AI-enabled Adaptive Learning Systems: A Systematic Mapping of the Literature

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AI-enabled adaptive learning systems: A systematic mapping of the literature

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A R T I C L E I N F O

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A B S T R A C T

Mobile internet, cloud computing, big data technologies, and significant breakthroughs in Artificial Intelligence (AI) have all transformed education. In recent years, there has been an emergence of more advanced AI-enabled learning systems, which are gaining traction due to their ability to deliver learning content and adapt to the individual needs of students. Yet, even though these contemporary learning systems are useful educational platforms that meet students' needs, there is still a low number of implemented systems designed to address the concerns and problems faced by many students. Based on this perspective, a systematic mapping of the literature on AI-enabled adaptive learning systems was performed in this work. A total of 147 studies published between 2014 and 2020 were analysed. The major findings and contributions of this paper include the identification of the types of AI-enabled learning interventions used, a visualisation of the co-occurrences of authors associated with major research themes in AI-enabled learning systems and a review of common analytical methods and related techniques utilised in such learning systems. This mapping can serve as a guide for future studies on how to better design AI-enabled learning systems to solve specific learning problems and improve users' learning experiences.

1. Introduction

Technology has had a significant impact on higher education institutions (HEIs). In fact, virtual reality flipped classrooms and technology-enhanced learning systems have been used in recent years in many HEIs (Arici et al., 2019; Radianti et al., 2020). Technology-enhanced learning uses learning and teaching systems that are technology based, allowing students to develop knowledge and skills with the help of lecturers, tutors, learning support tools and technological resources (Gros, 2016). The importance of such systems, especially in the times of a pandemic, has been highlighted further due to their ability to assist IT and IS educators, while they rethink and revise the learning design of their courses, in order to offer more meaningful learning experiences to their students (Pappas & Giannakos, 2021). Students also play an active role in the learning process using these technologies. Currently, the most commonly used learning systems include Blackboard, Moodle, Web CT and Canvas (Ushakov, 2017). The advantages of utilising such learning systems include constant availability and accessibility to course materials, cost savings, collaboration amongst students and lecturers, improved performance, feedback from users and effective communication (Criollo-C et al., 2018; Dunn & Kennedy, 2019; Katoua et al., 2016). Despite these advantages, most learning systems tend to focus on achieving their technical objectives (Katuk et al., 2013) and ignore course requirements and other pedagogical issues related to the whole learning–teaching process (Mouakket & Bettayeb, 2016). Due to the dominance of the technical aspects of these learning platforms, students and lecturers perceive them as not adaptive to their needs, resulting in their negative attitudes toward these systems. Hence, more advanced learning systems have emerged in recent years.

Progress in using new data analytics and artificial intelligence (AI) techniques to develop learning systems has led to the development of more successful learning systems in the education sector. These contemporary learning platforms are 'systems that strive to incorporate analysis of historical data about the previous users of the system by modelling learning process [es] from the learners' viewpoint, and, thus, be able to adapt to a rapidly changing environment by providing learners not only accurate and high-quality learning material, but also taking into account the individual learner's needs' (Kurilovas et al., 2015, p. 945). Increasingly, AI-enabled learning systems are being integrated with new techniques to develop more personalised educational settings (Moreno-Guerrero et al., 2020; Mousavinasab et al., 2018; Smutny & Schreiberova, 2020). Such systems are gaining traction due to their ability to

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deliver learning content and adapt to individual students' needs. Students are thriving in these digital environments, where current technologies shape their expectations and 'abilities to access, acquire, manipulate, construct, create and communicate information' (Green & Donovan, 2018). The physical and virtual resources in these learning environments are designed to deliver effective learning by helping students construct their knowledge. Good examples of AI-enabled learning environments include intelligent tutoring systems, adaptive learning systems and recommender systems. An intelligent tutoring system 'uses techniques of artificial intelligence to model a human tutor in order to improve learning by providing better support for the learner' (Hasanov et al., 2019). Recommender systems are 'software tools based on machine learning and information retrieval techniques that provide suggestions for potential useful items to someone's interest' (Syed et al., 2017). Adaptive learning systems are personalised learning platforms that adapt to students' learning strategies, the sequence and difficulty of the task abilities, the time of feedback and students' preferences (Pliakos et al., 2019; Xie et al., 2019). These platforms encourage students to monitor their learning journeys via automated feedback cycles within the systems, allowing them to progress independently of the course instructor. AI-enabled learning systems have been developed based on research on AI (intelligent tutors), learning analytics and educational data mining techniques. The rapid advancement of these systems has been facilitated by the influence of AI in the education field (Hwang et al., 2020; Moreno-Guerrero et al., 2020). Indeed, in the education sector AI has helped to provide personalised feedback and support to students through the above-mentioned systems. It is predicted that there will be a growing number of technology-enhanced learning environment studies that will apply AI in education (Moreno-Guerrero et al., 2020).

The application of AI in the educational field has brought new prospects for the design and development of better technology-enhanced learning systems (Hwang et al., 2020; Moreno-Guerrero et al., 2020; Papamitsiou et al., 2018). AI-enabled learning systems offer numerous benefits, including an improved learning experience, time flexibility, the provision of timely feedback, flexibility in managing students' learning experiences and faster student progression (Chou et al., 2018; Moreno-Guerrero et al., 2020; Pliakos et al., 2019). Due to the capabilities and benefits of these systems and their huge potential to transform the education sector, many companies have begun to invest in AI. It is estimated that 1047 billion US dollars were invested in AI-based education from 2008 to 2017 (Guan et al., 2020).

The current literature reviews regarding AI-enabled learning systems concentrates on the existence of these AI-enabled learning systems (Du Boulay, 2019; Moreno-Guerrero et al., 2020); technological trends and approaches in adaptive learning (Somyürek, 2015; Xie et al., 2019); targeted outcomes, such as student performance and identification of personal traits (Afini Normadhi et al., 2019; Guan et al., 2020); educational fields and disciplines that are involved in AI-enabled learning systems (Mousavinasab et al., 2018; Zawacki-Richter et al., 2019); and how AI and machine learning techniques are integrated into learning systems (Pliakos et al., 2019). Studies have also examined the potential use of AI techniques to improve existing learning systems (Wakelam et al., 2015); the pedagogical deployment of these AI-enabled systems, such as intelligent tutoring systems (Du Boulay, 2019; Guan et al., 2020); and the technologies being deployed, such as virtual reality (VR) (Guan et al., 2020). However, these reviews did not examine the implementation status of the AI-enabled learning systems and whether they were fully utilised to address students' challenges.

There are few studies of AI-enabled learning systems implemented in educational settings. Thus, the implementation of these systems in education settings seems to be in the infancy stage. As Verdú et al. (2015) stated, 'Many of these learning systems as well as Intelligent Tutoring Systems are described in the literature, and their effectiveness has been proven. However, these systems are rarely used in real educational settings practices in ordinary courses.' The problem remains, and recent studies highlight the lack of successful AI-enabled learning systems, such as adaptive systems, implemented in practice (Cavanagh et al., 2020; Imhof et al., 2020; Somyürek, 2015). Thus, in an attempt to better understand the status quo of AI-enabled learning systems, our study maps the recent literature and presents the findings related to the utilisation of these systems.

