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Development and techniques in learner model in adaptive e-learning system: A systematic review

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ABSTRACT

Adaptive e-learning systems (AeLS), which emerged in the late 1990s, offer an alternative to the 'one-size-fits-all' approach by addressing the demand for individualized learning experiences. These systems typically consist of five elements, including a domain model, a media space, an adaptation model, a user interface, and a learner model. Despite the increasing academic interest in this topic and the rapid development of techniques for adaptation over the past decade, there remains a significant gap in reviews that investigate learner characteristics and the techniques used for characteristic identification. To bridge this gap, we conducted a systematic review with a total of 57 studies reported from 2013 to 2023 to provide a comprehensive overview of the current trends in adaptive e-learning system research. While this review may serve as a reference for setting up a learner model as it provides the landscape of techniques utilized in recent studies, our review revealed a scarcity of research on the development of the learner model, particularly the studies that share clear theoretical or empirical justification of the techniques used for adaptation. We recommend incorporating multiple relevant learner characteristics in learner model and providing clear rationales for selecting these characteristics. We also suggest that future research should consider incorporating adaptive assessment more extensively in AeLSs.

1. Introduction

1.1. Adaptive e-learning

Adaptive learning and adaptive learning systems have received growing attention with the emphasis given to tailored learning experiences (Xie et al., 2019). While there are slight distinctions between adaptive and personalized learning, with the former often being more reliant on technology, they are frequently used interchangeably in literature (Xie et al., 2019). The 2017 U.S. National Education Technology Plan defines personalized learning as an instructional approach that optimizes the pace of learning and instructional approach to suit each learner's needs (U.S. Department of Education, Office of Educational Technology, 2017). Vandewaetere et al. (2011) describe adaptive learning as the process of utilizing learning analytics to tailor individual learning pathways based on a student's strengths, weaknesses, and learning speed. Regardless of the adaptation of technology, both adaptive and personalized learning aim to enhance the learning experience by considering individual differences, thereby increasing learner satisfaction and ultimately improving learning outcomes (Aroyo et al., 2006; Gómez et al., 2014; Liu et al., 2017). In this study, we use the term, *adaptive learning*, with a focus of adaptation with technology-enhanced learning environments.

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Before the twenty-first century, adaptive or personalized learning was primarily offered through private school education and elective course systems (Dockterman, 2018; Peng et al., 2019). In this context, teachers acted as curators, using their judgment to provide customized instruction by selecting materials and establishing objectives with each student to address their specific educational needs (Childress & Benson, 2014). Students were also encouraged to shape their own learning based on their personal goals and interests (McCarthy et al., 2020). Although this traditional adaptive learning approach allowed more personalized and flexible instruction, which typically contributed to improved student outcomes, it required a greater time commitment from educators. Teachers were responsible for evaluating individual student needs, creating personalized learning experiences, and monitoring progress (Walkington & Bernacki, 2020). Consequently, scalability was limited, especially in larger classrooms where providing individualized instruction is challenging without technological support (Fake & Dabbagh, 2020).

1.1.1. *Adaptive e-learning systems and its components*

Adaptive e-learning systems (AeLSs), also referred to as adaptive hypermedia systems (Mavroudi & Hadzilacos, 2016), are commonly defined as those that utilize educational technology to individualize the learning process to accommodate the unique needs of each student (Brusilovsky, 2000). The emergence of adaptive e-learning provided a potential solution to address the challenges associated with traditional adaptive learning methods, making personalized learning accessible and affordable to individuals irrespective of their geographical location or financial situation (Normadhi et al., 2019).

The typical framework of an AeLS (e.g., Karampiperis & Sampson, 2005) includes five main components (as shown in Fig. 1): a domain model, a media space, an adaptation model, a user interface, and a learner model. A domain model typically includes the structure and specific knowledge of a particular domain, while concept selection rules will be applied to identify suitable concepts for learning from the domain model. A domain model serves as the foundation for generating appropriate contents, activities, and assessments tailored to each learner based on their current knowledge and learning objectives (Brusilovsky, 1996; Gao, 2022). A media space functions as a repository for various instructional resources and their descriptions (Chen & Zhang, 2008). An adaptation model enables the system to guide learners toward the acquisition of target knowledge by presenting relevant learning materials (Chen & Zhang, 2008), with the content adaptation rules and the adaptive navigation support rules. These components facilitate the identification and selection of relevant concepts from the domain model and the extraction of appropriate resources from the media space, respectively (Karampiperis & Sampson, 2005). A user interface provides the interaction function between learners and the AeLSs.

Finally, a learner model, also referred to as a student model (e.g., Esichaikul et al., 2011), serves a crucial role in personalization (Gu & Sumner, 2006) and is the central focus of this systematic review. The learner model captures learners' personal characteristics, such as age, gender, previous scores, and learning activities, including the number of requests for learning support and learning duration (Chen & Zhang, 2008). Learner characteristics can be broadly categorized into several types (Nakić et al., 2015): learning styles, cognitive styles, affective characteristics (e.g., emotional states, anxiety levels, and motivation levels), learning behaviors (e.g., interaction with the system, log data, course attendance, and selected learning sequences), knowledge and ability, personal profile (e.g., age, gender, account information), and other information like personality types. With the available or target learner's information, individual learners can be later classified as certain groups for adaptation.

1.1.2. *Three steps in a learner model: a closer look*

In the learner model, there are three main steps for incorporating learner characteristics for adaptation, as illustrated in the upper right part in Fig. 1(Hlioui et al., 2016). First, a proper learning theory(s) is applied to guide the selection and categorize certain learner characteristics for adaptation, although this step is not always executed and may be skipped in practice (e.g., Wu, 2019). Second, the

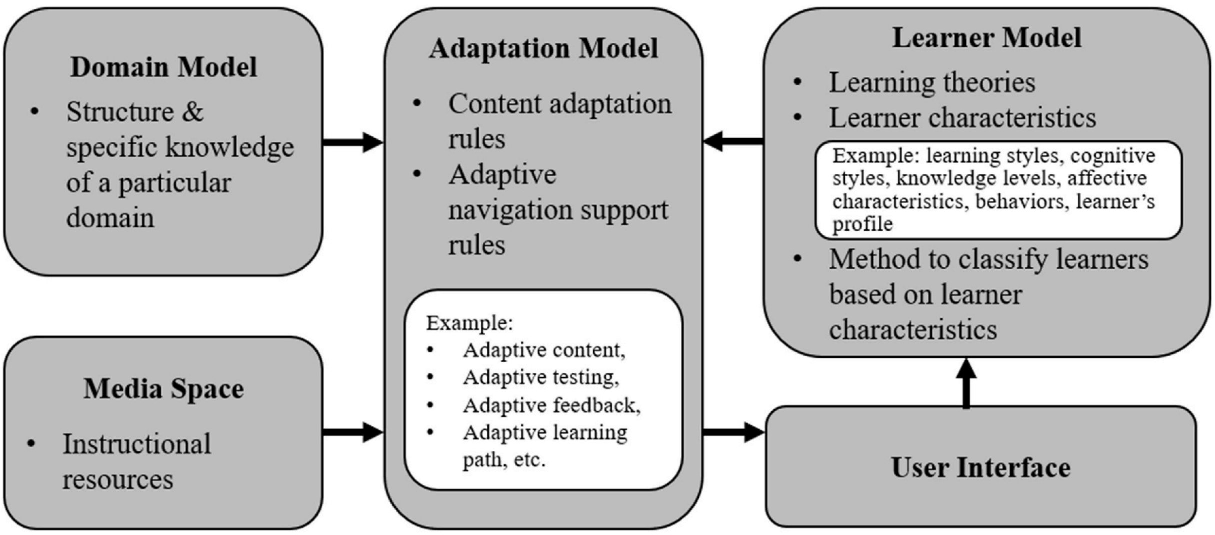

Fig. 1. Architecture of an Adaptive e-learning system (AeLS).

