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Intelligent techniques in e-learning: a literature review

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Abstract

Online learning has become increasingly important, having in mind the latest events, imposed isolation measures and closed schools and campuses. Consequently, teachers and students need to embrace digital tools and platforms, bridge the newly established physical gap between them, and consume education in various new ways. Although literature indicates that the development of intelligent techniques must be incorporated in e-learning systems to make them more effective, the need exists for research on how these techniques impact the whole process of online learning, and how they affect learners' performance. This paper aims to provide comprehensive research on innovations in e-learning, and present a literature review of used intelligent techniques and explore their potential benefits. This research presents a categorization of intelligent techniques, and explores their roles in e-learning environments. By summarizing the state of the art in the area, the authors outline past research, highlight its gaps, and indicate important implications for practice. The goal is to understand better available intelligent techniques, their implementation and application in e-learning context, and their impact on improving learning in online education. Finally, the review concludes that AI-supported solutions not only can support learner and teacher, by recommending resources and grading submissions, but they can offer fully personalized learning experience.

Keywords Artificial intelligence · E-learning · Intelligent techniques · Intelligent tutoring systems · Personalization

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1 Introduction

In the last years, education at all levels has witnessed a substantial increase in the number of learning technologies supporting the traditional classroom environments. Moreover, online and distance learning has become increasingly essential, considering the latest events with the pandemic, imposed isolation measures, and closed schools and campuses. Due to these recent trends and circumstances, teachers and learners need to embrace learning technologies (e.g., digital tools and platforms) to bridge the newly established physical gap between them and consume education in various new ways. Therefore, the focus is shifting from developing infrastructures and delivering information online to joining interdisciplinary efforts to improve the overall online learning experience (Shute and Towle 2003). These changes in our educational systems have brought a growing interest in exploiting digital traces that learners leave behind while interacting with learning technologies through artificial intelligence (AI), big data (Daniel 2015), and learning analytics (Siemens 2013) innovations.

Moreover, teachers are frequently challenged by the demands of providing scalable yet personalized and adaptive feedback that can promote learning in the online setting. Those efforts largely depend on correctly identifying the characteristics of a particular learner, as they differ in knowledge and skills, cognitive abilities, performance, and the learning strategies they tend to use (Van Seters et al. 2012).

Based on the research needs identified in Becker et al. (2018), Mangaroska and Giannakos (2017), Mote et al. (2016), the paper summarizes intelligent techniques used in e-learning and presents findings on their roles in enhancing educational systems. The goal is to discover and evaluate AI-based techniques used in e-learning and quantify the benefits they offer to the learning process. Thus, we propose the following goals is to:

- classify and analyze the publications from the area,
- identify and categorize various intelligent techniques used in online learning,
- identify their roles in the specific systems and provide an overview of gain results concerning learner engagement and performance,
- discuss the future trends and challenges in the e-learning context.

To address the defined goals, the paper addresses the following research questions:

- RQ1 Which intelligent techniques are designed, implemented, and used in e-learning environments, and for which purposes?
- RQ2 How do different intelligent techniques impact learners' attitudes, motivation, and overall performance in online learning platforms?
- RQ3 What are the challenges and unreached potential of implementing intelligent techniques in e-learning?

Special focus will be directed towards identifying the influence on learners' attitudes–how learners respond towards something (Smidt et al. 2014), motivation–reason or desire for learning (Rakic et al. 2019), and performance–how well students are learning in terms of knowledge and skills development (Elezi and Bamber 2021). Even though the paper does not focus on any specific e-learning domain, the majority of the identified systems are from the computer science education area. However, the review also identified numerous systems for learning languages, mathematics, physics, biology, etc.

A thorough literature review has been conducted to answer the proposed questions, and a detailed categorization of the concepts that synthesize and extend existing research in the area of intelligent techniques in online education is offered. By summarizing the state of the art in the area of intelligent techniques in online education, the authors will try to outline past research, highlight its gaps, and indicate essential implications for practice. By creating the review of earlier and recent work, it will become possible to understand theoretical concepts and terminology and identify areas in which further research would be beneficial.

The remainder of the paper is organized as follows. Section 2 presents the related work relevant to this study, including intelligent techniques in e-learning and previous review studies. The used methodology is presented in Sect. 3 describing the studies selection and analysis process. Section 4 presents the research findings, qualitative and quantitative, derived from the collected data. Section 5 answers the defined research questions before discussing the results in Sect. 6. Finally, Sect. 7 concludes the paper and provides suggestions for future research.

2 Related work

The use of intelligent techniques in e-learning has a role in providing context-aware and context-sensitive resources based on what is available and relevant to the needs or motivations of the learner, considering the learners' emotional states too (FitzGerald et al. 2018). Researchers have identified the need to incorporate emerging intelligent technologies to enable e-learning systems to offer personalized learning content, automatic guidance, feedback, and adaptive learning paths and interfaces (Tang et al. 2021).

An overview of the recent findings in this research field has been presented in several literature reviews (Table 1). The reviews are mainly focused on specific areas of use of intelligence, such as the use of machine learning techniques (Alenezi and Faisal 2020; Farhat et al. 2020; Khanal et al. 2020; Tang et al. 2021), educational data mining (Al-Razgan et al. 2014; Du et al. 2020; Dutt et al. 2017; Martins et al. 2018; Silva and Fonseca 2017), knowledge tracing (Am et al. 2021; Dai et al. 2021), learning analytics (Banihashem et al. 2018; Bruno et al. 2021; Leitner et al. 2017; Melesko and Kurilovas 2018b; Mangaroska and Giannakos 2018), learner modeling (Abyaa et al. 2019; Chrysafiadi and Virvou 2013; Jando et al. 2017), and different kinds of intelligent agents (Hobert and Meyer von Wolff 2019; Martha and Santoso 2019; Soliman et al. 2010) in e-learning. In addition, intelligent techniques might be used to visualize learners' data (Bodily et al. 2018; Hooshyar et al. 2020; Matcha et al. 2019a) or for different purposes in intelligent tutoring systems (Alkhatlan and Kalita 2019; Dermeval et al. 2018; Mousavinasab et al. 2021) and learning management systems (Alshammari et al. 2016; Kasim and Khalid 2016; Oliveira et al. 2016).

Contrary to these review studies that focus on the narrow segments of AI in e-learning research, this study tries to grasp the broad picture of used methods and techniques and form the theoretical framework of technology-based learning models. The study will identify the core research trends based on longitudinal publication evidence. However, without a whole picture regarding the advancements of AI and the use of intelligent techniques in e-learning, some important research directions could be ignored, and some could be overemphasized, particularly by novice researchers in this field. Therefore, the importance of conducting a systematic literature review in this area is of great importance. The findings of the presented study can serve as a reference for educators and researchers from the area.

Table 1 Available literature reviews

Category	Publications
Techniques	
Machine learning	Alenezi and Faisal (2020), Farhat et al. (2020), Khanal et al. (2020), Tang et al. (2021)
Educational data mining	Al-Razgan et al. (2014), Du et al. (2020), Dutt et al. (2017), Martins et al. (2018), Silva and Fonseca (2017)
Knowledge tracing	Am et al. (2021), Dai et al. (2021)
Learning analytics	Banihashem et al. (2018), Bruno et al. (2021), Leitner et al. (2017), Mangaroska and Giannakos (2018), Melesko and Kurilovas (2018b)
Learner modeling	Abyaa et al. (2019), Chrysafiadi and Virvou (2013), Jando et al. (2017)
Environments	
Intelligent tutoring systems	Alkhatlan and Kalita (2019), Dermeval et al. (2018), Mousavinasab et al. (2021)
Learning management systems	Alshammari et al. (2016), Kasim and Khalid (2016), Oliveira et al. (2016)
Intelligent agents	
Multi-agent	Soliman et al. (2010)
Pedagogical agents	Hobert and Meyer von Wolff (2019), Martha and Santoso (2019)
Visualization of learners' data	
Open learner models	Bodily et al. (2018), Hooshyar et al. (2020)
Learning analytics dashboards	Bodily et al. (2018), Matcha et al. (2019a)

Visualizing of a research network will help researchers identify core papers in the focal network and highlight networking relationships among core papers for future research directions.

Based on the suggestions of several systematic review studies (Mousavinasab et al. 2021; Tang et al. 2021), this study analyzes research conducted in the past decades on the application of AI in e-learning and presents the patterns of publications and research trends.

3 Methodology

To conduct the literature review, we followed the guidelines given by Kitchenham and Charters (2007). This methodology was chosen as: (1) it provides precise and excellent guidance for performing reviews; (2) it has been proven as effective for similar literature reviews the authors have performed in the past; and (3) it is applicable to almost any field.

The selection of publications has been executed into two phases. First, we determined keywords that will be used to search the papers. After detailed consideration, the following keywords were selected: e-learning, intelligent, techniques, approach, personalization, implementation, system. To get the best search results, the combination of these keywords was applied in search using Boolean operators AND and OR.

The following search string queries were used to obtain papers from various databases:

- E-learning AND Intelligent AND (Techniques OR Approach)

- E-learning AND Personalization AND Intelligent AND (Techniques OR Approach)
- E-learning AND Intelligent AND (Techniques OR Approach) AND Implementation
- E-learning AND Intelligent AND (Techniques OR Approach) AND System

To get as many papers available on the internet, related to the topic of intelligent techniques in e-learning, we used seven different databases for the searching process. The following databases were searched using the defined search string queries: Google Scholar, Scopus, Springer Link, Science Direct, Web of Science, IEEE Xplore, and ACM Digital Library. After initial search, a total of 8729 papers were found.

The Second phase included filtering insufficient and irrelevant papers. After the removal of duplicate papers, 5820 papers remained. Afterwords, the following inclusion criteria has been defined:

1. Presentation of intelligent technique(s) applied in e-learning,
2. Specific use of intelligent technique(s) in e-learning,
3. Overview of e-learning systems that implement intelligent technique(s),
4. Inclusion of specific roles of intelligent technique(s) in e-learning,
5. Articles that had full text,
6. Article is available in English.

First, we filtered all papers by screening titles, abstracts, and keywords. The papers that met the inclusion criteria were then selected, a total of 782.

The exclusion criteria to determine which papers would enter the final selection is:

1. Not applicable to this research,
2. Not related to the research questions,
3. Multiple publications covering the same topic/system.

After excluding some papers with the above exclusion criteria and rechecking the inclusion criteria, a total of 305 papers entered the final selection. Papers from this final selection were then fully analyzed, classified, and categorized.