The significance of using systematic mapping analysis instead of other types of literature analysis, such as bibliometric analysis, is its unique characteristic of analysing literature in a wide area. Further, systematic mapping generates new knowledge through meta-analysis of the existing knowledge published in the field (Farshchian & Dahl, 2015; Petersen et al., 2015). In recent studies, bibliometric analysis has been used to analyse a wide range of research issues with a large-scale dataset (Chen, Zou, Cheng, & Xie, 2020). This technique is particularly useful for better understanding 'what has been investigated in the past and further make predictions about what will happen in the future' (Chen, Zou, & Xie, 2020). Studies that have used bibliometric analysis (e.g. Guan et al., 2020; Moreno-Guerrero et al., 2020) have identified the performance of the scientific production of AI in the education field, the evolution of AI in the field, keywords associated with AI-enabled learning research, geographical distributions, the most incident/cited authors in the area and the historical trends. These studies, however, had a notable lack of evidence concerning the potential association between certain problems faced by students and lecturers and AI-enabled learning interventions that solve these problems. This systematic mapping study highlights such an association. In relation to the association, our systematic mapping analysis identifies AI-enabled learning interventions, challenges, and potential future research topics in this field.

This study also sheds light on the significance of utilising AI-enabled learning systems in educational settings. We hope that the findings of this research provide practitioners and researchers with insights into AI-enabled learning systems, especially in terms of how they are being utilised to address several challenges faced by the students who use them. The rest of the paper is organised as follows. First, Section 2 introduces the systematic mapping process applied. Section 3 presents the results of the research. This is followed by section 4, which discusses the findings from the retrieved literature. Section 5 highlights the contributions of this study. Finally, the limitations of the study are discussed in Section 6, followed by the conclusion of the paper.

2. Methodology

This study was conducted using the systematic mapping guidelines proposed by Petersen et al. (2015). Systematic mapping is a survey method that is used to 'give an overview of a research area through classification and counting contributions in relation to the categories of that classification' (Petersen et al., 2015). Systematic mapping is useful for analysing properties of the research papers in a certain research field. Compared to other types of content-based analysis, such as bibliometric analysis, systematic mapping is unique in creating a map of a wide research field (Farshchian & Dahl, 2015). Bibliometric analysis is a popular literature analysis technique that aims at providing quantitative assessment and evaluation of academic outlets in a particular research area (Chen, Zou, Cheng, & Xie, 2020; Chen, Zou, Cheng, & Xie, 2020). Systematic mapping is concerned with structuring a research area and identifying gaps in knowledge (Petersen et al., 2015). Another unique characteristic of systematic mapping is answering general research questions that aim to discover research trends. Systematic mapping studies have been used by many researchers in this field of AI in education (Dicheva et al., 2015; Farshchian & Dahl, 2015; Marques et al., 2020; Pelanek, 2020). In our case, we employ systematic mapping as the most appropriate method to capture what has been researched in the field of AI adaptive learning systems and to identify knowledge gaps.

The systematic mapping process comprises three major phases (i.e., planning the mapping, conducting the mapping and reporting the results of the mapping). The essential steps of a systematic mapping study are defining the research question, conducting a search for relevant papers, keywording, screening of papers, data extraction and mapping. For this process, the researchers utilised EndNote X9, NVivo 11 and Excel spreadsheets to extract publication outlets, find duplicates and organise the information. Planning a well-structured mapping is the first step in conducting any systematic mapping of literature. This step starts with identifying research objectives related to the literature on AI-enabled learning environments. By considering the possible impacts of AI-enabled learning systems, this study proposes three research questions (RQs):

- RQ1: What are the main research motivations and objectives of studies on AI-enabled learning environments?
- RQ2: What are the core research problems and concerns in the field of AI-enabled learning systems and the interventions/solutions proposed to address them?
- RQ3: What are the common AI and data analytics techniques utilised to design the interventions?

A protocol was used to guide the overall research method. The study applied both formal and informal searches to identify the above-mentioned research target goals. Previous works published in the past five years were selected to avoid outdated research. After planning the mapping, the next phase involved a systematic mapping of the literature.

The first step in conducting the systematic mapping was to formulate the search strategy, which was formulated based on a mapping protocol to reduce research bias. The search strategy was formulated by following and expanding the RQs. Then, the search keywords were identified, and search strings were generated to minimise the number of articles. Synonyms and substitute spellings were also identified. We focused on two main terms of interest to perform database searches: 'adaptive learning system' and 'artificial intelligence'. Two parallel searches were conducted, as the two main terms of interest were sometimes used interchangeably. 'Adaptive learning ecosystem', 'adaptive learning environment', 'adaptive learning platform', 'adaptive learning setting' and 'adaptive learning technology' were used as synonyms for adaptive learning systems. Further, along with the term 'Artificial Intelligence' we included the term 'machine learning'. These are the two most popular terms when it comes to AI-enabled adaptive learning systems and are typically supersets of other more specific techniques (e.g. data mining, text mining). The Boolean operators *OR* and *AND* were used along with these terms. These operators were included to incorporate synonyms and substitute spellings and to connect the keywords and form the final search string, respectively.(see Table 1)

This study seeks to capture and map the state of the art in the field, taking into account the vast advancements that have occurred in recent years. To this end, we have limited our search to include articles from 2014 onwards. The search was done on eight databases (i.e. ACM, Web of Science, EBSCO Host, Wiley, SAGE Journals, IEEE Xplore, Scopus and Taylor and Francis). These eight databases were chosen due to their wide selection of relevant and recent articles. The databases included numerous AI-related academic journals, such as *Journal of Artificial Intelligence and Soft Computing Research*, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *British Journal of Educational Technology* and *International Journal of Intelligent Systems*. The search was carried out on titles, abstracts, and keywords. A total of 1864 articles were retrieved using the above-mentioned search strategies. To reduce the number of articles, the study underwent further refinement, and several articles were selected based on criteria listed below. This was done to ensure that the selected articles were relevant and answered the RQs. All retrieved documents went through duplicate removal using EndNote software. A total of 1492 articles were retrieved after removing duplicates. All articles that met the inclusion criteria, which considered the title, abstract and keywords, were considered relevant for the study. The inclusion criteria were as follows:

A total of 147 papers were included in the study after undergoing the data extraction process. The study selection criteria proposed by Petersen et al. (2015) were adopted to have a standard form to extract data from the chosen articles. EndNote software was used to extract the basic information of the articles, such as the title, authors, year of publication and digital object identifier (DOI). Publication details, such as journal name, publisher, volume, issue, page, abstract and keywords, were also extracted. Then, specific data were extracted from each article for study categorisation. The following data were also extracted:

- Reference type (journal, conference paper, etc.)
- Type of paper based on the research approach classification proposed by Wieringa et al. (2006).
- Common techniques (AI, Machine Learning data mining or soft computing) utilised to design interventions
- Research motivations of these articles
- Type of interventions utilised
- Problems and concerns

The required information on whether an article was clearly reported was assigned the value 'N/A' in the equivalent cell in the extraction table. The authors created and finalised an Excel spreadsheet after reviewing the primary data extracted (Fig. 1).

3. Research results

This section presents the results based on the analysis of the selected published studies, which were identified as relevant to this study.