target learner characteristic(s), which could be either singular or multiple, is specified, enabling the preparation of customized learning experiences suitable for each learner in a subsequent adaptation model. Third, as the last step, the system requires an appropriate method to classify learners based on those characteristics. The classification could be processed with AI or non-AI-based approach, such as using data collected with scales or questionnaires. With the identified characteristics of a particular learner in the learner model, adaptive service for learning is provided in an adaptation model.

The accurate identification of learner characteristics is critical as it determines the system's capability to customize learning experiences, thereby affecting learning efficiency. The two learner characteristics that are commonly involved in the learner models are learning styles and learners' knowledge levels (Alshammari, 2016). Various theories have been applied for classifying learners into different groups for adaptation. For instance, with Fleming's VARK (Visual-Auditory-Reading-Kinesthetic) model (Fleming & Mills, 1992), learners can be classified into four types based on their learning style: visual, auditory, reading/writing, and kinesthetic. In contrast, in Rishard et al.'s (2022) study, learners were classified into four different dimensions, i.e., Sensory-Intuitive, Visual-Verbal, Active-Reflective, and Sequential-Globa, with the Felder-Silverman Learning Style Model (Felder & Silverman, 1988). Honey and Mumford's model (Honey & Mumford, 1986), on the other hand, focuses on learners' preferred activities and classify them into four types: Activists, Reflectors, Theorists, and Pragmatists.

In addition, to classify learners for target characteristics and update learning information, a range of techniques has been utilized, which include Bayesian network, neural network, fuzzy logic, decision tree, K-nearest neighbor, factor analysis, and others (Normadhi et al., 2019). For example, Khachatryan et al. (2014) applied condition-action rule-based reasoning in an AeLS called 'Reasoning Mind Genie2' to update the learner model and offer adaptive learning content and navigation. Similarly, Nihad et al. (2017) employed a Bayesian network in an AeLS for several computer science courses, in which students' performance data were used to group students into different learning styles for adaptive learning experiences in these courses.

1.2. Existing reviews on learner models in adaptive e-learning

The learner model is one of the most frequently discussed or studied components in AeLSs, particularly regarding its critical role in optimizing personalized learning experiences (Martin et al., 2020). The fast-growing field of research resulted in producing abundant information, necessitating the systematic evaluation of empirical findings. This process is crucial for effectively translating knowledge gained from research into practice, ultimately enhancing stundet learning outcomes. In addition, there is increased emphasis on utilizing empirical evidence to inform decision-making for policies and practice in education (Newman & Gough, 2020). Systematics reviews are appropriate for this purpose as they aim to synthesize relevant empirical evidence to address specific questions by adhering to explicit and structured process for literature gathering and data extraction, thereby minimizing potential biases (e.g., Garg et al., 2008). High-quality systematic reviews can provide a less biased, succinct summary of available research evidence on a particular topic, promoting evidence-based decision-making in practice. Accordingly, several reviews have appeared in recent years to summarize the learner characteristics, theories, and techniques applied in learner models in existing AeLSs. Available reviews can be broadly classified into four categories based on their primary objectives: (1) summarizing fundamental research topics and trends, (2) assessing the efficacy of AeLSs, (3) exploring factors considered in a learner model, and (4) synthesizing the techniques or algorithms adopted to identify learner characteristics or to update information. The first type of review mainly focuses on providing a comprehensive summary of the methodology used in selected studies, and basic information about the specification of AeLSs, such as the subject areas covered and the target population (e.g., Tang et al., 2021). The second type of systematic review summarizes the effectiveness of AeLSs in various settings, with the majority reporting the synthesis of effect sizes with a meta-analysis (e.g., Gao, 2022; Kulik & Fletcher, 2016). Given that the reviews aimed for the first two objectives diverge from the purpose of the current systematic review, these reviews are not discussed further in this study.

The third type of review reports learner characteristics or behavior incorporated in AeLSs. In Table A in Appendix, we provide a summary of recent reviews as examples from the third and fourth categories. A majority of the reviews listed in Table A fall under this category. For instance, Truong (2016) explored the integration process of learning styles, learning style predictors, and corresponding theories for 51 studies. Although his review provided an in-depth summary of how learning style was applied for adaptation in the learner model, it is not comprehensive because the researcher focused only on one specific learner characteristic (i.e., learning style) in his review. To present a more extensive overview of learner characteristics used in AeLSs, Martin et al. (2020) synthesized 61 studies to explore what learner characteristics and measurement tools researchers used in AeLSs. Normadhi et al. (2019), Vandewaetere et al. (2011), and Nakić et al. (2015) also summarized learner characteristics, and they further categorized the nuanced learner characteristics into more general types, including cognitive, affective, behavioral, or psychomotor, and mixed types. While these reviews highlight learner characteristics and behaviors included in various learner models across studies, the researchers did not review the method or quality of characteristic identification in these studies, offering limited guidance for improving customization of AeLSs.

The fourth type of review primarily focuses on the method or algorithm utilized to identify learner characteristics or update their profiles in AeLSs. For example, Mousavinasab et al. (2021) conducted a systematic review on the studies published between 2007 and 2017, summarizing the adoption of AI techniques, their purposes, and the evaluation methods employed. Despite the quality overview it presents, the scope of this review is narrow as it only includes studies with AI techniques. Omitting some frequently used non-AI techniques in adaptive learning, such as factor analysis and *k*-means clustering limited the generalization of their synthesis findings. Kabudi et al. (2021) addressed this research gap by providing a comprehensive overview of AI and data analytic techniques employed in 147 studies published from 2014 to 2020. However, these authors also noted certain limitations, one of which is not including the purpose of applying specific techniques in learning systems.

Although the existing reviews detail the use of various techniques for identifying learner characteristics, they do not delve deeply into the techniques used in a learner model. Additionally, they fail to offer suggestions on selecting suitable techniques under various learning contents. Apart from the above limitations in existing review research, the rapid growth of the field and data analytic techniques made some earlier reviews obsolete and no longer fully capture the current state of the art in AeLSs. This evolving landscape underscores the need for a comprehensive and updated systematic review that not only fills the existing gaps but also reflects the current state of a learner model. Thus, we conducted a systematic review of the research on adaptive e-learning reported since 2013. The primary objective of this review is to provide a comprehensive overview of current trends in learner model configurations within AeLSs, with a focus on commonly used learner characteristics and the various techniques employed for their identification. With the findings from this review, we offer practical recommendations for future researchers aiming to develop or investigate learner models in AeLSs. To achieve these objectives, the study was guided by the following research questions.