4 Intelligent techniques in e-learning—findings

An e-learning course should not be designed in a vacuum; rather, it should match learners' needs and desires as closely as possible, and adapt during course progression (Graf and List 2005; Ruiz et al. 2008; Mikić et al. 2022). To achieve that, online learning environments must:

- Create and build **learner model** by collecting data about learners, identifying their progress, activities, and needs using various **data mining** techniques, but also provide learners with possibilities to view and analyze their data through means of **open learner model**.
- Measure, collect, analyze, and report data about learners via **learning analytics**.
- Offer **adaptive assessment** customized to each examinee based on their previous performance.

- Customize learning towards each learner's strengths, needs, skills, and interests by implementing fully **personalized approach**.

Online learning environments must meet these four requirements in order to provide a truly adaptive teaching and learning experience (Vesin et al. 2018; Chatti et al. 2013). Supporting these elements in online learning environments could allow learners to efficiently acquire a variety of professional skills and competencies. E-learning systems use different intelligent techniques, primarily AI-based algorithms, intelligent agents, and data mining, to successfully implement such a personalized approach. In that regard, this review will cover the intelligent techniques, used in online education in four broad areas: learner modeling (profiling and prediction); learning analytics; adaptive assessment and evaluation; and adaptive and personalized learning (Zawacki-Richter et al. 2019). Even though most of the techniques presented in this review clearly represent AI or can be applied in AI (techniques like artificial neural networks, fuzzy logic, Bayesian network, etc.), some of them are not regarded as AI (item response theory, Elo rating algorithm) but are used in e-learning to provide intelligent approaches to achieve adaptation, assessment or learner modeling.

4.1 Qualitative findings

4.1.1 Learner modeling

Learners have different motivations, prior knowledge, personalities, emotions, and learning habits, all of which can have an impact on their educational process (Abyaa et al. 2019). As a result, supplying each learner with tailored learning content is no longer an option, but a necessity. Understanding the learners may help teachers design better instruction and materials, but it can also assist learners in becoming more aware of how they learn best.

Learner modeling is the act of gathering and updating data about a learner over time using well-defined procedures. The stages of this procedure are (1) obtaining initial data on the learner's attributes, (2) model construction, and (3) updating the learner model by watching and tracing the learner's activities (Abyaa et al. 2019; Vagale and Niedrite 2012).

Literature review, presented in Abyaa et al. (2019) analyzes the works in the area and identifies three main areas of interest regarding learner modeling: the **modeling approaches**, the **modeling techniques**, and the **learner characteristics being modeled**. In addition, we identified another aspect of learner modeling that should be investigated in more detail - **used technologies and standardization efforts**.

The learner model can be implemented using two different **modeling approaches**: knowledge-based and behavioral-based (Ahmed et al. 2017). These two approaches are used in e-learning to acquire substantial information about learners needed to create a learner model. Knowledge-based approach gathers learner data through examination, questionnaires, learner interests, and learners' learning routines. The behavioral-based approach collects learner data only by observing learners' system activities and processes.

Regarding the question of which learner's data is being collected, six major categories of **modeled characteristics** were identified in the literature, depending on the used approach: the learner profile (mostly learner personal information and static data), knowledge (knowledge level, competencies, skills errors, misconceptions), cognitive characteristics (learning and thinking styles, cognitive states, learner's behavior), social characteristics (interactions, culture, social style), motivation (interests, learning goals, engagement and affect), and personality (Abyaa et al. 2019). These characteristics represent the type of learner data that is being collected and then used for modeling.

Influenced by the modeling approach and the defined goals of e-learning system, five **modeling techniques** can be identified (Abyaa et al. 2019): predictive modeling techniques (De Morais et al. 2014), clustering and classification techniques (Moubayed et al. 2020), overlay modeling (Ahmadaliev et al. 2019), uncertainty modeling (Al-Shanfari et al. 2017), and ontology-based learner modeling (Akharraz et al. 2018; Rezgui et al. 2014). These techniques are used for modeling learner models using collected data.

Some typical examples of e-learning systems that use a knowledge-based approach for learner modeling are Zebra (Nguyen 2014) (ontology-based learner modeling technique, with modeled characteristic knowledge), AdaptLearn (Alshammari et al. 2015) (uncertainty modeling technique, with cognitive modeled characteristics), and Learning Java (Yau and Hristova 2018) (uncertainty modeling technique, with cognitive modeled characteristics). Some typical examples of e-learning systems that use a behavioral-based approach for learner modeling are DEPTHS (Jeremić et al. 2012) (overlay technique, with modeled characteristic knowledge), INSPIREus (Papanikolaou 2014) (clustering and classification technique, with modeled characteristics knowledge and motivation), and My Math Academy (Thai et al. 2021) (predictive modeling technique, with modeled characteristic knowledge).

Numerous online courses and e-learning platforms have been created independently, frequently at great expense. Furthermore, such content and systems are often, if not always, unprepared to communicate or share data. Systems must be able to read and understand other systems' data structures to communicate and interoperate, therefore need extensive **standardization efforts**. Shareable Content Object Reference Model, or SCORM, is a set of technical standards for e-learning software products (Poltrack et al. 2012). Due to current web trends and the SCORM standard inflexibility for formal education, a new strategy and transition to the development of a new standard were needed, and it was necessary to switch to Experience API (xAPI). The xAPI represents a specification that enables different learning technologies to capture data about a person's or a group's wide range of learning experiences in a consistent format using the xAPI vocabulary (Karoudis and Magoulas 2018). It provides a learner-centered model for learning data collection and learning process recording (Sun et al. 2020). With this technology, experiences can be collected in the form of statements and stored in a learner record store that syncs learning activities across platforms and devices (Smith et al. 2018; Zapata-Rivera and Petrie 2018). As a result, learning applications could make use of much more complete data to support learners with visualizations and interventions (Neitzel et al. 2017). E-learning systems can more effectively adapt instruction when they have more accurate models of the learner's prior knowledge or competency (Sottilare et al. 2017).

4.1.1.1 Open learner models Open Learner Model (OLM) is a contemporary approach to represent the current state of the learner's knowledge (Ahmad 2013). OLM can be understood as learner models that allow a user, usually the learner, to view the internal system's learner model data in a human-understandable form (Kay and Bull 2015). They externalize the inferred learner model contents to the learner (or another user), usually with some kind of visualization (Bull et al. 2016). Through the OLM, where this information is modeled, learners can access information about their current level of knowledge, difficulties in the subject area, and any misconceptions they may have. Opening the learner model to the learners can offer them a useful additional learning resource (Vesin et al. 2018), help them to understand better their learning (Barria Pineda and Brusilovsky 2019), promote reflection, and encourage learners to take greater responsibility for organizing their learning (Long and Aleven 2017).

In OLM, the knowledge level of learners is typically represented in the form of skillometers (Albó et al. 2019), concept maps (Bull 2020), and hierarchical tree structures (Conejo et al. 2011). In addition to these three most used display models, there are also other types of visualization in OLM such as bar graphs and pie charts (Papanikolaou 2014), the grids (Guerra et al. 2018), bullets (Brusilovsky and Yudelson 2008), circles (Hsiao et al. 2013), smilies (Bull and McKay 2004), treemaps (Brusilovsky et al. 2011), stars, gauges, word clouds, tables, histograms, network diagrams, and radar plots (Bull et al. 2015, 2016).

Based on the main goal of the implemented OLM, Bull and Kay (2010) identified several categories of OLMs:

- *Inspectable*–which promote reflection and planning (Bull et al. 2010).
- *Editable*–where the user can directly change the model assessment and system's representation of their knowledge at will (Conati et al. 2018).
- *Challenged*–where learner may challenge their model, and justify the changes they make to the model (Bull and Kay 2010).
- *Co-operative*–where learning model is built together by both learners and system (Hamzah 2018).
- *Persuaded*–which allow learners to change their learner models but they are required to demonstrate their competency before the system can agree with the changes they made (Suleman et al. 2016).
- *Add-evidence*–where learner can contribute additional evidence for changing his learning model (Kay and Kummerfeld 2019).
- *Negotiated*–which allow learners to negotiate and potentially modify their model (Thomson and Mitrovic 2009).

For challenged, cooperative, persuaded, add-evidence, and negotiated OLMs, there is a variety of guiding tools for learners to use during the negotiation process, some regular like menu selection, collaborative tools, and negotiation with the teacher, but also some AI guiding tools such as pedagogical agents, conversational agents, and dialogue games (Nakahashi and Yamada 2021; Bull and Kay 2010; Zapata-Rivera et al. 2007). A negotiation mechanism using these AI guiding tools has been used in OLM to enhance learner model accuracy and provide opportunities for learner reflection (Suleman et al. 2016). More detailed overview of intelligent agents and their use in e-learning will be provided in Sect. 4.1.7.

Employing OLM in e-learning systems is very important for learners because it can assist their learning and enable them to monitor and analyze their advancement and development. Learner modeling and OLM are not intelligent techniques per se, but to fully grasp their potential, e-learning environments use various **data mining** techniques to successfully collect and visualize data about learners, their knowledge, activities, and needs, and **knowledge tracing** techniques for modeling and predicting learners' knowledge, performance, and future interaction.

4.1.2 Educational data mining

Data mining is an effective tool to extract meaningful and interesting patterns from the current and historical data stored in data warehouses or data repositories, to be analyzed and predict future trends (Prabha and Shanavas 2015). In the context of educational research, data mining is known as Educational Data Mining (EDM). EDM is defined as the area of scientific inquiry centered around the development of methods for making discoveries within the unique kinds of educational data and using those methods to understand learners better and the environments in which they learn (Baker 2010).

The most common uses of EDM are for supporting learners in course selection, learners' profiling, finding problems leading to dropout, learners' targeting, curriculum development, predicting learners' performance, and as a support for decision-making at learner enrollment (Zorić 2020).

The benefits of EDM are numerous, including enhancing the quality of education, improving current study programs and educational practice, improving teaching, advancing the process of studying, improving learners' academic performance, reducing learners' failure rates, increasing course completion percent, and helping educational management to be more efficient and effective (Abu Tair and El-Halees 2012; Kumar and Chadha 2011; Zorić 2020).

The five most commonly used techniques in the educational domain found in the literature are: prediction, clustering, relationship mining, distillation for human judgment, and discovery with models (Bienkowski et al. 2012). Each of these techniques can be used to quantitatively analyze large data sets to find hidden meaning and patterns (Huebner 2013).