3.1. Results overview

In terms of publication channels, 51% of the included papers were scientific journals, and 49% were conference papers published in conference proceedings. The articles were categorised based on the type of research approach used, following Wieringa et al. (2006). The most utilised research approach was evaluation research (43 articles), followed by literature review (32 articles). Validation research and the philosophical approach were third and fourth, with 30 and 22 papers, respectively. The distribution of documents per year is shown in Fig. 2.

3.2. Types of AI-enabled learning interventions

The articles were placed in five categories based on implemented interventions and solutions applied in AI learning environments: systems, frameworks, models, approaches and combinations of interventions. Many of the published documents used a system (adaptive learning system, intelligent mechanism, or adaptive learning platform) as an intervention (61 articles). The other main form of intervention used was adaptive learning frameworks (27 articles). Frameworks are constructs that define concepts, practices, values and assumptions as well as provide a set of guidelines on how to implement the frameworks. Most of the frameworks recommended as solutions in these papers comprised essential elements and features for implementation in learning

Table 1
Keywords used in the search string.

Item	Set of keywords used for the systematic mapping
For All RQs	'adaptive learning system' AND ('artificial intelligence' OR 'machine learning'), 'adaptive learning ecosystem' AND ('artificial intelligence' OR 'machine learning'), 'adaptive learning environment*' AND ('artificial intelligence' OR 'machine learning'), 'adaptive learning platform' AND ('artificial intelligence' OR 'machine learning'), 'adaptive learning setting' AND ('artificial intelligence' OR 'machine learning'), 'adaptive learning technology' AND ('artificial intelligence' OR 'machine learning')

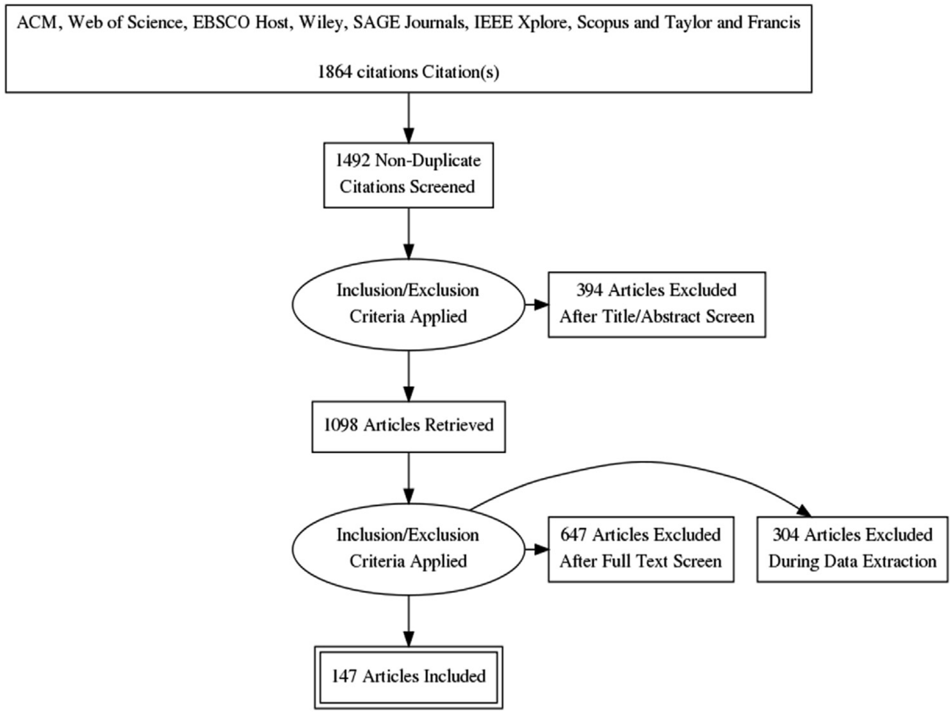

Fig. 1. PRISMA for the systematic mapping process.

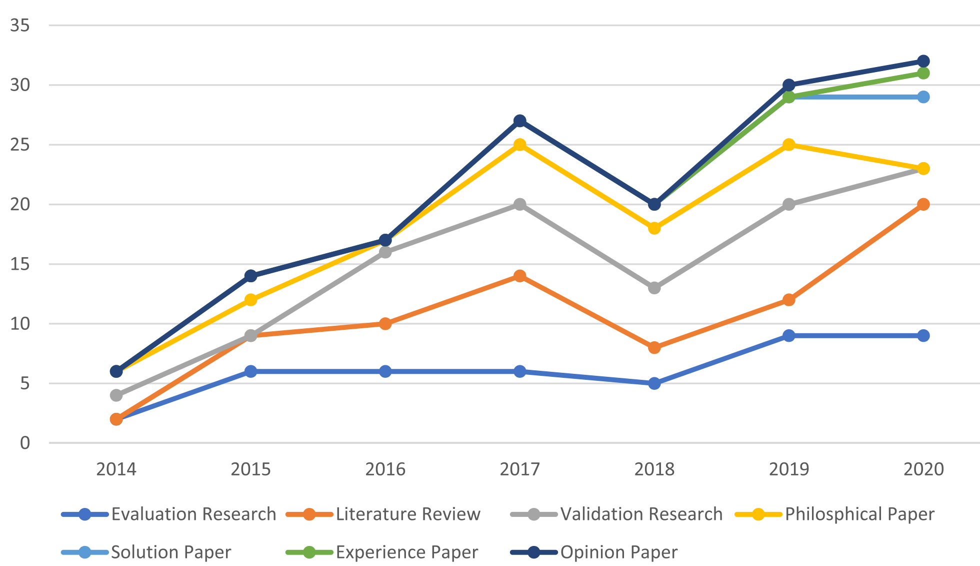

Fig. 2. The distribution of documents per year.

environments. The proposed items were in the form of AI techniques, user (learner) models and other adaptive techniques. The frameworks highlighted and described the relationships amongst the suggested elements. The coded frameworks provided numerous vital steps and actions for achieving a better adaptive learning experience. Meanwhile, 22 papers utilised models. A model is ‘a pattern of something to be made, a description or an analogy used to visualise and reason about the system to be developed and its likely effects’ (Stoica et al., 2015, p. 45). The models were either a problem-solving tool, experiment or abstract narrative of a component or system to be designed. Twenty papers explored an adaptive approach as a solution. An approach refers to a set of viewpoints or theoretical concepts applied to understand, explain and solve a problem observed in a particular phenomenon. The distribution of the research papers that utilised the above-mentioned AI-enabled learning interventions, published between 2014 and 2020, is depicted in Fig. 3. The distribution of the articles that used interventions published in conference proceedings and journal articles is illustrated in Fig. 4.

3.3. *Types and examples of AI-enabled learning systems*

The most identified AI-enabled learning systems in the mapping were Adaptive Learning Systems. Another most identified kind of AI-enabled learning system in the mapping is intelligent tutoring systems. Other categories of learning systems that were identified in this mapping and their examples are highlighted in Fig. 5.