1) Among all the learner information stored in the learner model such as learning style, cognitive style, knowledge level, and motivation, what learner information is frequently used for adaptation?
2) What theories have been utilized to guide classifying learners in a learner model?
3) What techniques, AI or other data analytic techniques, are utilized for classifying learners?

2. Method

We executed our systematic review by following five steps (Khan et al., 2003; Natal, 2018): 1) defined the research question and objective; 2) developed the review protocol; 3) identified and screened relevant studies; 4) summarized the evidence; and 5) reported and interpreted the findings. Note that we distinguish our study from a mapping review, which also involves categorizing existing literature and identifying gaps (Grant & Booth, 2009), as we applied rigorous selection criteria and review process for quality control in our review, which are typically absent in mapping reviews.

2.1. Selection criteria

Our systematic review targeted to include all or unbiased samples of empirical AeLS studies which report the development and implementation of a learner model and disseminated between 2013 and 2023. Eligible studies must be published in journals or conference proceedings. Included empirical studies should report sufficient details of the learner model executed in the study and should also demonstrate the effectiveness of the implemented AeLSs in achieving learners' desired outcomes. Studies that lacked technical details or provided no empirical example were also excluded from the current synthesis. Gamified AeLSs usually require highly interactive and some other unique settings, so that the studies focusing on this kind of AeLSs (e.g., Barbhuiya et al., 2013; Beyyoudh et al., 2018; Tang et al., 2020) were not included in this review. Only empirical studies reported in English were considered, and a narrative summary of previous empirical studies (i.e., literature or systematic reviews, including a qualitative or quantitative synthesis) on related topics was not included in this study as well. The full list of inclusion and exclusion criteria is shown in Table 1.

2.2. Search strategy

To identify as many relevant studies as possible for controlling sampling bias, the search was conducted in multiple databases, including *ProQuest, Google Scholar, ACM Digital Library, and IEEE Xplore Digital Library*. The keyword set was decided based on the research question and referred to some previous SRs with a close research focus on the current review. We used various combinations of keywords such as 'adapt', 'custom', 'personal', 'learning', 'instruction', 'tutor', 'education', 'system', 'environment', 'application', and 'software'. Additionally, we searched for phrases like "learner model" and "student model". Synonyms and variations of these words were searched to capture a broader range of relevant studies with Boolean operators. Sample search strings were listed in Table B in Appendix.

The specific process of study identification and screening was illustrated by the PRISMA flow chart (Fig. 2). The entire procedure, encompassing subsequent data extraction, was conducted using Covidence, a web-based software platform. Covidence employs machine learning to help improve efficiency by sorting studies based on their relevance, as determined by previous inclusion and

Table 1
Inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Publication date	2013–2023	Before 2013 or after 2023
Publication type	Peer-reviewed journals, or conference proceedings	Book chapters
Content of the studies	Studies focusing on AeLSs, including the development, implementation of AeLSs	Studies without sufficient details about learner model
	Studies reporting at least one learner characteristic used for adaptation Studies discussing at least one technique for either classifying learners or facilitating adaptation in a learner model Studies demonstrating the effectiveness of AeLS	Studies not mentioning any of the techniques utilized for classifying learners or facilitating adaptation Studies involving gamified AeLSs
Research type	Empirical studies	Review or meta-analysis of other studies
Language	Studies written in English	Studies written in any other language

exclusion decisions (Chelsea, 2023). Given the selection criteria, a total number of 57 studies were identified for the final analysis. Here are some examples of studies that were excluded during the screening process. Influential studies with a high number of citations, like those by Fatahi (2019), who utilized MBTI types for personalized instruction, and Yang et al. (2013), who evaluated the system providing adaptive services based on learning and cognitive styles, were excluded because they lack a detailed description of the techniques for classifying learners or facilitating adaptation. The study by Chrysafiadi and Virvou (2013), proposing enhanced navigation in adaptive e-learning systems, was also excluded for its exclusive focus on a domain model, omitting details about the design of the learner model, adaptation target, or adaptation process. Additional studies (e.g., El-Sabagh, 2021; Hariyanto et al., 2020; Papoušek et al., 2016) were excluded for the same reason.

2.3. Data extraction

In addition to gathering fundamental details from each eligible study, such as the author(s), title, and publication year, we tailored the data extraction template for this study to correspond with our research questions with the insights from prior reviews, specifically those by Normadhi et al. (2019) and Mousavinasab et al. (2021). Following the coding schemes outlined by Normadhi et al. (2019), we coded details related to theoretical frameworks, learning domains, issues addressed, and citation counts. Similarly, in accordance with Mousavinasab et al. (2021), we coded aspects of research design, including sample characteristics, education fields, and criteria for evaluating system performance.

Before initiating the coding process, we piloted our coding scheme with a sample of the included studies. This pilot coding led us to modify a few items in the initial coding protocol. For example, the coding item, asking 'the purpose of adaptation', previously used in Mousavinasab et al. (2021) was deleted due to unnecessity as our focus of the study is narrower than Mousavinasab et al. (2021) with only purpose of the adaptation is for either classification or prediction of learners. Additionally, we added a new question to more thoroughly capture detailed information about the adaptation techniques in learner model.