Prediction entails developing a model that can infer a specific element of the data (predicted variable) from a set of predictor variables (Bienkowski et al. 2012). This technique is used in e-learning to analyze learner data and predict outcomes. The types of prediction methods are classification (target variable is a category), regression (target and background variables are numbers), the density score (predicted value is the probability density function) (Grigorova et al. 2017). Examples of e-learning systems using prediction are AL-TESL-e-learning system (Wang and Liao 2011) for the classification of learner characteristics and learning performances and Junyi Academy (Paquette et al. 2020), which uses regression to analyze and extract information from both human annotations and usage logs.

Clustering is the process of grouping a set of objects into classes of similar objects (Asif et al. 2017). In e-learning, cluster analysis can be used to investigate similarities and differences between learners, courses, teachers, etc (Zorić 2020). Typical examples of e-learning systems using this technique are dotLRN (Köck and Paramythis 2011) for monitoring and interpreting sequential learner activities and ESURBCA (Suresh and Prakasam 2013), which uses this technique to get consistency in content delivery, quality content in learning materials, learners' self-learning concepts, and performance improvement in their examination.

Relationship mining is the process of identifying relationships among variables in a dataset and encoding them as rules for subsequent use (Wibawa et al. 2021). The key application of this technique in e-learning is identifying relationships in learner behavior patterns and diagnosing learner difficulties (Romero and Ventura 2020). Different types of relationship mining exist, such as association rule mining (relations between variables), sequential pattern mining (temporal association between variables), correlation mining (linear correlation between variables), and causal data mining (the causal relationships between variables) (Grigorova et al. 2017). Typical examples of e-learning systems using relationship mining are eDisiplin (Man et al. 2018), which uses association rules to disclose some useful patterns for decision support, ESOG (Ougiaroglou and Paschalis 2012), which uses this technique to discover all hidden associations that satisfy some user-predefined criteria, and Blockly programming App (Shih 2018), which uses sequential pattern mining to find the sequence patterns of app functions accessed by users.

Distillation for human judgment is a process of representing data using visualization and interactive interfaces to enable humans to quickly identify or classify data features (Wibawa et al. 2021). The key application of this technique in e-learning is helping instructors visualize and analyze the ongoing activities of the learners and their use of information (Romero and Ventura 2020). A typical example of an e-learning system for distillation for human judgment is Canvas (Arnold and Pistilli 2012), which utilizes this technique to model learner and instructor usage data and to examine the relationship between these models and learner learning outcomes.

Discovery with models is a technique that uses a model developed via prediction, clustering, or by human reasoning knowledge engineering and then used as a component in further analysis (Hicham et al. 2020). It can be used to find relationships between learner behavior and learner characteristics or contextual variables, analysis of research questions in various contexts, and integration of psychometric modeling frameworks into machine learning models (Bienkowski et al. 2012). A typical example of an e-learning system using this technique is the Cisco Networking Academy (Mislevy et al. 2012), which uses it for online assessment.

Using data mining in e-learning will enable the analysis of learners' data collected from e-learning environments to discover hidden knowledge and recognize patterns, which can then be used to improve learning.

4.1.3 Knowledge tracing

The rapid development of computer-supported education environments and e-learning platforms provide abundant learners' exercise data for Knowledge Tracing (KT) (Chen et al. 2018). KT is the task of modeling learner knowledge over time so that we can accurately predict how learners will perform on future interactions (Piech et al. 2015). Its working mechanism is to take observations of a learner's performance (e.g. the correctness of the learner response in a practice opportunity) or a learner's actions (e.g. the time he stayed for a question), and then use those to estimate the learner's underlying hidden attributes, such as knowledge, goals, preferences, and motivational state, etc (Gong et al. 2010).

The following are the most important advantages of KT in e-learning environments:

- Predicting learner's performance. KT records learners' knowledge states over time in order to estimate their progress toward mastering the required knowledge components and, as a result, can predict a learner's performance (Yang and Cheung 2018).
- Giving strong feedback to teachers. Data obtained from KT could be used to warn the teacher in case the learner has not mastered the skills that are required by a given subject (Casalino et al. 2021).
- Helping in the process of personalization. KT assists an e-learning system in providing learners with more effective and personalized instruction material (Penmetsa 2021).

- Assisting the learner's needs. KT enables us to grasp the current needs of learners and to recommend questions accurately (Zhang et al. 2020).
- Maintaining learners' motivation during the learning process. KT can help learners improve their self-motivation in learning and achieve personalized guidance by automatically detecting their weak knowledge points (Zou et al. 2020).
- Improving learners' learning efficiency. Predicted learners' performance can be used to personalize their learning schemes and increase their learning efficiency (Shen et al. 2021).

The most known techniques for KT are Bayesian knowledge tracing and deep knowledge tracing.

A family of methods called *Bayesian Knowledge Tracing* (BKT) uses probabilistic methods and machine learning to model learners' skill acquisition in e-learning systems (David et al. 2016). The original BKT model was proposed by Corbett and Anderson (1994). E-learning systems that utilize BKT can predict learner performance (Qiu et al. 2011). BKT is a specific type of dynamic Bayesian network, or more precisely, of hidden Markov models consisting of observed and latent variables (performance and skills) (Schodde et al. 2017). BKT takes learner performances and uses them to estimate the student's level of knowledge (Gong et al. 2010). BKT assumes that student knowledge is represented as a set of binary variables, one per skill (the skill is either mastered by the student or not) (Yudelson et al. 2013). They are updated based on the correctness of students' answers to questions that test the skill under investigation; hence observations are also binary (Käser et al. 2014). Some of the typical e-learning systems based on BKT are CRYSTAL ISLAND (Rowe and Lester 2010), ASSISTment (Pardos and Heffernan 2010), edX (Pardos et al. 2013), Coursera (Wang et al. 2016), Robot language tutor (Schodde et al. 2017), and SITS (Hooshyar et al. 2018).

Deep Knowledge Tracing (DKT) proposed by Piech et al. (2015) utilizes recurrent neural network to model student learning. DKT aims to automatically trace learners' knowledge states by mining their exercise performance data (Yang and Cheung 2018). In the DKT algorithm, at any time step, the input to recurrent neural networks is the learner performance on a single problem of the skill that the learner is currently working on (Xiong et al. 2016). As a learner progresses through an assignment, the DKT algorithm attempts to utilize information from previous timesteps, or problems, to make better inferences regarding future performance (Zhang et al. 2017b). Specifically, based on learner historical answered questions, it can predict learner performance on future questions with high accuracy (Wang et al. 2019). Typical examples of e-learning systems based on DKT are Khan academy (Piech et al. 2015) and Udacity (Kim et al. 2018).

Many other authors have developed their own models for KT through the years. Dynamic Key-Value Memory Networks (DKVMN) presented in Zhang et al. (2017a) can exploit the relationships between underlying concepts and directly output a learner's mastery level of each concept. DKVMN is a variant of memory-augmented neural networks, a type of model that adds storage modules and corresponding read-write mechanisms based on traditional neural networks (Sun et al. 2021). Sequential Key-Value Memory Networks (SKVMN) (Abdelrahman and Wang 2019) is also a deep learning model for KT proposed by Abdelrahman & Wang, which unifies the strengths of recurrent modeling capacity and memory capacity of the existing deep learning KT models for modeling learner learning. Pavlik Jr et al. (2009) presented Performance Factors Analysis (PFA) as a new alternative to KT, where they compared these two models, and results suggested that the PFA model was somewhat superior to the KT model overall. PFA predicts learner performance based on the item difficulty and learner historical performances (Gong et al. 2010). Pu et al. (2021) presented Deep Performance Factors Analysis (DPFA) for KT, which consistently outperforms PFA and DKT and has results comparable to those of DKVMN. Chen et al. (2018) developed a new KT model named PDKT-C to estimate learners' knowledge states better. González-Brenes et al. (2014) presented FAST (Feature Aware Student Knowledge Tracing), an efficient, novel method that allows integrating general features into KT. Pandey and Karypis (2019) proposed a self-attention-based knowledge tracing model named SAKT, which models a learner's interaction history and predicts his performance on the next exercise by considering the relevant exercises from his past interactions. Trifa et al. (2019) proposed Mod-Knowledge, an intelligent agent that analyzes the learner interaction to trace the learner's knowledge state using machine learning algorithms.

The main current challenge is to support KT with the psychological and behavioral aspects of the teaching process, linked specifically to learning design.

4.1.4 Learning analytics

Educational data is growing rapidly as an increasing number of education systems are going online (Krikun 2017). Extensive data sets are available from learners' interactions with educational software, and online learning (Koedinger et al. 2010; Siemens and Baker 2012). E-learning environments automatically capture system-based records of users' activities, recording who accessed what and when (Phillips et al. 2011). The analysis of this data can improve learning models to predict the results of learners, for example, to distinguish who needs extra help or who can solve a more complex task to develop additional skills (Mamcenko and Kurilovas 2017).

Learning Analytics (LA) can be defined as the analysis of electronic learning data, which allows teachers, course designers, and administrators of learning environments to search for unobserved patterns and underlying information in learning processes (Agudo-Peregrina et al. 2014). LA has the ability to interpret the unusual behaviors of learners, recognize patterns in learning, identify potential issues or gaps, conduct appropriate interventions, and increase learners' awareness of their actions and development (Mangaroska and Giannakos 2018; Siemens and Long 2011). It employs sophisticated analytic tools and procedures to investigate and visualize large institutional data sets in the service of improving learning and teaching (Brown 2011; Macfadyen and Dawson 2012; Shum and Ferguson 2012). The majority of techniques employed by LA are derived from EDM, but in addition to these techniques, LA also incorporates social network analysis and statistical analysis (Bienkowski et al. 2012; Romero and Ventura 2020).

EDM techniques used for LA include prediction, clustering, relationship mining, distillation for human judgment, and discovery with models. Examples of e-learning systems that use some of the EDM techniques are Desire2Learn, Shehata and Arnold (2015) which uses prediction to improve learner success, retention, completion, and graduation rates, and Blackboard Vista (Arnold and Pistilli 2012), which employs distillation for human judgment for LA.

Social network analysis records learners' online interactions to gauge their participation and engagement level (Czerkawski 2015). The purpose of social network analysis is to determine and understand the relationships between learners in a network environment such as discussion forums or social media (Wibawa et al. 2021). A typical example of an e-learning system that uses this technique is OSBLE+ (Olivares et al. 2019), which uses social network analysis to determine whether exposure to automated interventions would positively affect the relationship among learners over time.