The table below highlights the various themes of the designed aims of

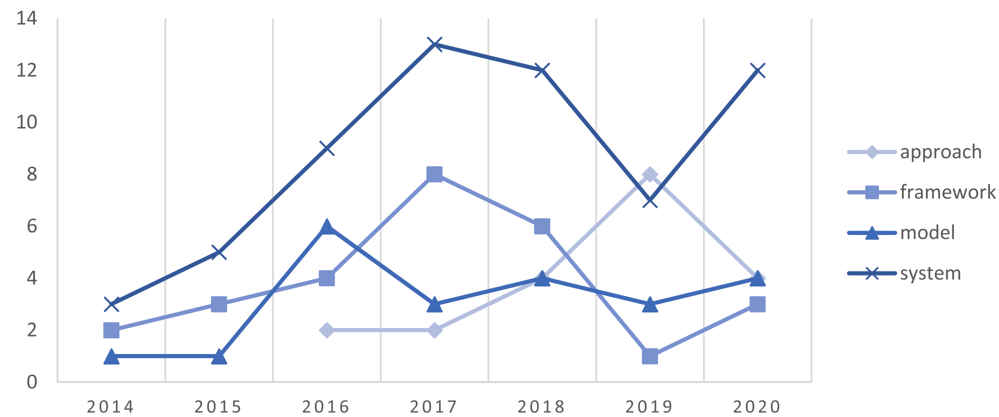

Fig. 3. Types of AI-enabled learning interventions.

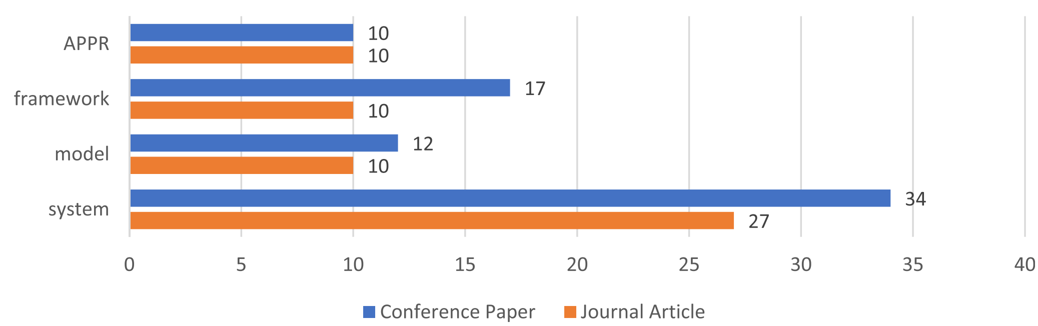

Fig. 4. Distribution of AI-enabled learning interventions per publishing outlet.

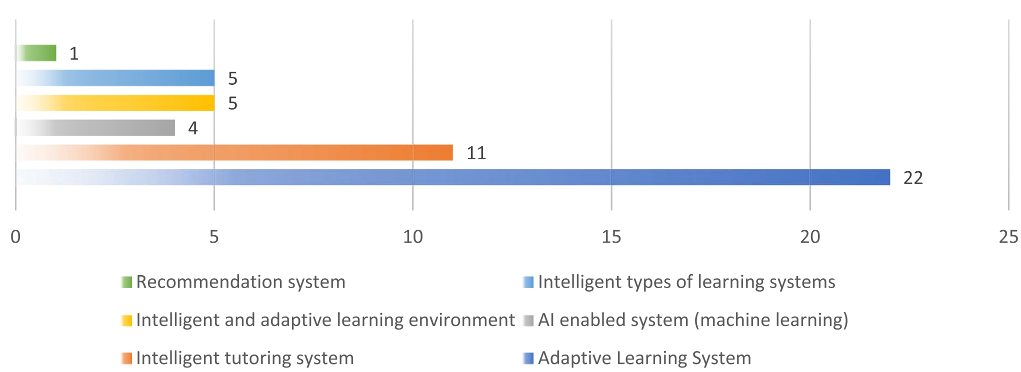

Fig. 5. Types of AI-enabled learning systems.

these AI enabled learning environments. Many of the published papers identified that the AI enabled learning environments were designed to assist with teaching several courses. These courses included mathematics, physics, psychology, nursing, computer literacy and biology. It was also identified that these systems were designed as platforms to teach and learn languages. The identified languages that were taught in these systems include English, German, and Greek. Another category of what AI enabled learning environments were designed to do is improve students' performance through Personalization of Learning. These systems were designed to act as platforms to provide personalised content based on their level. Also, the AI enabled learning environments are designed to teach and learn programming languages such as SQL and Java. The remaining identified themes are shown in the Table 2.

3.4. AI and data analytics techniques

Various AI and data analytics techniques were identified in our mapping. The graph below shows the frequency of the studies that mentioned or utilised these techniques. The Bayesian networks technique was the most frequently mentioned in these studies. A total of 14 articles proposed, mentioned and utilised this technique in studies involving AI-enabled learning environments. The next most frequently mentioned technique was neural networks (11 studies). Decision trees, genetic algorithms and K-nearest neighbour (KNN) techniques were also identified in this mapping, each with seven studies, followed by Support Vector Machines (SVMs) and Bayesian Knowledge Tracing (BKT) (six studies each). The rest of the identified techniques are presented in the graph below (see Fig. 6).

Table 2
Designed Aims AI enabled learning environments.

Category	Examples of the Mentioned Systems
Teach Courses	System developed by Realizeit, OPERA, ACTIVEMATH, AutoTutor, Ms. Lindquist, UZWEBMAT, AutoTutor, Crystal Island, Oscar, Wayang Outpost, ANDES, Guru, ACTIVEMATH, English Tutor, Student Diagnosis, Assistance, Evaluation System based on Artificial Intelligence (StuDiAsE), Yixue, Lumilo, Squirrel AI
Platforms for Teaching and Learning Languages	QuizBot, AutoTutor, Passive Voice Tutor, BOXFiSH, E-Tutor, Ms. Lindquist AutoTutor, the DARPA Tutor
Improve Students' Performance through Personalization of learning	Adaptive Mobile Learning System (AMLS), INSPIREus MeuTutor Knewton, INSPIRE, Units of Learning mobile (UoLmP), An Online Web-based Adaptive Tutoring System, Connect ™
Platform for Quizz, Exercises, Training	Smart Sparrow, Tamaxtil, affective tutoring system (ATS), QuestionIT
Teach and Help with Programming Language	SQL-Tutor, The intelligent Teaching Assistant for programming (ITAP), ALEA, QuizGuide and Flip, FIT Java Tutor, Gerdes' tutor
Evaluate and Improve Students' Knowledge	LearnSmart, Personal Assistant for Life-Long Learning (PAL3), DeepTutor, Protus
Consider and Examine Learners Requirements	Personalised Adaptive Learning Dashboard (PALD)''MostSaRT'' system, INTUITEL, KGTutor, MaTHiSiS, AL (an Adaptive Learning Support System for Argumentation Skills), the Web-based Inquiry Science Environment (WISE) system, NetCoach
Identify and Inform Students	The LeaPTM system, The Early Recognition System

4. Discussion of findings

4.1. Visualisation of the co-occurrences of authors associated with major research themes in AI-enabled learning studies

In this mapping, we identified several major themes, which we grouped according to the purpose and motivations of the research studies (Fig. 7). We visualised the authors' connections to the main objectives in conducting the selected studies. We chose to visualise the co-occurrences of authors associated with the purpose-related themes to identify the prominent themes and their connections in the field of AI-enabled learning systems. This was done by applying network analysis to a matrix of co-occurrences using the corpus analysis platform *CorTexT* (https://www.cortext.net/). This step allowed the mapping of the papers by clusters (Fig. 7). The papers were numbered and presented as small nodes, while the main themes of purposes were represented by cluster shapes. Clusters of closely associated authors were organised into specific subdomains (groups of highly interconnected nodes), which were instinctively detected by a clustering algorithm and colour-coded accordingly. The clusters provide an indication of topics that were intensely studied by researchers. In Fig. 7, the limits of the clusters are represented by coloured circles, and their surfaces are proportional to the number of small nodes they incorporate.