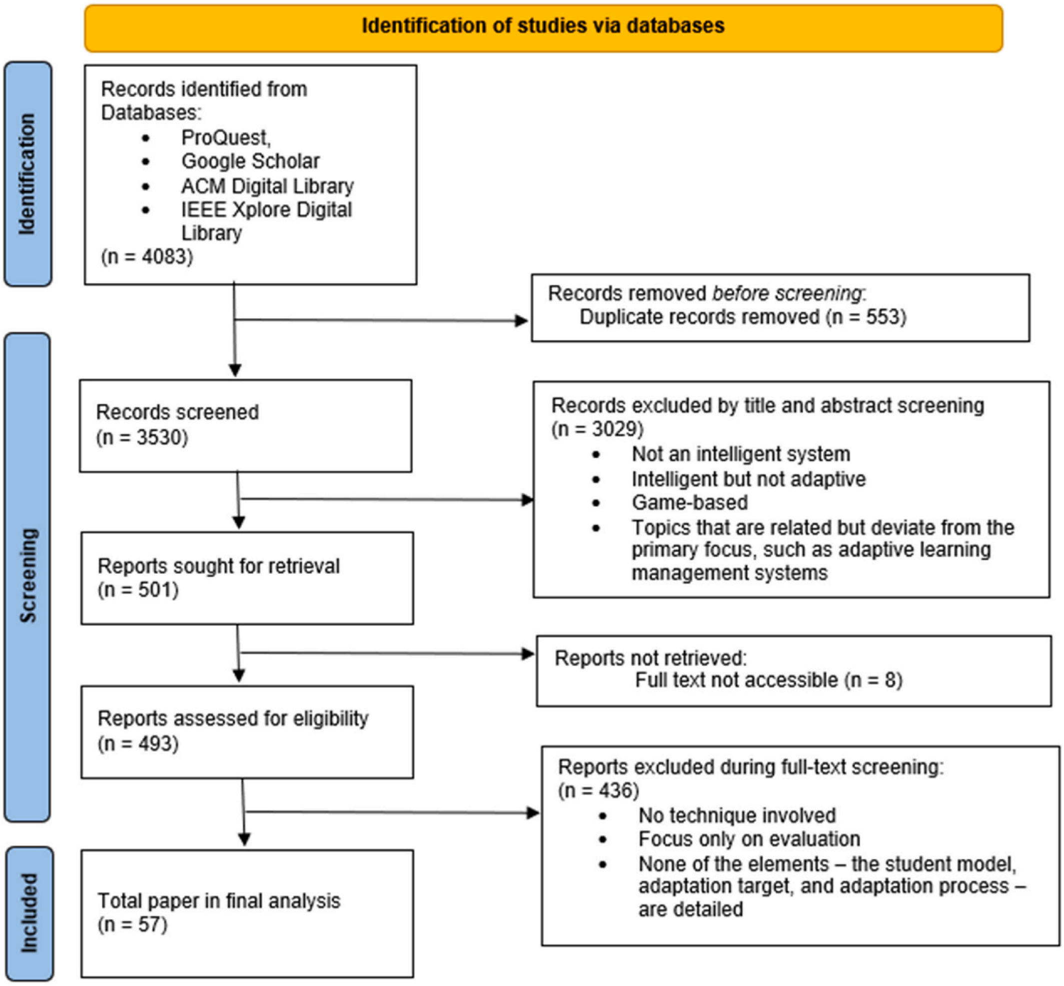

Fig. 2. PRISMA process of study identification and data analysis.

Next, to ensure coding reliability, two researchers were involved in the data extraction process and coded about five studies first independently. Ambiguities in coding processes were discussed at weekly research meetings. We further clarified wordings of some questions in the coding protocol and reached full agreement on coding on these studies and proceeding in coding in the same manner for the rest of the studies. The data we exacted from each study were.

- **Study information**: Details such as the title of the study, author(s), country of origin, publication or conference name, year of publication, and the number of citations received by the end of 2023;
- **Study objectives**: Classification of the study's primary goal, whether it's to develop, implement, or evaluate an AeLS, or to propose methods for identifying characteristics or enhancing the effectiveness of existing AeLSs;
- **System terminology and conceptual framework**: Terms used to describe the AeLSs, along with any provided definitions and frameworks;
- **Basis for adaptation**: Identification of the learner characteristics or characteristics used as a basis for adaptation, such as learning styles, cognitive styles, affective characteristics, behavior, or knowledge levels;
- **Methods for measuring the target learner characteristic**(s): Information about the instruments or techniques employed for measuring these characteristics and the theoretical basis for their use;
- **Types of adaptive services**: The adaptive services provided by the system, such as adaptive content delivery, adaptive learning paths, adaptive feedback, adaptive assessment, and adaptive presentation as well as the specific techniques used to facilitate these adaptations; and
- **Empirical information**: The methods used in the studies, the specific subject areas targeted by the AeLSs, and the age level of the intended AeLS users.

Coded information from two authors was tracked using Covidence. Any discrepancies or ambiguities in the coding were discussed until we reached an agreement on the assigned codes, resulting in consensus on all data extracted from the studies.

3. Results

We first present the general findings for each question from the analysis of the 57 selected studies. While not every detail is extensively discussed, we also highlight interesting patterns or insights, particularly into those pertinent to aspects not anticipated with

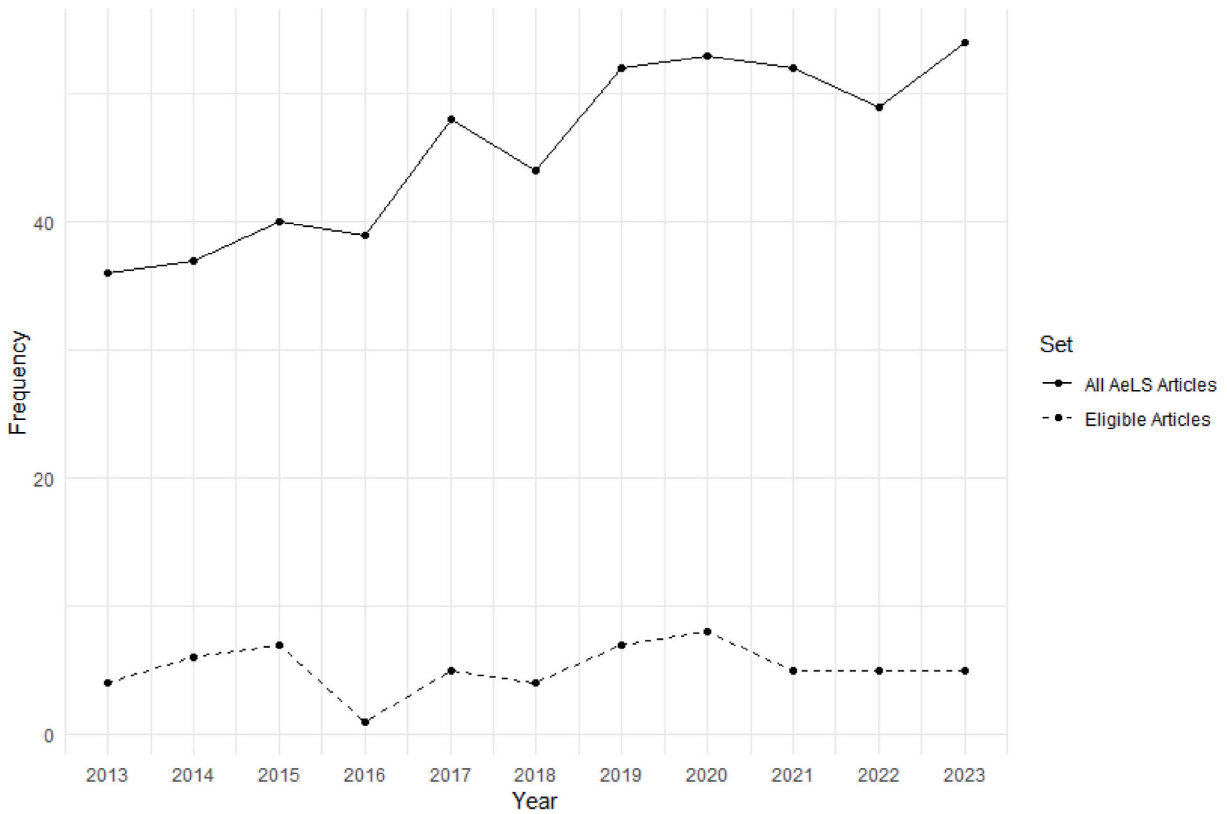

Fig. 3. The number of AeLS studies reported between 2013 and 2023 and the number of the studies meeting the inclusion criteria for the present systematic review.

our initial research objectives.