Statistical analysis is used for the analysis and interpretation of quantitative data for decision-making (Leitner et al. 2017). By using statistical analysis in e-learning environments, we can count the number of visits, analyze mouse clicks, and calculate time spent on tasks (Khalil and Ebner 2015). A typical example of e-learning system using this technique is OU Analyse (Herodotou et al. 2020), which uses a variety of advanced statistical approaches to identify learners who are at risk of failing their studies.

Visualization of data obtained using these techniques is mainly done using learning analytics dashboards. For learners and teachers alike, they should be able to see a visual representation of their activities and how they relate to those of their classmates or other participants in the learning process (Duval 2011).

A *Learning Analytics Dashboard* (LAD) is a single display that aggregates different indicators about learners, learning processes, and learning contexts into one or multiple visualizations (Schwendimann et al. 2016). LAD provides educators and learners with a comprehensive snapshot of the learning domain (Ramaswami et al. 2022). LAD display insights, trends, and changes in data over time, mainly using different types of charts and various widgets. They present data clearly and efficiently, and they are very intuitive for both teachers and learners. The main goal of LAD for educators is to assist them in getting learners' feedback either during or after lectures so they can use this information to modify and adjust their instructions, lessons, guidance, and tutoring (Verbert et al. 2014). Also, teachers can use this feedback for checking each learner's learning progress and providing proper interventions (Kim et al. 2016).

The LAD and OLM have similar goals. Both the LAD and OLM aim to make data available to help learners interpret aspects of their learning (Kay and Bull 2015). OLM shows the learner model to users, with some visualization, to assist their self-regulated learning by, for example, helping prompt reflection, facilitating planning, and supporting navigation (Guerra-Hollstein et al. 2017). Even though OLM and LA are similar areas concerning the visualization of learners' data (in general), they are different in that OLM is more inclined toward visualization of the learner's level of knowledge (progress), difficulties, and misconceptions, while LA is rather more based on results towards prediction, recommendation, and also semantic aggregation (Hooshyar et al. 2019; Kay and Bull 2015). In addition, a significant difference is that OLMs are grounded on work in "student modeling", "learner modeling", and even the broader "user modeling", whereas dashboards are more broadly grounded in data-driven decision-making, which often includes goals, stakeholders, and decision-making outside of the context of the learner model (Bodily et al. 2018).

LA has the potential for a tangible positive impact on learner learning by supporting **learning strategies** and **tactics** (Knight et al. 2020). Learning strategies can be defined as the behaviors of a learner that are intended to influence how the learner processes information (Mayer 1988; Gasevic et al. 2017). A learning tactic is a single or a very short sequence of operations a learner applies to information (Winne and Marzouk 2019). Traditionally, learning strategies and tactics are usually discovered using surveys, questionnaires, or think-aloud protocols. In e-learning, LA has the potential to detect and explain characteristics of learning strategies and tactics through analysis of trace data and communicate the findings via feedback (Matcha et al. 2019b). Such LA approaches provide a direct analysis of the users' "actual" behavior in lieu of the learners' perception, and recall of events (Jovanović et al. 2017).

After collecting the learners' data and discovering their learning strategies and tactics via LA, learning designers use this valuable information for learning design. **Learning**

design can be defined as an application of a pedagogical model for a specific learning objective, target group, and a specific context or knowledge domain (Koper and Olivier 2004). Learning designers use summative, real-time, and predictive LA to increase the quality of the curriculum, materials, scaffolds, and assessments (Ifenthaler 2017). Learning design and LA can help teachers in designing quality learning experiences for their learners, evaluate how learners are learning within that intended learning context, and support personalized learning experiences for learners (Lockyer and Dawson 2011).

LA can be a powerful tool in e-learning environments. Using LA in e-learning can assist in identifying potential issues or gaps in learners, and then instructors can use this information to optimize learning and improve learners' success.

4.1.5 Adaptive assessment

In traditional education, most assessments present the same set of questions to all learners. While such examinations are relatively simple to develop, they do not reveal what each learner is genuinely capable of. There may be learners who know more than their test results display. Alternatively, learners may answer some questions poorly but might demonstrate a higher level of knowledge if given more straightforward questions. If all learners are asked the same questions, the information provided by the results may be limited.

In contrast, adaptive assessment is adjusted to learner responses by analyzing their range of skills and proficiency levels and defining a tailored learning route for a specific learner. Such adaptive assessment systems are also known as computerized adaptive testing, which represents a special case of computer-based testing where each examinee takes a unique test that is tailored to their ability level (Triantafillou et al. 2008). With the use of adaptive testing, the evaluation system is more accurate in measuring the ability of the learner. It can accommodate the diversity of learner capabilities to provide learning materials for the system according to the level of learner's proficiency (Kustiyahningsih and Cahyani 2013). A computer-based adaptive assessment provides highly accurate results that can recognize the mastered competencies of each learner, determine educational requirements, track educational advancement throughout time, and place learners in educational programs that suit them (Raman and Nedungadi 2010).

The most valuable benefits of adaptive assessments in online learning environments are:

- Increased assessment precision. Adaptive testing allows quickly identifying a candidate's accurate knowledge level by precisely narrowing down the range of a learner's ability (Chrysafiadi et al. 2020; Krouska et al. 2018).
- Increased effectiveness. Compared to traditional assessments, the adaptive element of the assessment allows for more accurate estimates of a candidate's knowledge (Hubalovsky et al. 2019; Mangaroska et al. 2019).
- Enhanced learners' experience. Matching questions to the learner's actual level of ability prevents learners from seeing questions that are too difficult or too easy and reduces the likelihood that they will feel overwhelmed, discouraged, or bored. A more learner-friendly assessment experience can increase learners' acceptance level (Hariyanto and Köhler 2020).

The most common intelligent techniques used in e-learning software development to match learners' proficiency level are item response theory, Elo rating algorithm, and TrueSkill.

Item Response Theory (IRT) is a conceptual framework that is based on basic measurement concepts using statistical and mathematical tools (Salcedo et al. 2005). IRT has roots in psychometrics and is concerned with accurate test scoring and the development of test items. It is usually used in the adaptive assessment systems domain to calibrate and evaluate items in a test and to score learners' abilities, attitudes, or other latent traits (Dahl and Fykse 2018). IRT models enable estimation of the skill level of each learner and its evolution over time, as well as the difficulty and the discrimination of each question (Benedetto et al. 2020). Some typical examples of e-learning systems that implement adaptive assessment based on IRT are UZWEBMAT (Özyurt et al. 2014), MISTRAL (Oppl et al. 2017), Amrita Learning (Gutjahr et al. 2017), SIETTE (Conejo et al. 2018), UTS (Bernardi et al. 2018), English vocabulary learning system (Chen et al. 2019), SamurAI (Uto et al. 2019), PEL-IRT (Ferjaoui and Cheniti Belcadhi 2020), and Lexue 100 (Jia and Le 2020).

Elo rating algorithm represent an alternative to IRT. The Elo rating algorithm, developed to measure player strength in chess tournaments, has also been applied for educational research and used to measure learner ability (Pankiewicz and Bator 2019). To adapt the concept of a chess game to the educational measurement, a learner is considered a player, an item is considered an opponent, and a correctly answered item is considered a win for the learner (Park et al. 2019). Some typical examples of e-learning systems that implement adaptive assessment based on Elo rating algorithm are ProTuS (Mangaroska et al. 2018), Math Garden (Brinkhuis et al. 2018), Matistikk (Dahl and Fykse 2018), and ACT Academy (Yudelson et al. 2019).

TrueSkill is another approach for adaptive assessment, which can be viewed as a generalization of the Elo rating system used in chess (Herbrich et al. 2006). TrueSkill was developed for ranking players in video games. By interpreting problem-solving as a match between learner and problem, it is possible to use the TrueSkill rating system to estimate the ability of learners to solve a series of issues in the e-learning environment (Lee 2019). A typical example of an e-learning system that implements adaptive assessment based on TrueSkill is APACTS (Kawatsu et al. 2017).

Adaptive assessment can change the difficulty level based on a learner's responses, making it more efficient, targeted, and precise than traditional tests. They are, however, extremely complex, time-consuming, and resource-intensive to create.

4.1.6 Personalization in e-learning

Personalized learning is a learning experience in which the pace of learning and the instructional approach are tailored to each learner's specific needs (Mikić et al. 2022). The pace of learning, sequence, technology, instructional strategy, instructional content, and other aspects of personalized learning may all vary based on learner needs. This more tailored education aims to provide relevant learning activities motivated by their interests and are frequently self-initiated.

Personalized e-learning systems customize various features of online learning, such as the user interface, learning content, or activities. These features can be personalized based on different factors such as learners' prior knowledge, preferences, habits, behavior, etc. AI shows its true potential when designing personalized training, providing a wide range of methods and techniques that could be applied to customize the learning process in online environments. The most commonly used personalization methods in e-learning today are:

- *Recommendation of content*. Learners can receive recommendations of study materials that best suit their learning preferences with the use of AI to identify patterns in learners' data (Tarus et al. 2018a).
- *Resource/curriculum sequencing*. Using pattern recognition, AI can detect specific concepts that learners fail and adjust the sequence of course material presented to a learner (Muhammad et al. 2016).
- *Providing automatic feedback*. AI can capture, aggregate, and analyze learners' submissions and activities and provide personalized feedback (Matcha et al. 2019b).

With the implementation of personalized learning, AI will assist learners in achieving academic success while also helping teachers in becoming more effective.

4.1.6.1 Recommendation of content Recommender systems can often be defined and perceived as systems that aim to provide specifically tailored recommendations according to individual user preferences (Zhang et al. 2021b). Deployment of these systems in various e-learning contexts and scenarios can aid learners in locating the proper learning materials and resources, allowing them to accomplish their learning goals.

Often, the learner profile, which can be identified as a construct consisting of learners' preferences, knowledge level and interests, represents an important segment related to learning success (Manolis et al. 2013). In the ideal circumstances, recommender systems in e-learning environments should help learners to determine the best-matching resources and actions regarding their learner profile (Zhang et al. 2021b).