Using the clustering algorithm, all 147 papers were positioned and connected to these themes. As depicted in Fig. 7, the one paper that describes the partnerships between educational institutions in terms of using adaptive learning systems forms cluster PARTN (cluster presented in light green on top right). Then, 22 studies related to redesigning courses to adopt adaptive learning systems or adaptive learning modules form the REDESIGN cluster (green cluster on the right). Next, 61 papers that designed, described, proposed or developed AI-enabled learning systems are connected to the SYSTEM cluster (light orange right below). Twenty papers that aimed to design, develop, identify and propose approaches for AI-enabled learning systems form cluster APPROACH (the dark red in the middle), and 36 studies that proposed and utilised algorithms, mechanisms and AI/ML techniques can be found in the ALGORITHMS cluster (blue in the lower centre). In addition, 41 studies that presented general or comprehensive literature reviews are grouped in the LITERATURE REVIEW cluster (yellow on the left). Other topic clusters depicted in Fig. 7 can be found in the maroon EVALUATION cluster (29 studies focused on proposing evaluation methods or evaluating AI-enabled learning systems and adaptive courses), FRAMEWORK (orange cluster on the top left with 27 studies that focused on proposing and developing frameworks for adaptive learning and adaptive learning systems) and the MODEL triangle (light green cluster with 22 studies that develop models for AI-enabled learning systems).

Interestingly, most of these papers are linked to more than one cluster. For example, SLM_32 is connected to the SYSTEM and REDESIGN clusters, indicating that Dziuban et al. (2018) proposed adaptive learning systems and described an institutional partnership between educational institutions involving the use of adaptive learning systems. This is seen in the diagram by cluster overlapping. The proximity between certain nodes and clusters indicates the relatedness and close connections among the identified research themes. Thus, the EVALUATION node is positioned in the APPROACH cluster and close to SYSTEM. This indicates that studies whose main purpose is to evaluate adaptive learning systems are more linked to studies that proposed approaches for AI-enabled learning systems and which designed adaptive learning systems. This is supported by examples of projects and studies in our mapping that have developed AI-enabled learning interventions, such as the PTIME system (Berry et al., 2017), Early Recognition System (Ciolacu et al., 2019) and Yixue Squirrel AI system (Cui et al., 2019; Wang et al., 2020). More of these should be conducted and published to increase the use of these adaptive learning systems in educational settings. Further, studies that proposed or used algorithms or techniques are closely linked to clusters of studies that aimed to design adaptive approaches and the literature review studies, as seen in Fig. 7 (where ALGORITHMS is between the LITERATURE REVIEW and APPROACH clusters). The PARTN node is connected to REDESIGN node only, indicating low relatedness of institutional partnership to the other topics.

The largest clusters in our diagram are the SYSTEM, LITERATURE, ALGORITHMS, EVALUATION and FRAMEWORK clusters. This indicates that most AI-enabled learning interventions are systems and frameworks and use algorithms, as shown in Fig. 4. However, some of these designed and proposed systems and frameworks are in their experimental phases and have yet to be used in practice (Dargue & Biddle, 2014; Kasinathan et al., 2017). Hence, these learning systems cannot be easily adopted in real educational settings. If the designed systems or frameworks are not tested, then one cannot understand the consequences of implementing such interventions in terms of their benefits and drawbacks. This factor may have contributed to the fact that these learning systems are not used extensively in real educational settings (Verdú et al., 2015). The smallest cluster, PARTN, includes only one study on partnerships among institutions to collaborate on using adaptive learning systems. In APPROACH, 20 studies have designed, developed, identified and proposed approaches for AI-enabled learning systems. However, this finding shows that only a few studies have utilised adaptive approaches for AI-enabled learning systems.

Another interesting insight from this mapping relates to the number of general literature reviews that have been conducted in the past seven years. However, there are few studies on recent advanced AI-enabled learning systems that have been used as solutions to address more complicated challenges faced by students. Moreover, comprehensive reviews of adaptive learning systems are lacking, especially of those that have utilised modern AI techniques (Mavroudi et al., 2016; Wakelam et al., 2015). Several reviews have been conducted, but they are outdated in terms of the application of novel AI techniques (Hasanov et al., 2019). In the current study, we found that AI-enabled learning systems are simply used as platforms for teaching languages and programming courses and for improving performance. However, a few studies on more advanced learning systems have utilised AI to address the design issues of

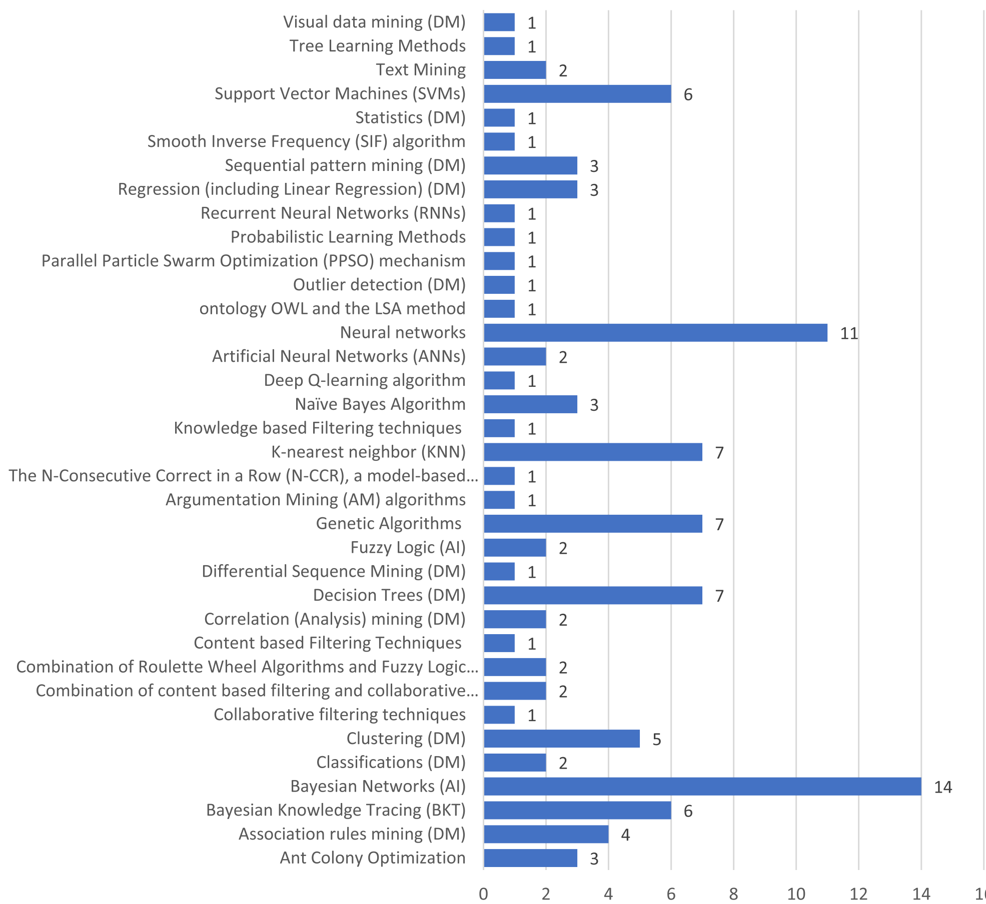

Fig. 6. AI and data analytics techniques utilised in the extracted studies.