3.1. Summary of the reviewed studies

Fig. 3 illustrates the trend of research on learner characteristic identification in the learner model within AeLSs from 2013 to 2023. The solid line represents the total count of AeLS studies identified during the search. In contrast, the dotted line reflects only the studies deemed eligible for this analysis, which must include the process of identifying learners' characteristics and the techniques used for identification. While the figure highlights the general trend of increasing attention to the learner models in AeLS research, the gap in two lines depicted scarcity of research on the development of learner models.

3.2. Adaptive source and the underlying theories

In Table 2, we outlined the specific meaning of each type of learner characteristics and listed the corresponding examples found in reviewed studies. Among all the learner characteristics, knowledge levels and learning styles are the two most frequently used characteristics for adaptation; they both were involved in 33 studies. In addition, 32 of these 57 studies focused on a singular learner characteristic, with examples found in Alfaro et al. (2018), Rahman and Budivanto (2019), and Jeong and Yi (2014). The system employing a single characteristic for adaptation predominantly uses either learning style or knowledge level. For instance, the Flowchart-based intelligent tutoring system developed by Hooshyar et al. (2015) customizes learning sequences with the student's knowledge level, specifically, the probability that the student knows a concept, to decide the corresponding personalized learning sequences.

Researchers integrated multiple learner characteristics to inform adaptation in the remaining 25 studies. For example, Grivokostopoulou et al. (2019) incorporated learning style, knowledge level (both performance and skills), learner behavior (reflected through activity data), and the learner profile (includes social information) into their AeLSs.

3.2.1. Learning style and the underlying theories

Learning style was one of the most prevalent characteristics utilized in AeLSs, and the exploration of it in educational research has been predominantly based on four theoretical models: Felder-Silverman Learning Style Model (FSLSM, 1988), Fleming's VARK Model (1992), Honey and Mumford's Model for Learning style (1986), and Kolb's Experiential Learning model (1999). The FSLSM has been applied in most of the AeLSs we reviewed ($n = 18$), indicating its widespread recognition and application. The difference among these studies lies solely in the tools or techniques they employed to identify learning styles, with some used questionnaires, while others used applied data analytic techniques, and a few adopted both methods. Specifically, the Index of Learning Styles (ILS) questionnaire, developed by Felder and Silverman (1988), was a common tool used to identify learning styles. In contrast, Fleming's VARK Model was utilized in four studies. Honey and Mumford's Model (1986) was mentioned in three studies (e.g., Alfaro et al., 2018), and two studies applied Kolb's model (e.g., Hibbi et al., 2023).

Recently, in response to the diverse needs of educational practices, some researchers also refined these theories and corresponding methods for identifying learning styles to enhance their applicability and relevance. For instance, Hamada and Hassan (2017) extended the ILS questionnaire by introducing a 'realistic' dimension (social/emotional) and employed it in their study. Similarly, Vagale, Niedrite, and Ignatjeva (2020) developed a hybrid visual-aural style that leverages the VARK framework, offering a more nuanced approach to accommodating individual learning preferences. Beyond established frameworks, other classifications also exist, such as the intensive/non-intensive learning style (Lin et al., 2019). Additionally, some scholars applied a broader interpretation of learning styles. For instance, Jeong and Yi (2014) consider factors such as gender, academic level, learning environment, interests, and learning scores as integral to defining learning styles. However, there is variation in the details provided among studies, as not all of them specify their definition of learning styles or the underlying theories supporting the operationalization. For example, Ming and Li (2020) identified learning styles based on the learner's utilization of learning resources, leaving the exact styles undefined. Similarly, Hafidi and Bensebaa (2015) mentioned employing the Multiple Intelligence test to measure learning styles without detailing the styles

Table 2
Learner characteristics used for adaptation and examples applied in reviewed studies.

Type of Learner characteristics	Examples of Characteristics (Author[s], year)	*N*
Knowledge or ability level	knowledge and misconceptions (Taufik & Nurjanah, 2019); pretest score for the required knowledge (Widiastuti & Fanani, 2014)	33
Learning style	intensive/non-intensive learning style (Lin et al., 2019); VARK (Visual, Auditory, Read/Write, Kinesthetic) learning style (Bayasut et al., 2013)	33
Learner's Profile	gender, educational level (Dominic et al., 2015); learner's background (Anantharaman et al., 2018)	8
Behavior	engagement level during learning activities (Almohammadi et al., 2014); browsing history (Wang & Lv, 2022); interaction with the systems (Widiastuti & Fanani, 2014)	12
Cognitive style	psycho-cognitive information (Hafidi & Bensebaa, 2015); cognitive states of learning and forgetting (Chrysafiadi & Virvou, 2014)	4
Affective characteristics	classroom anxiety level (Pandey et al., 2014); motivation status (Mwambe et al., 2020)	3

Note: *N* indicates the number of reviewed studies that used a specific type of learner characteristic for adaptation.

considered.

3.3. Techniques used to identify learner characteristics

3.3.1. Overview of techniques for learner characteristic identification

In Table 3, we listed all the techniques used to identify learner characteristics in the reviewed 57 studies. Overall, a wide range of methods has been employed aiming to accurately capture learner characteristics. Fuzzy logic is the most frequently used technique in the reviewed AeLS studies ($n = 16$), followed by decision tree and Bayesian methods. Compared to other techniques, the prominence of fuzzy logic is likely due to its flexibility in handling uncertain and imprecise information (Alfaro et al., 2018). This was also exemplified by Hamada and Hassan (2017), who successfully applied fuzzy logic in their design to achieve a sophisticated and precise depiction of individual learning preferences. Regarding its scope of applications, this technique has been employed to discern and classify a broad spectrum of learner characteristics, ranging from learning and cognitive styles to engagement levels, emotional states, and knowledge levels (Alfaro et al., 2019; Arellano et al., 2022; Chrysafiadi & Virvou, 2014; Zataraín-Cabada et al., 2013). However, despite the persistent interest in using fuzzy logic, our review noted the growing adoption of a more diverse range of techniques in learner models

Table 3
Techniques used to identify learner characteristics.