Recommender systems have been developed and integrated in e-learning using multiple forms of recommendation: *collaborative filtering* (Hidayat et al. 2020; Liu 2019; Murad et al. 2020), *content-based filtering* (Lops et al. 2011; Raghuwanshi and Pateriya 2019; Wang et al. 2018), and *knowledge-based filtering* (AbuEloun and Abu-Naser 2017; Alawar and Abu-Naser 2017; Hiles and Agha 2017; Tarus et al. 2018b)

In addition to these three basic techniques of recommendations, many *hybrid recommender systems* can be found in the literature (Cobos et al. 2013; De Medio et al. 2020; Tahmasebi et al. 2019; Tarus et al. 2018a; Zhou et al. 2018).

Hybrid recommender systems represent the combination of more than one recommender system approach, all in favor of overcoming the common issues and drawbacks related to using singular recommendation approaches. These types of recommendation systems are utilized to achieve an increase in performance while cutting back the downsides and limitations. Hybrid recommender system factors in the strengths of the techniques integrated to generate valid recommendations (George and Lal 2019). Some typical examples of hybrid recommender system approaches that can be found in literature are: support vector machine based collaborative filtering (Ren and Wang 2018), sequential pattern mining with collaborative filtering (Chen et al. 2014), association rules with content-based and collaborative filtering (Xiao et al. 2018), sequential pattern mining with knowledge-based filtering (Tarus et al. 2017), etc.

The likes of the singular recommendation approaches undoubtedly represent essential segments of personalized e-learning environments. Nevertheless, the trends in the literature point out that the usage of hybrid recommender systems is higher than those based on single recommendation techniques (Alyari and Navimipour 2018).

4.1.6.2 Resource/curriculum sequencing To achieve their learning goals, learners should study appropriate and relevant learning resources (Premlatha and Geetha 2015). After the identification of proper learning resources by the instructor, these resources should be constructed into a learning path for learners. A learning path refers to organizing learning activities in a suitable sequence so that learners can effectively study a subject area (Yang and Dong 2017). Designing an ideal learning path for learners represents one of the main challenges in e-learning adaptation. Resource sequencing is used in e-learning to generate a personalized learning path and resources for each learner based on learners' prior knowledge, learning goals, progress, and personal preferences (Queirós et al. 2014). Instead of all learners having the same learning path, which can cause learner disorientation and confusion, a personalized learning path enables learners to achieve curriculum goals easier and increase their motivation and commitment to learning.

In e-learning, there are a number of different techniques for generating a personalized learning path, such as *genetic algorithm* (Agbonifo and Olanrewaju 2018; Albadr et al. 2020; Dwivedi et al. 2018), *memetic algorithm* (Nguyen et al. 2012; Shishehchi et al. 2021), *ant colony optimization* (Benabdellah et al. 2013; Niknam and Thulasiraman 2020), *particle swarm optimization* (Alhunitah and Menai 2016; Liu et al. 2019), and *artificial bee colony* (Hsu et al. 2012; Venkatesh and Sathyalakshmi 2020).

Using these techniques for implementing resource sequencing in e-learning systems can give learners a clear, systematic, and organized approach to learning, which can help them to master their lessons easier and thereby accelerate their progress. An adaptive e-learning system that offers a personalized learning path can increase learning quality and enhance learners' performance (Vanitha et al. 2019).

4.1.6.3 Providing feedback to learners The essential part of e-learning is that learners must receive feedback and assistance throughout the whole process (Shvets et al. 2020). Feedback represents a system's response to learners regarding their activities or performance, used by the learners to improve the quality of their work or learning practices. The success of e-learning systems relies on engaging experience and timely and accurate feedback to the learners on their performance (Hassan et al. 2019).

To be able to provide adaptive feedback in the broad sense, an e-learning system needs to have the intelligent capability to analyze learners' activities (Le 2016). Learners can better comprehend their cognitive processes and engage in online learning activities by receiving timely, personalized feedback. For feedback to be adaptive, different characteristics of learners are taken into account, such as prior knowledge, learning progress, and preferences (Bimba et al. 2017). Many systems for providing adaptive learner feedback exist through literature, and most of them support *textual feedback* (Kakeshita and Ohta 2016; Tawafak et al. 2019; Vijayakumar et al. 2018), while some deliver *video feedback* (Crook et al. 2012).

Implementing adaptive feedback in e-learning has a relevant impact on the learners, who value it because it makes their learning process simpler, richer, and more significant (Martínez-Argüelles et al. 2013). Also, evidence suggests that e-learning systems with adaptive feedback can significantly improve learner performance (Hassan et al. 2019).

4.1.7 Intelligent agents

Intelligent agents as a conception has been around since the early years of e-learning. These so-called assistant programs are located inside the e-learning system, and they make the whole learning process more active to suit the learner's demands. Intelligent agents are used to collect, process, and analyze learners' data to understand and optimize the learning environment (Kotova 2017). In general, intelligent agents can monitor behavior, evaluate learners' performance and the importance of the way of transmitting recommendations, and improve the quality of learning (Saeidi Pour et al. 2017). Agents can perform repetitive tasks, remember things learners forgot, intelligently summarize complex data, learn from learners and even make recommendations to them (Meleško and Kurilovas 2018a).

The utilization of agents in e-learning systems assists in referring to many of the restrictions of these systems by promoting the design and distribution of e-learning objects that match learner preferences. These agents observe the learner's responses to the introduced learning object to provide convenient content for the learner's abilities. Agents are concentrated task-resolving units with defined task margins and can perform independently without directions.

Up-to-date extraction of learning contents, easy, comfortable, fast contact between teacher and learner, and supervision over the teacher's and learner's performance during the learning process are considered advantages provided by a system based on intelligent agents in e-learning (Fasihfar and Rokhsati 2017).

Some typical examples of autonomous intelligent agent systems are eTeacher (Chung 2015), which tracks the learning activities and performance of learners and provides them with personalized content, and Mod-Knowledge (Trifa et al. 2019), which is responsible for analyzing the learner's interactions to trace their knowledge state.

A *multi-agent system* is a collection of autonomous agents that work together to solve problems that are beyond the capabilities of individual agents (Xu et al. 2014). They can be described as an assembly of agents with their trouble-fixing capabilities.

Examples of multi-agent systems are MAS-PLANG (Asselman et al. 2018), which provides content, navigation strategy, and navigation tools according to the learners' learning habits, EMASPEL (Bokhari and Ahmad 2014), which takes the facial expression of the learner and provides help accordingly, ALLEGRO (Asselman et al. 2017), which manages the content for learners, F-SMILE (Alkhatlan and Kalita 2019), used to generate default assumptions about learners, ISABEL (Aguilar et al. 2015), where the idea is to divide the learners in groups with similar profiles and where each group is managed by a tutor agent, IAELS (Tsai et al. 2012), for improving learners' learning capabilities, MIPITS (Lavendelis 2015), used to provide different types of tasks and adapt tasks to the needs of individual learners, ADOPT (Ajroud et al. 2021), whose agents analyze the traces left by the learner, calculate various indicators, and propose the most suitable adaptations for the learner, PowerChalk (Rosado et al. 2015), whose agents are used for identification in order to get individual user profiles and to create educational content, and MetaTutor (Trevors et al. 2014), which interacts with the learner's prior domain knowledge to affect their note-taking activities and subsequent learning outcomes.

Personalized approaches based on intelligent agent technology imply that each learner has its own personal (pedagogical) agent, tutor respectively, that directs learner towards learning (Kuk et al. 2016). These agents are in the form of a virtual character or simple chat interface equipped with AI that can support the learners' learning process and use various instructional strategies in an e-learning environment (Martha and Santoso 2019).

In e-learning, there are two types of these agents: *pedagogical agent* and *conversational agent*. The difference between these two is that a pedagogical agent will merely hold a monologue, give hints and solutions, while a conversational agent can engage in a dialogue with the learner (Davis 2018; Wellnhammer et al. 2020). Conversational agents use natural language processing, which enables them to understand text and spoken words and converse with humans in a natural way (Van Pinxteren et al. 2020). The main goals of these agents are to motivate and guide learners through the learning process by asking questions and proposing solutions (Klašnja-Milićević et al. 2017).

Typical examples of e-learning systems with pedagogical agents are ISLA (Mondragon et al. 2016) with pedagogical agent Jessi, who is capable of detecting the affective state of an autistic child in mathematical learning, ATS (Thompson and McGill 2017), in which pedagogical agent Jean responds to the affective state of the learner, CALL system (Carlotto and Jaques 2016), with pedagogical agent Patti who explains the material on the content screens and reacts to learners' exercise results, APLUS (Matsuda et al. 2014) has a pedagogical agent named SimStuden, who helps learners learn to solve algebraic equations by tutoring, and a second agent, Mr. Williams, on whom learners can click to ask for help, and the EC Lab (Osman and Lee 2014), which also has two pedagogical agents, Professor T., who gives accurate information and explains new concepts to the learners, and Lisa, who learns together with the learners and provides motivation and encouragement to the learners to complete the tasks and exercises in the module.

Typical examples of e-learning systems with conversational agents are Geranium (Griol et al. 2014), with conversational agent Gera, which poses questions to the learners that they must answer either orally or using the graphical interface, and Curiosity Notebook (Chhibber and Law 2019), which supports conversational interaction between learners and AI agents.

Including agents in e-learning will push the learning process to a more functional level. With intelligent agents, e-learning systems have the chance to learn and use their acquired knowledge to fulfill their goals (Fasihfar and Rokhsati 2017).

4.1.8 Other intelligent techniques in e-learning

Previous chapters represent the overview of different e-learning processes and intelligent techniques that are used to support them. However, most popular intelligent techniques found their way into e-learning by offering multiple different roles, most notably artificial neural networks, Bayesian network, fuzzy logic, decision tree, and hidden Markov model.

Artificial neural networks are a powerful class of machine learning algorithms that learn complex patterns from data using collections of simple trainable mathematical functions (Hassan and Hamada 2017). In e-learning systems, they are mostly used for predicting a learner's performance (Şuşnea 2010), analyzing learners' online interactive behaviors (Poitras et al. 2019), recognizing the cognitive state of learners (Bhattacharya et al. 2018), detecting human expression using psychological signals (Dogmus et al. 2014), or predicting difficulties a learner will experience in a digital design course (Hussain et al. 2019).