learning systems, evaluation standards or methods for such systems, complex and outdated models of learning systems and personalization issues (Almohammadi et al., 2017; Chen et al., 2018; Standen et al., 2020; F. Wang & Han). In terms of learning systems that are adaptable to the profiles and backgrounds of students, only two systems have been proposed: the LeaPTM system and the Early Recognition System (Ciolacu et al., 2019; Liu, McKelroy, et al., 2017). Appendix A presents several challenges that have few interventions.

Most of the authors indicated what these learning interventions (in the form of systems, models, frameworks and even approaches) can do and how they can overcome various complicated challenges found in learning environments. However, several authors in our mapping (e.g., Hou & Fidopiastis, 2017; Padron-Rivera et al., 2018; Xie et al., 2019) have shown that most adaptive learning systems in practice are used simply as platforms for teaching languages, programming languages and other courses. Thus, there is a discrepancy between what an AI-enabled learning intervention can do and how it is actually utilised in practice. Arguably, users do not understand how to extensively use such systems, or such systems do not actually overcome complex challenges in practice, as the literature claims. Therefore, this is a research gap that needs to be addressed. The presented topic analysis based on themes is useful for identifying what areas of concentration related to AI-enabled learning systems have and have not been addressed so far.

4.2. Problems and AI-enabled learning interventions

In this mapping, we identified several problems faced by students and lecturers in their respective learning environments, including one of the most common, which is the learning process. Learning process-related challenges include difficulty sharing learning resources, the high redundancy of learning materials, learning isolation and inappropriate information load (Syed et al., 2017). Several studies have applied AI-enabled learning interventions to address this concern. One good example is the proposed novel adaptive e-learning model based on big data, which can improve the quality of the learning process by providing the most suitable learning content for each student. This model was designed to address inaccurate and incorrect learning material selection processes in adaptive learning systems. Another example is a personalised adaptive online learning analysis model that analyses the structure of a learning process using big data analysis (Liang & Hainan, 2019). In addition, Nihad et al. (2020) proposed a multi-agent adaptive learning system that can collect and detect information describing the learning process of students in a deductive way. This system aims to make real-time decisions and offer students training according to their dynamic learning pace. One study (Hou & Fidopiastis, 2017) proposed a generic conceptual framework for intelligent adaptive learning systems in order to address the lack of guidance in transferring learning effectiveness to field training when designing such systems. Several concerns, such as poor feedback, have been considered. Bimba et al. (2017) proposed a cognitive knowledge-based framework for adaptive feedback, which combined pedagogical, domain and learner models. Another intelligent model has been proposed, which uses both supervised and unsupervised ML techniques to adaptively select the appropriate learning material for a particular student (Idris et al., 2017).

Another interesting concern is related to the profiles and backgrounds of students. Existing educational systems utilise standardised teaching methods that do not fit the individual characteristics of each student (Oliveira et al., 2017). This highlights the need to use AI techniques so

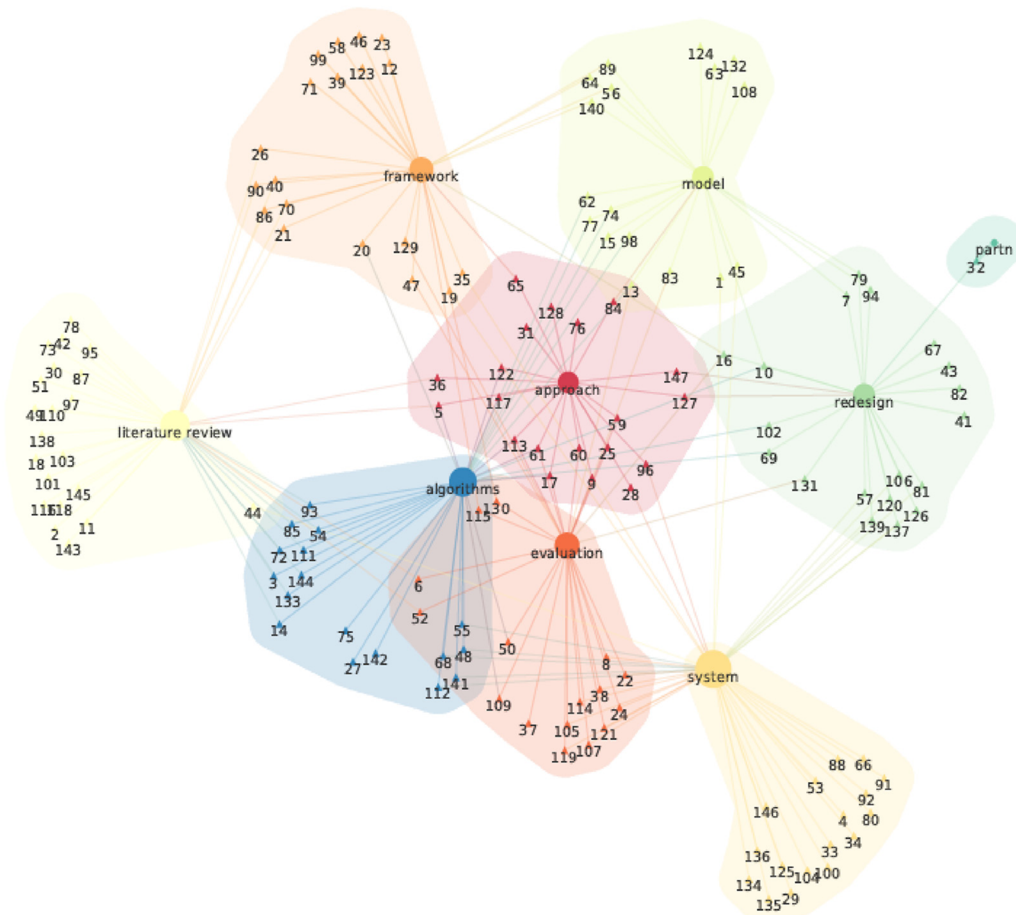

Fig. 7. Visualisation of the co-occurrences of authors associated with major research themes (Note: the number in the figure corresponds to the paper number in the Appendix for References).

that learning systems can cater to the distinct backgrounds and characteristics of each student. Several studies have applied AI-enabled learning interventions to address this issue. For example, Tommy et al. (2016) developed an intelligent and adaptive test system to tackle the problem of system inefficiency in capturing student proficiency. Similarly, Hampton et al. (2018) designed a mobile adaptive learning system called the Personal Assistant for Life-Long Learning (PAL3) to prevent knowledge decay. Hssina and Erritali (2019) presented an adaptation approach for their developed adaptive e-learning system. This approach allowed the generation of learning paths that can adapt according to the profiles of students. They used a genetic algorithm to search for optimal learning paths and then tested and evaluated their adaptive learning system. Troussas et al. (2020) proposed and presented a framework that recommends collaborative activities to students, considering their needs and preferences. The authors used Artificial Neural Network (ANN) and the Weighted Sum Model (WSM).

