barker describes as being based on adaptive testing not only suggests extra materials and challenges to students but also finds the best responses for each student based on Bloom's cognitive levels. This can assist alleviate cognitive overload.

Academic integrity, student involvement, and concept comprehension evaluation Three articles discussed techniques that students use to get help with specific concepts and have their grasp of those concepts evaluated. Amigud, Arnedo-Moreno, Daradoumis, and Guerrero-Roldan employed machine learning algorithms to verify students' academic honesty by determining the probability that their work was similar to their previous work; Hussain et al. utilized machine learning algorithms to assess students' involvement in a social science course at the Open University, including final grades, assessment scores, and the amount of clicks students make in the virtual learning environment (VLE), which can notify teachers when intervention is necessary. With a mean accuracy of 93%, this raises questions about the necessity of invigilators or access to student accounts, which might lead to a decrease in worries about privacy.

The evaluation of instruction was the subject of four studies that employed data mining algorithms to assess professors' effectiveness via student assessments of their courses. One of these studies, conducted by Agaoglu, utilized four distinct categorization methods to determine that a large number of the survey items were unneeded. Online homework with immediate feedback outperformed clickers in an algorithmic evaluation of teaching methods for a differential equations class. The study also discovered that while past exam scores are generally good predictors of future exam scores, they reveal very little about students' expected performance in project-based tasks.

When it comes to adaptive systems and personalization, the vast majority of research (85%, $n = 23$) focus on the classroom setting, whereas just four instances take an administrative or institutional perspective. While two research looked at academic advice for undergraduates, Nguyen et al. zeroed particularly on artificial intelligence to bolster university employment services. The development of an agent-based remote learning management system was detailed by Ng, Wong, Lee, and Lee. The system's goals included resource management, policy and decision support, and the facilitation of the study flow of undergraduates (including intake, exam, and course management) through the provision of cross-disciplinary data access rather than that limited to individual faculty areas.

The many roles that adaptive systems play likely contribute to the lack of consensus on a consistent definition throughout research, which in turn lends credence to the categorization of such systems. Words like "intelligent agents" and "ITS" share some common ground. The most common ones include adaptive learning systems, intelligent e-learning systems, and online educational platform. Similar to ITS, the majority of research either outlines the platform or

incorporates a pilot study, but fails to document outcomes over an extended period of time. With the exception of Vlugter, Knott, McDonald, and Hall, where the experimental group using the dialogue-based computer-assisted language-system performed worse than the control group on the delayed post-tests, the results of these pilot studies are often good.

There are five subcategories that the 23 studies that dealt with education fell into. One was assisting instructors with course content ($n = 7$), another was offering personalized content ($n = 5$), still another was assisting educators with learning and teaching design ($n = 3$), utilizing academic data to track and direct students ($n = 2$), and the last was assisting with knowledge representation through concept maps ($n = 2$). Some studies, however, defied easy categorization owing to the unique and specific roles they played; for example, some helped set up online study groups for people with shared interests, while others supported business decisions through simulation or helped people with Anorexia Nervosa alter their mindset and behavior through the use of embodied conversational agents. In their study, Aparicio et al. focused on how students perceive the use of information systems in biological education and generally, as well as intelligent information access systems, rather than analyzing adaptive system applications.

Adaptive systems are used to teach a wide variety of subjects in the classroom, such as biology, language arts, and environmental education. Nevertheless, Walsh, Tamjidul, and Williams describe, without mentioning a particular field, an adaptive system that relies on a symbiotic relationship between machine learning and human machine learning.

This group discusses adaptive systems that tailor courses, materials, and exercises to each student's behavior in computer science and business administration. In contrast, Tai, Wu, and Li provide an e-learning recommendation system to assist online students in selecting courses, and Torres-Díaz, Infante Moro, and Valdiviezo Día highlight the practicality of adaptive recommendation systems in massive open online courses (MOOCs) to propose actions, new items, and users based on students' individual preferences.

Three papers were found in this category that support instructors in learning and instructional design. An article describes a metadata-based model to apply automatic learning designs that can solve detected problems, while another study highlights a hybrid recommender system of pedagogical patterns to assist teachers in defining their strategies for instruction based on the context of individual classes. Intelligent agents, according to Li's descriptive study, free up online teachers to concentrate on creative work by taking care of the most mundane, repetitive jobs.

An example of an adaptive system that uses academic data to monitor and guide students is the Learner Diagnosis, Assistance, and Evaluation System based on AI (StuDiAsE) for engineering learners. This system extracts students' academic information to perform diagnostic tasks, which in turn helps tutors provide more proactive personal guidance. Adaptive systems in this category also include performance evaluation and personalized assistance and feedback.

Concept maps are a great tool for supporting students' understanding and increasing their self-awareness of conceptual frameworks. In two of their studies, this group used expert systems to do things like help EFL college students build their reading comprehension through mental maps of referential identification, incorporate system-guided instruction, practice, and

feedback, and incorporate selected peer ideas into integrated concept maps. Teachers could also use these systems to flexibly decide in what ways to merge the selected concept maps.

Conclusions

Perhaps the area of educational technology as a whole suffers from a lack of theory. More than 40% of publications in three leading journals for educational technology were completely non-theoretical, according to a recent analysis by Hew, Lan, Tang, Jia, and Lo. This absence of overtly educational viewpoints in the examined papers was also highlighted in the systematic review conducted by Bartolomé et al. The bulk of the studies that made it into this comprehensive review mainly concerned themselves with applying mathematical theories and machine learning methods from decades ago to analyze and predict data for use in student and teacher facing applications or to back up administrative decisions. The proliferation of huge digital student data and the exponential rise in computer power have made this type of study feasible. Nevertheless, there is currently minimal evidence to support the development of pedagogical and psychological theories of learning in relation to educational technology powered by AI. To better understand the reasons and mechanisms behind this dynamic development—which will have enormous impact on higher education institutions in the various areas we have covered in this review—researchers are encouraged to be explicit about the theories that underpin empirical studies about the development and implementation of AIED projects. This will help expand the scope of research and provide a better understanding of the topic.

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