A *Bayesian network* represents some conditional dependency of the random variables by the directed acyclic graph and conditional probability tables (Kondo and Hatanaka 2019). It is a combination of AI, probability theory, graph theory, and decision theory (Wang et al. 2020). Bayesian networks can learn and represent uncertain and coarse knowledge (Zhang et al. 2021a). It has significant advantages in dealing with uncertainty, mining the correlations among observable quantities, latent variables, and unknown parameters (Jiang et al. 2018). In e-learning systems, it is mostly used for detecting the learning habits of a learner (Leka and Kika 2018), managing learner models (Nguyen and Pham 2011), evaluating the teaching performance of university teaching assistants in an e-learning session (Xu et al. 2016), adaptively supporting students in learning environments (Eryılmaz and Adabashi

2020), or for the learners' acquisition of problem-solving skills in computer programming (Hooshyar et al. 2018).

Fuzzy logic is an extension of the traditional set theory, as statements can be partial truths, lying in between absolute truth and absolute falsity (Bajaj and Sharma 2018). In e-learning systems, it is mostly used for evaluation and assessment of learners' tasks (Jurado et al. 2014), checking the quality of the proposed solutions by the learners and monitoring the collaboration process (Ortega 2021), identification of the alterations on the state of learners' knowledge level and making dynamic decisions on how the teaching syllabus is presented to the learner to fit his/her personal needs (Chrysafiadi and Virvou 2014), identifying learners' preferred learning strategies and knowledge delivery needs that revolve around characteristics of learners and the existing knowledge level in generating an adaptive learning environment (Almohammadi et al. 2016), or for describing, defining, and modifying the uncertainty in a student's behavior (Katz et al. 1994).

A *decision tree* is a tree in which each branch node represents a choice between several alternatives, and each leaf node represents a decision (Bajaj and Sharma 2018). It is frequently used to acquire information and then use it to predict outcomes, and therefore facilitates decision-making (Al Karim et al. 2021). In e-learning systems, it is mostly used for analyzing data and sharing the results (Akyuz 2020), building a learner model that predicts each learner's final learning state (Uto et al. 2019), providing personalized learning paths for optimizing the performance of creativity (Lin et al. 2013), extracting and highlighting important information from learners' data (Karkar et al. 2020), or for the classification of learners' learning mistakes (Faeskorn-Woyke et al. 2020).

A *hidden Markov model* is a collection of unobserved states which follow the rules of the Markov property in a situation where the interrelationship between the true observation and an unobserved state takes birth from a probability distribution (Almohammadi et al. 2017). In e-learning systems, it is mostly used for the adaptability of course content according to the learner's performance in the pre-test and post-test (Rani et al. 2017), predicting students' navigation actions (Homsi et al. 2008), measuring motivation and prior knowledge of the learners (Van Seters et al. 2012), enhancing navigational abilities and easing the search for suitable learning content for the visually impaired (Azeta et al. 2014), or automatic recognition of e-learning activities based on the mouse movement of learners (Elbahi et al. 2016).

AI and other emerging technologies are transforming modern e-learning. AI integrated into e-learning solutions aids in creating custom-tailored learning paths, personalizing online courses, providing relevant materials to appropriate learners, analyzing the content to improve learner engagement, and automating the learning and grading processes. Without a doubt, AI has limitless potential in the e-learning industry, where technology integration can reshape the way we learn.

4.2 Quantitative findings

In this section, we present the quantitative results of the review. Figure 1 shows the research trend of publications from 2010 until 2021 for each category. The graph was created using data from the Google Scholar database, retrieved using Harzing's Publish or Perish tool. Results from this tool were obtained by filtering publications based on titles. The Google Scholar database was chosen because it represents the largest and most known repository of scientific papers. The other databases were not included in order to avoid a large number of duplicates.

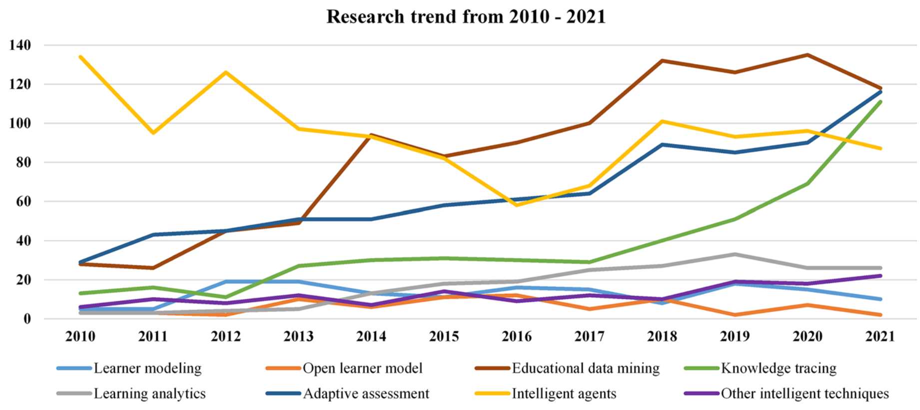

Fig. 1 Distribution of the trends identified by the review

The total number of papers used to create the graph is 3972. The number of papers by category is as follows: learner modeling 154, OLM 73, EDM 1026, KT 458, LA 202, adaptive assessment 782, intelligent agents 1130, and other intelligent techniques 147.

According to this graph, it can be seen all intelligent techniques and roles identified in this literature review have a stable and constant flow of publications per year. Intelligent agents were most popular for the first years but later were surpassed by EDM in 2016, which has the most publications up until 2021. It is worth mentioning that adaptive assessment and KT have a constant increase in trend.

The categorization of intelligent techniques, used strategies, and their roles in e-learning environments identified by the review are presented in the Appendix 1. More than 100 e-learning systems were found and shown in this table that implements at least one of the intelligent techniques or roles from the findings section.

5 Results

This section presents the main insights of the performed literature review in light of previous research on intelligent techniques in e-learning. Moreover, we will provide answers to three research questions and highlight the main aspects that should be addressed by future research in the field.

RQ1: Which intelligent techniques are designed, implemented, and used in e-learning environments, and for which purposes? Almost all most common intelligent techniques have found their way in e-learning (Fig. 2) while supporting four main roles: learner modeling, learning analytics, adaptive assessment, and personalized learning.

Figure 2 displays the intelligent techniques used by the four main roles in e-learning. Learner modeling represents the first role, which employs the open learner model to enable learners to view and analyze their learner model; educational data mining for collecting data; and knowledge tracing for modeling and predicting learners' knowledge. After the learner model is created, learning analytics can be employed for the measurement, collection, analysis, and reporting of learners' data. The results generated by LA present the input data for implementation of adaptive assessment, tailored towards each examinee to

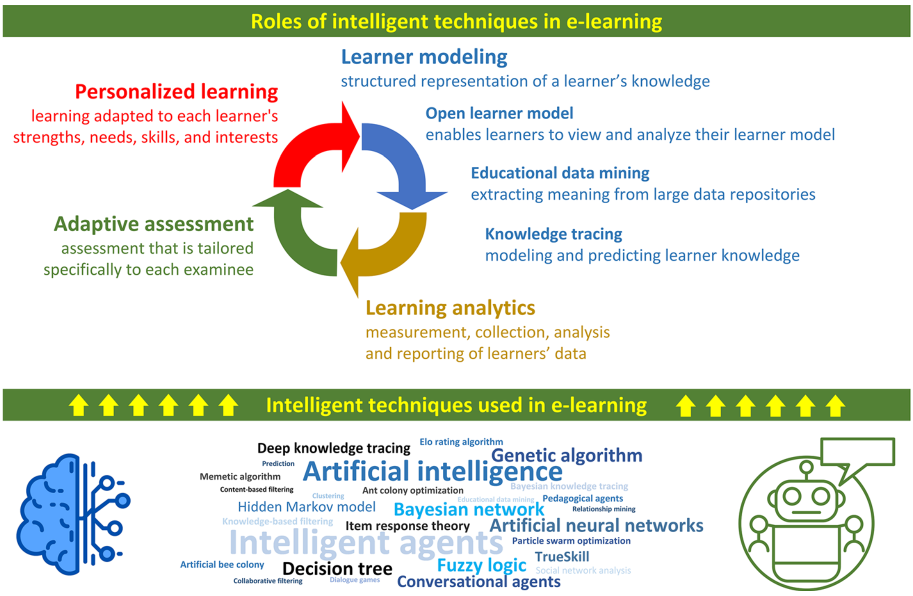

Fig. 2 Intelligent techniques in e-learning

precisely determine the learner's ability. After assessing learners, learning can be adapted to each learner's skills, interests, strengths, and needs, and offer fully personalized learning.

RQ2: How do different intelligent techniques impact learners' attitudes, motivation, and overall performance in online learning platforms? Adaptive assessment, knowledge tracing, learning analytics, educational data mining, resource sequencing, open learner model, pedagogical agents, and conversational agents all play important roles in impacting learners' attitudes, motivation, and overall performance in e-learning environments. However, none of these elements could have a significant effect without a learning modeling process that detects and records specific student attributes and learning patterns.

Some learners need constant encouragement and motivation to keep a positive attitude while taking e-learning courses. In contrast, others are self-motivated and perform well regardless of the academic environment (Montebello 2018). Motivation and self-determination are directly linked to the process of **learner modeling**, in which specific learner characteristics and learning patterns are identified and used to tailor academic content to the same learner. The opening of the learner model can also benefit learners by providing them with an additional learning resource, assisting them in better comprehending their learning, stimulating reflection, and encouraging them to take more responsibility for their learning.

When discussing the impact of AI in e-learning, one of the anticipated benefits is increased motivation in learners as part of encouraging them to take action to achieve their goals. Recent research has shown that adapted assessment and increased input into the assessment process can improve student engagement and motivation (Wanner and Palmer 2015). **Adaptive assessment** plays an important role in motivating learners by giving each of them questions tailored to their level of knowledge (Mangaroska et al. 2019). In that regard, adaptive assessment stimulates learners while avoiding their disappointment and frustration. Improvements in educational experience and learner performance are among the advantages of this type of assessment.

Knowledge tracing can help learners stay motivated during the learning process as it increases their self-motivation in learning and achieves personalized guidance by automatically detecting their weak knowledge points (Zou et al. 2020). KT accomplishes this by estimating a learner's underlying hidden qualities, such as knowledge, goals, preferences, and motivational state, among other things, based on observations of the student's performance or activities.

Creating a **personalized learning path** for each student with relevant topics saves not only time but also boosts learner' motivation. Adaptive presentation and navigation support can improve motivation, keep people interested, and improve comprehension. However, it is not sufficient to support learners to attain the learning outcomes or goals, as every time a learner revisits a particular page, the presentation and navigation support may be different, which may confuse them (Vanitha et al. 2019).