Name of Techniques (Frequency)	Target Learner Characteristics	Studies Adapted the Technique
Fuzzy Logic and Systems (16)		
Fuzzy Logic Fuzzy Knowledge State Definer (FuzKSD) Fuzzy C Means (FCM) algorithm Fuzzy Cognitive Maps (FCMs) Zero-order Sugeno fuzzy inference model Type-2 Fuzzy Logic Fuzzy Item Response Theory Tahani Model of Fuzzy Database	Learning styles Cognitive status Learner's behavior, e.g., *learning sequence, engagement level* Affective status, e.g., *emotional states* Knowledge and ability, e.g., *prior knowledge, metacognitive awareness level*	Aissaoui et al. (2019); Alfaro et al. (2018); Alfaro et al. (2019); Almohammadi et al. (2014); Arellano et al. (2022); Azzi et al. (2019); Chrysafiadi and Virvou (2014, 2015; 2021); Crockett et al. (2013); Hafidi and Lamia (2015); Hamada and Hassan (2017); Kausar et al. (2018); Sweta and Lal (2017); Ulfa et al. (2021); Widiastuti and Fanani (2014); Yankovskaya et al. (2015)
Decision Trees (7)		
J48 Decision Tree Algorithm (C4.5 Decision Tree Algorithm) Random Forest NBTree (Naïve Bayes and decision tree)	Learning styles Knowledge level	Abdullah et al. (2015); Al-Chalabi et al. (2021); Anantharaman et al. (2018); Dominic et al. (2015); Hafidi and Bensebaa (2015); Ming and Li (2020); Rishard et al. (2022); Waladi et al. (2023)
Rule-Based (2)	Learning styles	Drissi and Amirat (2013); Kolekar et al. (2018)
Bayesian Methods (8)		
Bayesian Network Bayesian Knowledge Tracing (BKT) Dynamic Bayesian Network (DBN) Naive Bayesian NBTree (Naïve Bayes and decision tree)	Knowledge level, e.g., *knowledge, mastery of skills, misconceptions*	Abdullah et al. (2015); Alday (2018); Hidayat et al. (2020); Hooshyar et al. (2015); Hooshyar et al. (2015); Pardos et al. (2023); Taufik and Nurjanah (2019); Wu (2019)
Neural Networks (4)		
Long Short-Term Memory (LSTM) Algorithm Multi-Layer Feed-Forward Neural Network Kohonen Networks Backpropagation Neural Networks	Learning styles Affective status, e.g., *emotional states* Knowledge level	Alfaro et al. (2018); Alfaro et al. (2019); Bayasut et al. (2013); Zataraín-Cabada et al. (2013)
Statistical and Psychometric Models (7)		
Logistic Regression Item Response Theory (IRT) Rasch Model	Learning styles Knowledge and ability	Budiyanto et al. (2017); Islam et al. (2021); Jeong and Yi (2014); Jeong and Yi (2014); Le and Jia (2022); Rishard et al. (2022); Vagale et al. (2020)
Other Clustering and Classification Algorithms (4):		
Clustering by Fast Search and Finding of Density Peaks (CFSFDP) Hierarchical Cluster Analysis K-means Algorithm	Learning style Cognitive ability Personality attribute	Kausar et al. (2018); Mustapha et al. (2023); Waladi et al. (2023); Wang and Lv (2022);
Other Data Analysis Methods or Techniques (5):		
Weighted Overlay Model Stereotype Model OCC Cognitive Theory Buggy Model Sequential Pattern Mining (SPM) Genetic Algorithms (GAs)	Knowledge level, e.g., *knowledge, mastery of skills, misconceptions* Behavior	Benhamdi et al. (2017); Chen, Niu, Zhao, & Li, 2012; Chrysafiadi and Virvou (2014, 2015); Hibbi et al. (2023); Lin et al. (2019); Taufik and Nurjanah (2019)

in recent years.

Bayesian Methods, such as Bayesian networks and Bayesian Knowledge Tracing, are employed in eight adaptive systems among reviewed studies. These methods leverage probabilistic reasoning to predict future performance and make adaptive selections about subsequent learning activities, based on the assessed probability of a learner's mastery of the target content. In the Flowchart-based Intelligent Tutoring System (FITS) described by Hooshyar et al. (2015), the Bayesian network approach is used to manage uncertainties in students' knowledge levels. The system updates the Bayesian network to reflect changes in the student's mastery status, thereby enabling adaptive navigation support. Following Bayesian methods, decision trees and neural networks, favored by researchers for their "white-box" nature, were employed in seven and five studies, respectively. These two methods offer a transparent and interpretable framework for classification and decision-making processes. However, neural networks have not been utilized in the identified studies since 2019, whereas the application of decision trees appeared more recently. For example, Al-Chalabi et al. (2021), utilized the C4.5 decision tree algorithm to dynamically gauge a learner's knowledge level from their performance in a course, thereby enhancing the accuracy of student knowledge estimation.

Below is the general procedure for applying the four primary techniques used in the reviewed AeLS studies, although the level of details and thoroughness with which this information is reported in actual adaption process varies across studies. In the application of fuzzy logic, precise inputs are transformed into fuzzy sets through membership functions, a process known as fuzzification (Celikyilmaz & Türksen, 2009). Subsequently, IF-THEN rules are applied to evaluate these inputs, followed by fuzzy inference to process the information. The resulting fuzzy outputs are converted back into specific values through defuzzification, making them actionable for decision-making (Mendel, 1995).

Among the reviewed studies using fuzzy logic, half (8 out of 16) provided descriptions of membership functions (e.g., Azzi et al., 2019; Widiastuti & Fanani, 2014), while only four studies detailed the fuzzy rules used (e.g., Arellano et al., 2022; Hafidi & Lamia, 2015). Additionally, two demonstrated the use of fuzzy cognitive maps (e.g., Chrysafiadi & Virvou, 2015; Sweta & Lal, 2017). Notably, three of these studies presented comprehensive examples of how fuzzy logic applications, offering references for future researchers aiming to replicate the technique (i.e., Almohammadi et al., 2014; Azzi et al., 2019; Hafidi & Lamia, 2015). Conversely, four studies lacked even basic details about the techniques used.

Decision trees partition data into subsets by generating decision rules at each node to identify learner characteristics, such as learning styles. Each node represents a characteristic, such as a preference for media or text, or engagement with forums and answering activities (Song and Lu, 2015). Starting with a root node, the tree splits the data using the most relevant features, continuing this process until a stopping criterion—such as maximum depth or minimal meaningful splits—is met (Quinlan, 1986). Among the studies employing this technique, 3 out of 7 included a visual representation of the decision tree, with two providing detailed processes that enable replication (Aissaoui et al., 2019; Ming & Li, 2020). The remaining four studies only mentioned the basic concept of the technique or briefly compared it with other models, offering limited details.

Neural networks can handle relatively complex data, such as students' browsing activity (Haykin, 1994). They consist of layers of interconnected neurons, with data flowing from the input layer, through hidden layers, and ultimately to the output layer (Alfaro et al., 2019). During training, the model adjusts its weights to minimize errors, learning from patterns in the input data. Once trained, the network can classify learner characteristics, such as recognizing emotions or identifying learning styles (Zataraín-Cabada et al., 2013). In our reviewed studies, all four applied this technique presented plots of the neural network structures, with two studies providing detailed information (Alfaro et al., 2019; Zataraín-Cabada et al., 2013).

Unlike the other techniques introduced above, Bayesian methods represent a broad family of approaches grounded in probabilistic reasoning. The application of each specific Bayesian method may vary, so a general summary is not available. However, these methods generally share the characteristic of relying on prior information and updating estimations as new data are observed (Van De Schoot et al., 2021). Although eight studies utilized Bayesian methods, none provided a detailed procedure for adaptation. These studies either introduced the basic concept of the method, such as Bayes' theorem and its advantages, or simply presented the probability models used (e.g., Hooshyar et al., 2015; Pardos et al., 2023; Wu, 2019).