Problems related to engagement and motivation are also highlighted in this mapping. On the one hand, high levels of demotivation, passive attitudes, boredom, poor engagement and frustration among the students are specifically identified in this category. Examples of studies that applied AI-enabled learning interventions to mitigate these issues include Maravanyika et al. (2017), who proposed an adaptive recommender system-based framework for personalised teaching on e-learning platforms. An affective tutoring system (ATS) named Tamaxtil was developed to identify when students become frustrated and confused, at which point it offers them the help they needed (Padron-Rivera et al., 2018). On the other hand, some research evaluated existing systems to see how they could be improved. The researchers improved issues with the current systems by adding or utilising intelligent mechanisms, learning analytics, data mining techniques and plugins, such as Smart Adaptive Management for Flipped Learning (SAM-FL). For example, Min Liu, McKelroy, et al. (2017) used Brightspace LeaP™ adaptive technology to create adaptive intervention modules. The main objective of their research was to investigate the impact of adaptive learning on a large research university in the Southwestern United States. Their modules were embedded via the Learning Tools Interoperability integration in the Canvas learning management system. The growing use of systems and frameworks for adaptive learning is in alignment with past studies (Hampton et al., 2018; Tommy et al., 2016) on using AI-enabled learning systems to address challenges, such as student disengagement and poor student motivation. Thus, as seen above and in the Appendices, various examples of AI-enabled learning interventions have already been applied to address the problems faced by students.

However, there are still several problems that have yet to be addressed by AI-enabled learning interventions. One example of an overlooked problem is the use of outdated and highly complex models. Most of the models in the existing ITS, as noted by Dargue and Biddle (2014, p. 1), 'are quite complex to enable just about any learner to get the optimum tailored experience possible'. Brawner and Gonzalez, 2016, (p. 3) noted that the existing models use 'generalized data obtained from a large sample of human subjects, which lacks applicability to individuals'. To address the issue of complexity, existing adaptive learning models can be improved by AI techniques building on learning analytics (Papamitsiou et al., 2018; Pappas et al., 2019). Further, within complex relations in real life there are also asymmetric relations among variables and their different conditions, which can be captured by employing fuzzy-set Qualitative Comparative Analysis (fsQCA) (Ragin, 2009), as exemplified by Pappas and Woodside (2021). Other overlooked problems include personalization issues, designing and assessing adaptive courses, high instructor workload, no specific framework for implementing intelligent agents in the systems and high levels of attention among learners in the execution of the proposed tasks.

Our mapping revealed that problems still exist (e.g. difficulty in attaining learners' skills and issues related to students' backgrounds and profiles) despite evidence of AI-enabled learning interventions addressing such problems. Xie et al. (2019) noted that, when designing AI-enabled learning systems, designers of adaptive learning systems still give little attention to courses that have practical skills as a prerequisite. Mousavinasab et al. (2018) recommended and identified AI techniques for mitigating difficulties in attaining learners' skills. For instance, fuzzy-based techniques, condition-action rule-based reasoning, case-based reasoning and intelligent multi-agent and data mining methods are AI techniques that can be used in the field of computer programming. The presented topic analysis based on AI-enabled learning interventions is useful, as it helps identify the problems to which AI-enabled learning interventions have been applied and what problems have yet to be addressed. Appendix A presents this topic analysis.

4.3. Analytics methods and techniques that are utilised in AI-enabled learning systems

The present mapping of the literature shows that 46 papers proposed various techniques (*AI and data analytics techniques*), which we classified into three basic categories: descriptive, predictive and prescriptive analytics (Appendix B). The most common and utilised method involves predictive analytics, which deals with 'forecasting and statistical modelling to determine the future possibilities based on supervised, unsupervised, and semi-supervised learning models' (Sivarajah et al., 2017, p. 266). This analytical method is based on statistical methods that seek to reveal patterns and 'capture relationships in data' (Sivarajah et al., 2017, p. 276). Predictive analytics has been used for detecting and classifying questions that are applied to establish students' knowledge levels as well as selecting the required items for students. In our mapping, predictive analytics methods and related techniques, specifically naïve Bayes, fuzzy logic, Bayesian networks, neural networks and Bayesian knowledge tracing (BKT) and association rules mining, have been shown to enhance students' learning performance, personalised learning, motivation and achievements, thus addressing learning process challenges and student disengagement. Based on their capabilities, we recommend the use of predictive analytics to address the complexity of learning systems models and students' failure to attain target skills.

The other type of analytics method identified in this mapping is descriptive analytics. This category is the simplest BDA method that involves 'the summarization and description of knowledge patterns using simple statistical methods, such as mean, median, mode, standard deviation, variance, and frequency measurement of specific events in BD streams' (Sivarajah et al., 2017, p. 275). Usually, descriptive analytics help identify patterns and reveal what has already taken place. These methods and their related techniques identified in Appendix B are utilised to identify deviations in the behaviours of students or lecturers, analyse students' learning problems and evaluate their mastery and the knowledge they currently possess based on their success and failures. Thus, descriptive analytics techniques have been used to enhance students' learning performance. They can also be utilised to address issues such as the lack of evaluation standards and methods for AI-enabled learning systems as well as difficulties in finding an efficient way to organise complex information.

The least utilised analytics method is prescriptive analytics, which involves 'optimization and randomized testing' (Sivarajah et al., 2017, p. 266). The prescriptive analytics techniques we identified in the mapping include ant colony optimization and a combination of roulette wheel algorithms and fuzzy logic. These techniques, which select the more suitable solutions to problems, maximise learning path choice and thus establish optimal data. Prescriptive analytics can be used to solve several challenges highlighted in this mapping, such as limitations in adaptive learning systems, the failure to address process-oriented adaptation and difficulties in finding an efficient way to organise complex information.

5. Implications of this study and recommendations

5.1. Theoretical implications

The study contributes to the previous research (specifically literature reviews and the analysis of studies) by identifying the knowledge gaps in the field of AI adaptive learning systems. We identified research gaps and provided insights in three main areas. The first is a visualisation of the co-occurrences of authors associated with major research themes highlighted in AI-enabled learning systems. We visualised the authors' connections to the main purposes of the selected studies. We chose to visualise these co-occurrences to identify the prominent themes in the field of AI-enabled learning systems and demonstrate how they are connected to one another.

The second area is the types of AI-enabled learning interventions as well as what problems these interventions have and have not addressed. We identified several problems faced by students and lecturers in their respective learning environments. These included challenges in students' learning process in their learning environments and issues related to their profiles and backgrounds, engagement and motivation as well as how they can be addressed (Dunn & Kennedy, 2019; Papamitsiou et al., 2018) The third area we identified involves the analytics methods, their accompanying techniques and how they are utilised in AI-enabled learning systems (Almohammadi et al., 2017; Wang et al., 2020). The most utilised methods identified in our mapping were predictive and descriptive analytics. We also identified the different areas in which these two methods have been used, such as enhancing students' learning performance, motivation and personalised learning; analysing students' learning problems; and identifying deviations in behaviours among students and lecturers (Aldowah et al., 2019; Manjarres et al., 2018; Wakelam et al., 2015).