Learning analytics and **educational data mining** supported by AI allow instructors to understand learners' performance, progress, and knowledge, by decrypting their online activities (Seo et al. 2021). Accurate prediction of learners' academic performance is critical for learning design and providing better educational services (Zawacki-Richter et al. 2019). Numerous algorithms have been used to recommend e-learning content and have achieved good performances in adapting to rapid changes existing in learning environments (Wan and Niu 2018).

Pedagogical agents and **conversational agents** are designed to motivate students and guide them through the learning process. They motivate and encourage students to complete the tasks and exercises in the module. They accomplish this through asking students questions, providing hints, and proposing solutions, as well as participating in a discussion with the learner in the case of conversational agents.

The need to articulate a holistic evaluation criterion and measure the effectiveness of AI in e-learning has been expressed in (Zhai et al. 2021). The authors suggested adopting the multidimensional model, which includes technique, pedagogical design, domain knowledge, and human factors, to ensure the validity and reliability of the evaluation. The majority of intelligent techniques offer a generic approach and cannot address the needs of a particular domain, specific learning activities, or teaching goals (Zhai et al. 2021).

RQ3: What are the challenges and unreached potential of implementing intelligent techniques in online education? The quality of available data, limited public domain knowledge, and limited research on the attitudes of both learners and teachers towards AI systems have been identified as the main challenges of implementing intelligent techniques in online education. Their use towards understanding of relations of learning design and optimization of learning process, is recognized as the most significant unreached potential.

The main issues raised in the presented studies were related to **data quality**, especially adequate, efficient and relevant use of the information generated and collected by the technology (Nasiri et al. 2012; Reyes 2015; Zorić 2020). In addition, available data often cannot capture or present a complete picture of a learning process (Tsai and Gasevic 2017), while obtaining and integrating data from various sources represents a major challenge (Tsai et al. 2021). As learners interact with educational content, instructors should control their presence and follow their performance based on evaluation strategies and continuous data collection. The keys to providing the most effective learning are designing appropriate learning paths, analyzing the learners' data and performance, and providing activities and assessments adapted to their knowledge and learning goals.

The role of AI in e-learning should be about finding and guiding the learner to the needed information and making sure the learner is getting the most suitable, understandable, and relevant content. It allows efficient analysis of huge amounts of data and identifying patterns and trends to continuously optimize and improve learning experiences. Most of the presented research is directed towards enabling instructors to receive detailed information about each student's strengths, weaknesses, struggles, and performance, identifying patterns or trends and highlighting them to instructional designers. This makes decision-making more accessible and allow taking immediate and appropriate action. However, the available knowledge base, accessible by the AI search engines, is mainly limited to **public domain knowledge** (Borba et al. 2016; Rosenblit 2018). Even though, data availability has been less of an issue in recent years since universities more often record data on classroom and online courses, it is often not publicly available as education institutions frequently lack the means and resources to access and store it (Gašević 2018). Therefore, such knowledge represents the AI's weak point, as it is often incomplete and too generic, and as such, it can't be expected to find answers to some concrete questions.

Although the majority of existing research has been conducted to evaluate the use of various intelligent techniques, little has been done to understand **students' and instructors' concerns on AI systems** (Zawacki-Richter et al. 2019; Seo et al. 2021; Williamson and Eynon 2020). From the students' perspective, AI systems are expected to improve instructional communication but it could also provide unreliable answers and negatively impact their grades (Seo et al. 2021). The same study reported that students perceived that canned and standardized support might negatively influence their ability to learn effectively. In addition, privacy concerns also exist about monitoring and recording learners' activities while measurement of their unconscious behavior is performed (Zawacki-Richter et al. 2019).

On the other hand, the majority of studies included students as participants, while teachers and professor practitioners received less attention (Zhai et al. 2021). Teachers' attitudes towards AI have a significant influence on the effectiveness of its use in e-learning as inadequate or inappropriate professional development could generate resistance towards AI-supported learning among students. In addition, as reported by the study presented in (Seo et al. 2021), instructors expressed concerns that too extensive inclusion of AI could limit students' willingness for exploration and discovery.

With the implementation of personalized support, the risk emerges of over-standardizing the learning process by dictating how an engaged student should or would act (Seo et al. 2021). Despite the apparent value, intelligent techniques might limit learners' opportunities for exploration and discovery. Studies expressed that learners will miss out on opportunities to acquire new skills or learn from their mistakes. Therefore, the crucial solution is to keep teachers involved in instructional design. Intelligent techniques can quickly process vast amounts of data but can struggle to respond to complex contexts, thus proving that humans' flexibility, creativity, and adaptivity might be crucial.

6 Discussion and future research directions

AI can solve problems that can only be solved by humans, and e-learning technologies can significantly benefit from this emerging technology. This review identified the four most common applications of intelligent techniques in e-learning:

Learner modeling. Using AI to detect a learner's strengths and weaknesses has even more immediate applications than personalized courses. In addition to a simple skill overview, learner profiles can collect information on a person's learning ability, an affinity for specific skills, and ambitions. Where learner modeling benefited the most is with the use of EDM and KT (mainly BKT and DKT).

Learning analytics. The ability of computers to quickly evaluate massive data sets is one of the areas where they significantly outperform humans. Teachers and administrators may find it difficult to comprehend the rising volume of data supplied by modern e-learning technology. AI can make a significant difference by finding patterns or trends and highlighting them to both the learner and the teacher, helping them understand the data and make decisions, mainly with use of EDM techniques.

Automatic assessment and grading. More complex tasks, such as grading written submissions such as essays and presentations and providing feedback to learners on how they can improve their work, are likely to be automated by AI. The implementation of such solutions can speed up reviewing and evaluating the learners' work. It frees up time for teachers to prepare materials for online courses, communicate with learners, and so on. The most common techniques used for this purpose in e-learning environments are IRT, Elo rating algorithm and TrueSkill.

Personalized learning. AI can follow learners' progression within an e-learning course and assist in identifying concepts where each learner lacks proficiency and modifying the course accordingly. This review has identified several personalization techniques used in e-learning, mainly content recommendation, resource sequencing, and adaptive feedback. These techniques were used in e-learning environments to adapt content, learning activities, navigation, etc.

In addition, the review identified the main educational goals of using intelligent techniques in the e-learning context and their impact to the learning process. Many researchers investigated how various intelligent techniques influence the learning and reported its positive effect to students' motivation (Sharma et al. 2020), increasing of students' intrinsic motivation (Tenório et al. 2021), performance (Mangaroska et al. 2021a), and overall attitude (Wan and Niu 2018; Wanner and Palmer 2015). Notably, adaptive assessment has been proven as the most effective for increasing student performance (Kaliwal and Deshpande 2021; Mangaroska et al. 2019; Murphy 2017), pedagogical and conversational agents for motivation (Hobert and Meyer von Wolff 2019), and learning analytics for increasing engagement and awareness of the effect of online learning (Mamcenko and Kurilovas 2017; Kim et al. 2016; Bodily et al. 2018). Although the learning design will not be able to overcome the students' lack of self-motivation and time management in most cases, it can help by providing clear structure and instructions and making the workload manageable (Wanner and Palmer 2015). Simultaneously, some research suggests that the level of students' competencies, such as knowledge, understanding, skills, and attitudes/values, is strongly related to the level of application of individualized learning in pedagogical practice in e-learning environments (Kurilovas 2019; Mangaroska et al. 2021b).

Identification of the main challenges and unreached potential of AI in e-learning have been the ultimate goal of the review. The initial step towards implementing AI in e-learning is identifying the criteria that should be followed. The essential idea is to provide neutral interventions, disconnected from teachers' subjective and biased influence. Such interventions would make AI-supported instructions more precise and efficient, fair to learners, and at the same time based on the pedagogical models taking into account human factors, preferences, skills, and knowledge.

The majority of research included in this systematic review is merely focused on analyzing and finding patterns in data to develop models, making predictions that inform students and teachers, or on supporting administrative decisions using mathematical theories and several decades-old machine learning methods (Zawacki-Richter et al. 2019). This type of research is now possible thanks to advances in processing power and the widespread availability of large amounts of digitized student data. However, there is very little evidence that pedagogical and psychological learning theories related to AI-driven educational technology are evolving. Therefore, future research should explore developing a framework on capturing and systematizing learning design data grounded in learning analytics and learning theory, as well as documenting how educators' learning design choices affect subsequent learning activities and performances over time (Mangaroska and Giannakos 2018). Another study, presented in (Zawacki-Richter et al. 2019), has identified a lack of critical reflection of the pedagogical and ethical implications as well as risks of implementing AI-based e-learning environments. An essential goal of this systematic review is to encourage researchers to develop further the theories that support empirical studies about the development and implementation of AI in e-learning platforms. The need exists to understand and implement the learning design, thoroughly based on learning theory and specifically designed to stimulate specific learning mechanisms, thus expanding research to a broader level.

The need exists to articulate a universal evaluation standard and measure the effectiveness of AI in e-learning (Zhai et al. 2021). Although the significance of individual techniques has been demonstrated in numerous domains and platforms, direct comparisons of their effectiveness and efficiency in the learning process have yet to be conducted (Klašnja-Milićević et al. 2015). The reason is that no systems support multiple techniques (Klašnja-Milićević et al. 2018). Additionally, to establish the utilization of personalization techniques in education as an essential element of the learning process, there is also a need for a proper pedagogical approach and the appropriate use of learning design (Westwood 2018; O'Donnell et al. 2015). The authors in (Essalmi et al. 2015) emphasized the importance of examining and comparing personalization techniques to determine which one should be used to tailor each course. To ensure the validity and reliability of the evaluation, a multidimensional model that includes technique, pedagogical design, domain knowledge, and human factors must be used. Many intelligent techniques were designed for a general situation and cannot match the needs of specific learning strategies or topics being taught (Zhai et al. 2021). Finally, the lack of longitudinal studies, the substantial presence of descriptive and pilot studies from a technological standpoint, and the prevalence of quantitative methods indicate the potential for innovative and meaningful research and practice that could impact the AI-supported learning by adopting design-based approaches (Zawacki-Richter et al. 2019; Easterday et al. 2018).

6.1 Limitations

Although this review attempted to investigate various forms of AI application in e-learning, it might be possible that other intelligent techniques exist. The analysis of the results included a large number of publications and although we have clearly defined inclusion and exclusion criteria, it is possible that some unforeseen exclusions of papers have occurred. Considering the limitation of used publication selection methodology (Kitchenham and Charters 2007), the authors don't claim that all existing systems were included in the review but rather the most prominent or typical examples.