3.3.2. Techniques to measure different types of learner characteristics

When examining the application of techniques relative to the characteristics they assess, distinct patterns were observed. It is worth noting that these techniques are not always directly linked to the target learner characteristics they aim to estimate or identify. However, the nature of the learner characteristics (e.g., knowledge level) does influence technical preferences to some extent. To measure knowledge and ability level, Bayesian networks, decision trees, and psychometric models seemed to stand out as the primary methods. Bayesian network is used due to its consideration of probability and the ability to update a learner's information in AeLSs, while the latter is popular for its capacity to provide an accurate estimation of a learner's ability. For instance, Pardos et al. (2023) applied Bayesian Knowledge Tracing (BKT) for the dynamic estimation and updating of student skill mastery. Similarly, Budiyanto et al. (2017) utilized the Rasch Model (reference) for categorizing learners into levels ranging from beginner to advanced, showcasing the diversity of approaches in gauging knowledge and ability.

For identifying learning styles, fuzzy logic, decision trees, and neural networks are mainly used. Choosing the most appropriate method depends on practical needs, as each offers distinct strengths suitable for specific situations. Neural networks excel in modeling complex, non-linear relationships within large datasets, making them ideal for uncovering intricate patterns in learning styles (Almeida, 2002). Decision trees provide a straightforward approach for hierarchical, decision-based classification, offering clear, interpretable paths for determining learning styles (De Ville, 2013). Fuzzy logic, as previously discussed, excels in contexts where data are ambiguous or uncertain, and is consequently ideal for nuanced learner profiles (Almohammadi, 2016). Bayasut et al. (2013), for example, implemented a multi-layer feed-forward neural network (Svozil et al., 1997) for sorting learners into the four categories of the VARK model, capitalizing on the network's ability to generalize from specific examples and adapt quickly to new parameters, which is crucial for real-time applications. In another instance, Azzi et al. (2019) used the fuzzy c-means (FCM) algorithm to identify learners' styles, using fuzzy logic to align learning preferences with FSLSM categories effectively.

The application of these techniques, however, has been more limited to cognitive style identification with the only example by Chrysafiadi and Virvou (2014), who applied fuzzy logic to estimate learners' cognitive states related to learning and forgetting processes. In contrast, other characteristics—affective characteristics, behaviors, and learner profiles, including gender and age, —have not been extensively assessed using such technical methods. These characteristics are often gathered directly from the learners or automatically captured by AeLSs, such as browsing history and log data.

4. Discussion

A well-executed systematic review will not only provide a comprehensive understanding of the current state of adaptive e-learning but also help identify research gaps (Peters et al., 2015). By reviewing the learner characteristics and techniques employed in the recent AeLS studies that reported effective adaptation, we can gain insights into the direction for future improvement, by understanding which learner characteristics have been effectively utilized or underutilized. Additionally, we seek to highlight the strengths of the commonly used techniques. These insights can better guide researchers in designing future studies, thus enhancing the overall quality of research in adaptive e-learning (Hulland & Houston, 2020; Peričić & Tanveer, 2019). This discussion section is organized in an order corresponding to the research questions. Within each subsection, we first highlight and share our implications of noticeable patterns in the findings presented in the results section. Then the limitations of existing studies and potential directions for future research efforts are discussed.

4.1. Learner characteristics included in the learner model of AeLSs

We found that among the six classifications of learner characteristics, knowledge levels and learning styles are the most frequently used in learner model in AeLSs, both being utilized in 33 reviewed studies. In addition, we found that, for the 32 AeLSs that rely on singular characteristics, the selected characteristic for adaptation was either knowledge level or learning style. The predominant use of knowledge levels and learning styles may be attributed to their innate importance in adaptive e-learning systems. Learner's current knowledge level will provide a baseline for understanding what a learner knows, enabling AeLSs to adjust the difficulty and complexity of a material accordingly (Yankovskaya et al., 2015). Learning styles, on the other hand, offer insights into the preferred ways learners interact with and absorb new information, allowing for tailored presentation formats and instructional strategies (Hamada & Hassan, 2017; Hawk & Shah, 2007). Both types of learner characteristics will directly influence learners' engagement and outcomes, making them critical for effective adaptation.

However, this review also highlights the potential value of incorporating additional learner characteristics in the model for effective adaptation. For instance, higher motivation has been shown to positively impact student achievement across various studies (Özen, 2017, pp. 35–56), and, in fact, the AeLS developed by Mwambe et al. (2020) demonstrated enhanced personalization by incorporating learners' motivation along with their knowledge level in the learner model. Despite the importance and effectiveness of including knowledge level and learning styles in a learner model, expanding our focus to other characteristics is crucial for uncovering new dimensions of personalization. With a holistic and accurate understanding of learner's needs, adaptive learning environments will become more efficient and effective.

Additionally, articulating the process of and the rationale for these characteristic selections is essential when considering a diverse array of personal characteristics available for AeLSs (Normadhi et al., 2019). It also helps us for a better understanding of how a learner characteristic functions in adaptation, and thereby guiding us for meaningful applications in practice. However, we intend not to suggest researchers utilize all available learner data extensively, but rather emphasize the importance of carefully selecting a set of characteristics that will maximize efficiency for enhancing learning experiences for learning objectives. For instance, Almohammadi et al. (2014) integrated student anxiety levels assessed by the Foreign Language Classroom Anxiety Scale (FLCAS) with learning styles for adaptation. While the researchers did not provide a clear rationale for accounting for learners' anxiety in adaptation, the inclusion of such an affective state of learners in adaptation might reduce measurement error, as high anxiety can negatively affect a learner's performance and potentially lead to an underestimate of actual ability (Keogh et al., 2004). Nevertheless, an explicit explanation of the choice of learner characteristics should help leverage the findings from previous studies for future applications in the AeLS learner model.

4.2. Theories for categorizing learner characteristics in learner model

We focus our discussion regarding the theoretical foundations of learning style as we recognized notable variations in the classification of learning styles compared to other attributes of learners. First, we found significant variability in reporting practices on how studies present the selected theories, often without clear justification for their choice and/or the corresponding categorizations of learner styles. Second, authors often fail to elucidate the rationale behind selecting a particular learning style model over others, while most of them provide details on the theoretical model employed. This lack of theoretical underpinning in the model development leaves researchers with uncertainties about the applicability of the model. Furthermore, the importance of detailed reporting on the theoretical foundation for categorizing learning style in AeLSs cannot be overstated. Transparent reporting not only enhances comprehension of the AeLSs but also enables researchers to replicate and build upon successful interventions (Khosravi et al., 2020).

Alfaro et al. (2018) set a commendable example by explaining their choice of Honey and Mumford's model, noting its focus on how information is perceived and processed, as a distinction from other models that emphasize less pertinent aspects for web environment development.