5.2. Practical implications

The study provides important insights for practitioners in education settings who are interested in AI-enabled learning systems. The findings of this study indicate that most AI-enabled learning interventions are systems and frameworks. However, some of the systems and frameworks that were designed and proposed were mostly in their experimental phases (Dargue & Biddle, 2014; Kasinathan et al., 2017). Researchers, developers and practitioners can implement these interventions and use them in real educational settings. The frameworks and systems can be tested and evaluated to see how they perform in educational settings. This is supported by Costa et al. (2017), who tested the Drift Adaptive Retain Knowledge (DARK) framework, which deals with challenges of dynamic environments (e.g. adaptive learning environments). These challenges include the inability to easily discern crucial and accurate information. Another example is testing and evaluating an AI-enabled learning system, named Tamaxtil, which detects 'affective states in students while they are solving mathematic exercises in order to regulate negative emotions' (Padron-Rivera et al., 2018).

Moreover, few studies have involved adaptive approaches for AI-enabled learning systems and partnerships among institutions for collaborating in their use. Thus, there should be more collaborations among universities to design and use AI-enabled learning systems, following successful examples in the literature that have presented, experimented and evaluated adaptive approaches in the development of adaptive e-learning platforms (Hssina & Erritali, 2019; Papamitsiou et al., 2020). Further, more studies should use adaptive approaches for AI-enabled learning systems, as this could increase the use of AI-enabled learning systems and address students' challenges. The main aim of the adaptive approach is to 'allow to generate learning paths adapted to the profiles of the learners and according to the pedagogical objectives fixed by the teacher'.. (Hssina & Erritali, 2019).

Another practical implication of this study is how to address the issue of outdated and complex models in learning systems. We recommend that existing adaptive learning models should be improved by AI techniques building on learning analytics. Fuzzy-based techniques, along with condition-action rule-based reasoning, case-based reasoning and intelligent multi-agent and data mining methods can be used for issues related to difficulties in attaining learners' skills. These can be implemented in situations in which skills (e.g. programming skills) need to be attained. Existing systems lack modern techniques or tools for students to practice and master their skills (Doroudi, 2020). Thus, based on their capabilities, we recommend that the various techniques (AI and data analytics techniques), which we classified into three basic categories (descriptive, predictive and prescriptive analytics), be used to address the problems related to the complexity of learning systems models, the lack of evaluation standards and methods for AI-enabled learning systems and the difficulties in efficiently organising complex information to support students in skill attainment. In this study, we identified prescriptive analytics as the least frequently used method. It is possible that practitioners and stakeholders are not aware of its capabilities in designing and building AI-enabled learning systems. Prescriptive analytics can be used to address several concerns highlighted in this mapping, such as limitations in adaptive learning systems and difficulties in finding an efficient way to organise complex information.

Finally, one of the research gaps identified in our study that needs to be addressed is the discrepancy between what an AI-enabled learning intervention can do and how it is utilised in practice. Arguably, users do not understand how to extensively use such systems. At the same time, such systems—when implemented—have not actually overcome the complex challenges faced by students, as the literature claims. Thus, researchers, developers and designers of these AI-enabled learning systems could promote awareness of the actual potential and benefits of these AI-enabled systems among lecturers and stakeholders who implement systems in educational institutions. Moreover, the study provided examples of AI-enabled learning interventions applied to address students' problems, as shown in the Discussion section and in the Appendices. Some of these problems have only been addressed by a few AI-enabled learning interventions. Therefore, practitioners and developers could design interventions for problems that have not been extensively addressed, such as in supporting learners' attainment of skills and complex models in the systems.

6. Conclusion

In this paper, we conducted a systematic mapping of AI-enabled adaptive learning systems presented in the literature using 147 studies published between 2014 and 2020. We found that systems (adaptive learning system, intelligent mechanisms and adaptive learning platform) and frameworks for adaptive learning were the most proposed and utilised interventions for addressing the challenges faced by students and teachers. The importance of such systems has largely increased during the pandemic as they can assist teachers in maintaining high-quality teaching and learning and improving learning design in IT and IS education (Pappas & Giannakos, 2021). However, most of the systems and frameworks that have been designed and proposed are currently in their experimental phases. They have not been tested in practice or adopted in real educational settings. In summary, we find that the use of AI-enabled contemporary learning systems can offer significant benefits. Therefore, we urge HEIs to adopt them where feasible.

We contribute to the literature by mapping the recent literature on AI-enabled learning systems. We present the summarised findings of topics related to such systems. The major findings and contributions of this paper include the identification of the types of AI-enabled learning interventions used, a visualisation of the co-occurrences of authors associated with major research themes in AI-enabled learning systems and an analysis of the most utilised BDA methods and accompanying techniques used in AI-enabled learning systems. Such mapping is needed, as research on AI-enabled learning systems is on the rise, and it is expected to continue with great potential for higher education institutions. Our mapping can aid in identifying and selecting the right kind of AI-enabled learning intervention to address a specific challenge. The findings on AI-enabled learning systems presented in this paper contribute to a better understanding of learning systems.

Future research can address the above-mentioned overlooked problems by applying AI-enabled learning interventions. Moreover, studies should be conducted on the limited usage of AI-enabled learning systems in education and how this problem can be overcome. Specifically, the issue of designing and assessing courses that utilise AI-enabled learning systems should be given attention in order to increase the usage of these systems in real educational settings. Another significant recommendation is that future research should attempt to bridge the gap between pedagogy and emerging AI techniques. More studies are needed to address this gap and align technology platforms with course content, students' expectations and lecturers' needs. In sum, in future research, more systems, frameworks and models should be put in practice and tested so that researchers can determine whether they can provide solutions for overcoming the learning challenges faced by students.

This study has several limitations due to the nature of the research. Although the recommendations of Petersen et al. (2015) were followed to ensure a systematic literature mapping, the search words, strings and databases may have limited the mapping. The key strings were limited to adaptive learning systems, while AI-related terms were limited to AI and ML. This was done because these terms are the most popular. Indeed, the results identify papers that may deal with other AI more specific techniques (such as data mining or text mining). As AI-enabled learning systems evolve, future research should keep a close eye on the developments with regard to the inclusion of more advanced techniques, such as deep learning and natural language processing. Moreover, the selected databases, inclusion criteria and exclusion criteria may, by their nature, have excluded some research. Finally, questions like the methodological approaches applied and the purposes for which AI has been used in learning systems were not reviewed. These issues can be addressed in future research.

Statements on ethics

This material is the authors' own original work, which has not been previously published elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner. The results are appropriately placed in the context of prior and existing research. All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

Credit author statement

Tumaini Kabudi: Conceptualization, Methodology, Validation, Investigation, Data Curation, Writing – Original Draft

Ilias Pappas: Conceptualization, Methodology, Validation, Writing – Review and Editing, Supervision.

Dag Hakon Olsen: Conceptualization, Supervision.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.caeai.2021.100017.

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