7 Conclusion

AI in the e-learning area has the potential to benefit learners, teachers, and education as a whole. It can equip everyone with a high-quality education by providing a tailored and customized experience. AI-supported solutions can answer learners' questions, recommend personalized resources and grade submissions. It can be used to predict dropouts, provide extra support to learners, and automate learning and assessment. Although there is concern that AI may eventually replace humans, it is more likely that AI will act as an effective support system for human professionals.

Qualitative findings from this review gave us an overview, insights, and applications of all intelligent techniques used in online education, leaving us with the strong impression that AI can be successfully implemented and utilized in e-learning systems and can take learning to a whole new level. Quantitative findings gave us an insight into the research trend of publications, revealing the most popular categories of intelligent techniques as well as the number of discovered e-learning systems implementing these intelligent techniques.

As an answer to the first research question, the review identifies a large number of the intelligent techniques used in e-learning environments, supporting four main roles: learner modeling, learning analytics, adaptive assessment, and personalized learning.

The second research question shows that adaptive assessment, knowledge tracing, learning analytics, educational data mining, resource sequencing, open learner model, pedagogical agents, and conversational agents, each in their own way, play an important role in impacting learners' attitudes, motivation, and overall performance in e-learning environments, but without a learning modeling process that identifies and stores individual student characteristics and learning patterns, none of these elements could have a significant impact.

In response to the third research question, we identified data quality and limited public domain knowledge as the main challenges of implementing intelligent techniques in online education, as AI search engines can struggle to find answers to some concrete questions due to these problems. Also, additional challenges relate to the limited research into the attitudes of both learners and instructors regarding AI systems. The unreached potential of implementing intelligent techniques in online education refers to AI-supported learning by adopting design-based approaches; developing a framework on capturing and systematizing learning design data grounded in learning analytics and learning theory; improving responding to complex contexts; universal evaluation standards; and developing systems that support multiple techniques.

The aim of the paper was to provide comprehensive overview of innovations and intelligent techniques used in e-learning, to achieve personalized learning, adaptive assessment, content recommendation and generate deeper understanding of learning processes. The goal was to investigate how intelligent techniques can support personalized learning practices and how they can facilitate engagement in online and distance learning.

Personalization of e-learning is necessary to meet the specific needs of learners and optimize their learning. Personalization can improve the learning results with appropriate recommendations, customization of the curriculum, giving feedback, etc. A review of the most commonly used personalization techniques in e-learning has been published in (Mikić et al. 2022) that complements the study presented in this paper.

Based on the understanding of pedagogical (personalization techniques) and technical aspects (AI techniques), the next step would be performing comparative studies of different personalization techniques. In this way, the advantages and disadvantages of all the identified techniques in direct comparison should be more thoroughly investigated, and determined how to achieve them using AI. In addition, we also want to find the best combination of techniques that could be used in a single e-learning system to create an environment that can meet all learner needs and requirements.

Appendix 1: Intelligent techniques in e-learning

Strategies	Techniques	Implemented systems
Learner modeling		
Educational data mining	Prediction	AL-TESL-e-learning system Wang and Liao (2011), Junyi Academy Paquette et al. (2020)
	Clustering	dotLRN Köck and Paramythis (2011), ESURBCA Suresh and Prakasam (2013)
	Relationship mining	eDisiplin Man et al. (2018), ESOG Ougiaroglou and Paschalis (2012), Blockly programming App Shih (2018)
	Distillation for human judgment	Canvas Arnold and Pistilli (2012),
	Discovery with models	Cisco Networking Academy Mislevy et al. (2012)
	Autonomous agents	eTeacher Chung (2015)
	Multi-agent	ALLEGRO Asselman et al. (2017), ISABEL Aguilar et al. (2015), IAELS Tsai et al. (2012), PowerChalk Rosado et al. (2015)
Knowledge tracing	Bayesian knowledge tracing	CRYSTAL ISLAND Rowe and Lester (2010), ASSISTment Pardos and Heffernan (2010), edX Pardos et al. (2013), Coursera Wang et al. (2016), Robot language tutor Schodde et al. (2017), SITS Hooshyar et al. (2018)
	Deep knowledge tracing	Khan academy Piech et al. (2015), Udacity Kim et al. (2018)
	Autonomous agents	Mod-Knowledge Trifa et al. (2019)
	Fuzzy logic	IT2FLS Almohammadi et al. (2016)
Vizualization of learners' data	Open learner model	INSPIREus Papanikolaou (2014), Flexi-OLM Bull (2020), AMAS OLE Yousuf et al. (2018), UM toolkit Johnson (2018), Lea's Box Bull et al. (2016), ELM-ART Herder et al. (2017), EI-OSM Zapata-Rivera (2020), Mr. Collins Bull (2016), Next-TELL Bull et al. (2015), StyLE-OLM Dimitrova and Brna (2016), EER-Tutor Mitrović and Holland (2020), MasteryGrids Guerra et al. (2018), edCrumble Albó et al. (2019), SQL-Tutor El Agha et al. (2018), VisMod Kaliwal and Deshpande (2021), VCM Salem et al. (2017), INGRID Conejo et al. (2011), QuizMap Brusilovsky et al. (2011), GVIS Mazzola and Mazza (2010), NavEx Brusilovsky and Yudelson (2008), Progessor Hsiao et al. (2013), E-KERMIT Jones (2018), Subtraction Master Bull and McKay (2004), Fraction Helper Lee and Bull (2008), QuizPACK Murphy (2017), Doubtfire++ Law et al. (2017), TITUS Bastida et al. (2017), CALMsystem Leonardou et al. (2019), PAL3 Hampton et al. (2018), NDLtutor Suleman et al. (2016), Topolor 2 Shi and Cristea (2015)

Strategies	Techniques	Implemented systems
Learning analytics		
Data collection	EDM techniques	Desire2Learn Shehata and Arnold (2015), Blackboard Vista Arnold and Pistilli (2012)
Data analysis	Social network analysis	OSBLE+ Olivares et al. (2019)
	Statistical analysis	OU Analyse Herodotou et al. (2020)
	Decision tree	MLTutor Akyuz (2020)
Prediction and analysis of student behaviour	Artificial neural networks	ILIAS Şuşnea (2010), Research Quest Poitras et al. (2019), DEEDS Hussain et al. (2019), CBeL Bhattacharya et al. (2018), ReAct! Dogmus et al. (2014)
	Bayesian network	SAVER Leka and Kika (2018), CAMLES Nguyen and Pham (2011)
	Fuzzy logic	Sherlock II Katz et al. (1994)
	Decision tree	SamurAI Uto et al. (2019), UoK platform Karkar et al. (2020), EDB Faeskorn-Woyke et al. (2020)
	Hidden Markov model	AIWBES Homsi et al. (2008), Proteus Van Seters et al. (2012), iVeES Azeta et al. (2014)
Vizualization of learners' data	Learning analytics dashboard	MathSpring Muldner et al. (2015), SCELE Santoso et al. (2018), Cyber Campus Kim et al. (2016), OUJ system Furukawa et al. (2017), iTutor Wang and Han (2021), SoftLearn Ramos-Soto et al. (2017)
Adaptive assessment		
Student ranking, evaluation and assessment	Item response theory	UZWEBMAT Özyurt et al. (2014), MISTRAL Oppl et al. (2017), Amrita Learning Gutjahr et al. (2017), SIETTE Conejo et al. (2018), UTS Bernardi et al. (2018), English vocabulary learning system Chen et al. (2019), SamurAI Uto et al. (2019), PEL-IRT Ferjaoui and Cheniti Belcadhi (2020), Lexue 100 Jia and Le (2020)
	Elo rating algorithm	ProTuS Mangaroska et al. (2018), Math Garden Brinkhuis et al. (2018), Matistikk Dahl and Fykse (2018), ACT Academy Yudelson et al. (2019)
	TrueSkill	APACTS Kawatsu et al. (2017)
	Bayesian network	MILE Xu et al. (2016)
	Fuzzy logic	COALA Jurado et al. (2014), DomoSim-TPC Ortega (2021), FuzKSD Chrysafiadi and Virvou (2014)
Personalized learning		
Recommender systems	Collaborative filtering	PeerGrade Wind et al. (2018), LAMS Álvarez-González et al. (2017), LogCF Chen and Cui (2020)
	Content-based filtering	Quickstep Lops et al. (2011), CBNR Kandakatla and Bandi (2018)
	Knowledge-based filtering	MDB Hiles and Agha (2017), ADO-Tutor El Haddad and Naser (2017), CSS-Tutor Alawar and Abu-Naser (2017), ScholarLite Samin and Azim (2019)
	Hybrid techniques	CodERS Chen et al. (2014), RSPP Cobos et al. (2013), MoodleRec De Medio et al. (2020)
	Multi-agent	MIPITS Lavendelis (2015), ADOPT Ajroud et al. (2021), MetaTutor Trevors et al. (2014)

Strategies	Techniques	Implemented systems
Resource sequencing	Genetic algorithm	LPRS_EL Dwivedi et al. (2018)
	Memetic algorithm	TPG Nguyen et al. (2012)
	Ant colony optimization	ACSEL Benabdellah et al. (2013), LPR Niknam and Thulasiraman (2020)
	Particle swarm optimization	IDRCCS Wang and Tsai (2009)
	Artificial bee colony	PBREL Venkatesh and Sathyalakshmi (2020)
	Multi-agent	MAS-PLANG Asselman et al. (2018)
	Decision tree	PCLS Lin et al. (2013)
	Hidden Markov model	OPAESFH Rani et al. (2017), Equation Grapher Elbahi et al. (2016)
Automated feedback	Textual feedback	SQL Quizbot Vijayakumar et al. (2018), Pgtracer Kakeshita and Ohta (2016), UCOM Tawafak et al. (2019)
	Video feedback	ASSET Crook et al. (2012)
Learners' guidance	Pedagogical agents	ISLA Mondragon et al. (2016), ATS Thompson and McGill (2017), CALL system Carlotto and Jaques (2016), APLUS Matsuda et al. (2014), EC Lab Osman and Lee (2014)
	Conversational agents	Geranium Griol et al. (2014), Curiosity Notebook Chhibber and Law (2019)
	Multi-agent	EMASPEL Bokhari and Ahmad (2014), F-SMILE Alkhatlan and Kalita (2019)
	Bayesian network	FB-ITS Eryılmaz and Adabashi (2020)

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