Finally, we observe in recent research that authors have modified existing models to address specific needs within their study (e.g., Hamada & Hassan, 2017; Vagale et al., 2020). This ongoing improvement and adaptation process reflects the dynamic and evolving nature of research on learning styles in the development of AeLSs. Such efforts facilitate a more tailored approach, enabling AeLSs to accommodate the diverse behaviors and preferences of learners in real-world educational settings (Coffield et al., 2004; Kirschner, 2017). While certain theories are often applied for categorizing learning styles, the selection of theoretical foundations for modeling, possibly requiring some adaptation to fit specific empirical contexts, should primarily be driven by the objectives of the AeLSs. Thus, we encourage future researchers to provide a detailed description of how a theoretical model was selected for transparency and for better implications for practice.

4.3. Techniques utilized in the system for learner characteristics identification

We noticed a shift from predominantly relying on fuzzy logic to embracing a more diverse array of techniques, such as decision trees and Bayesian methods, during the last 10 years. This transition may reflect the evolving demands of educational systems for transparency, predictive accuracy, and adaptability. Fuzzy logic has been traditionally favored for its capacity to manage complex and nuanced data with reasoning that deals with uncertainty and imprecision (Zimmermann, 2010) through its flexible membership functions and rules. It could effectively address the intricate scenarios frequently encountered in analyzing learner characteristics (Chrysafiadi & Virvou, 2015). However, the emerging preference for decision trees and Bayesian networks seems to be driven by their unique features as well. For example, decision trees enhance the explainability of educational systems with their transparent decision-making process, providing educators with insights into the rationale behind system adaptations (Guleria & Sood, 2022). Conversely, Bayesian networks utilize a probabilistic reasoning approach, which is particularly beneficial for making decisions under uncertainty and has been evidenced as effective in dynamically updating learners' knowledge levels within AeLS (Hooshyar et al., 2015; Pardos et al., 2023). Furthermore, both decision trees and Bayesian networks play a crucial role in predictive analytics, offering established methods for seamless integration into the diverse workflows of data mining and machine learning that underpin learning analytics (How & Hung, 2019; Rincón-Flores et al., 2019). Therefore, while fuzzy logic remains advantageous for its in-depth approach to learner characteristic analysis, the increasing use of decision trees and Bayesian methods underscores their growing significance in meeting the needs of the current educational practices. However, unfortunately, the reviewed studies offer limited descriptions of their technical applications, providing insufficient guidance for future researchers. We encourage future studies to include comprehensive technical details to facilitate practical implementation and enable replication across diverse learning contexts.

With various techniques being used to identify learner characteristics in reviewed studies, comparing these techniques to ascertain their relative effectiveness becomes important. Yet, the current review unveils a scarcity of research directly comparing and evaluating the effectiveness of different adaptive methodologies under similar contexts and adaptation objectives. We noted that most of the reviewed studies highlight the superiority of the employed techniques in adaptation over the absence of such techniques. For instance, Rishard et al. (2022) demonstrated that students using the proposed AeLS achieved significantly higher learning gains compared to those learning without personalization. On the contrary, Kausar et al. (2018) provided an example of technique comparison by evaluating the proposed Fast Search and Finding of Density Peaks (CFSFDP) method against the K-means method, revealing that CFSFDP discovers significant clusters in a more spontaneous manner. Such comparative studies will guide future researchers toward selecting appropriate methods and effectively implementing AeLSs aligned with learning goals.

We also recommend that researchers adopt a combined approach, such as integrating both questionnaires and computational techniques, in identifying learner characteristics. This approach can mitigate the limitations of relying solely on questionnaires, including potential learner reluctance to finish the questionnaire, a lack of self-awareness in learning preferences, and the inherent biases and superficial understanding associated with self-reported data, as noted by Azzi et al. (2019). Maaliw's (2020) study exemplifies the effectiveness of this suggested approach by using both the Index of Learning Styles (ILS) questionnaire and the J48 decision tree algorithm, which together significantly improved the accuracy of learning style identification to a rate as high as 92%. The combined approach not only addresses the drawbacks of the sole use of questionnaires for data collection but also substantiates the precision that computational techniques can add to the analysis, offering a more accurate estimation of learner's preferences and abilities.

4.4. Adaptive assessments for AeLSs

Apart from the issues discussed earlier, during our review of the 57 studies, we noticed a shortfall in incorporating adaptive assessments in AeLSs—only included in four out of 57 studies (i.e., Arellano et al., 2022; Pardos et al., 2023; Pelánek, 2020; Widiastuti & Fanani, 2014). Adaptive assessments, which are usually computer-aided, help to select items based on the respondent's answers to previous items, enabling a more efficient and accurate estimation of the respondent's knowledge level (Vie et al., 2020). Considering this advantage and potential integration as an essential component of AeLSs (Badaracco & MartíNez, 2013; Ezzaim et al., 2023; Martin et al., 2020), their limited application in AeLSs highlights a noticeable gap requiring more attention in future research.

Various adaptive assessment approaches have been widely utilized and advanced to a point where they can be effectively integrated into AeLSs. These range from assessments relying on traditional measurement models, such as item response theory (IRT: e.g., Hambleton et al., 1991), which informs examinees' relative positions within a population, to multistage testing (Zenisky et al., 2009, pp. 355–372). Multistage testing adjusts the difficulty of questions in stages and has been used in exams like the Graduate Record Examination (GRE) (Davey & Lee, 2011). More advanced approaches, such as computerized adaptive testing (Chang & Ying, 1996), not only fine-tune the difficulty of each question but also select questions based on the individual's performance, adapting on an item-by-item basis. Other sophisticated measurement models, such as the Cognitive Diagnosis Model (CDM) (De La Torre, 2009) and its variants, can offer deeper insights into students' mastery of skills. The extension of the CDM model, such as the one proposed by Wang et al. (2017), integrating CDM with a Higher-Order, Hidden Markov Model and employing a Bayesian framework to model skill progression, may enhance personalization with precision and efficiency. Alternatively, techniques like on-the-fly IRT (Zheng & Chang, 2014, pp. 21–39) and computerized adaptive testing mentioned earlier, enable adjustments in the test item difficulty promptly for improved real-time estimation of learners' knowledge (Chang & Ying, 1996; Jiang et al., 2022). However, even among studies that used adaptive assessments, the methods used to measure students' learning performance were relatively simple. This creates a substantial disconnect between the advancement of psychometric research and its practical application in adaptive assessments. Thus, we encourage researchers to consider applying an appropriate measurement model for adaptive assessments suitable for learning purposes and contexts instead of defaulting to a similar methodology. With these considerations, we will maximize the adaptability and personalization capabilities of AeLSs, thereby making these systems optimal for being responsible for individual learning needs.

4.5. Limitations of the current study

Although we carefully designed the current systematic review to address our research objectives, the study is not free from limitations. For example, with the use of multiple databases for a comprehensive search and a careful attention given to the systematic sampling with the following pre-determined inclusion criteria, we attempted to control sampling bias. Consequently, these 57 studies included in the current systematic review should represent the available recent research related to AeLS in the last 10 years to discuss the prevailing recent trends of AeLS research accurately. Despite this, there remains a probability of missing relevant studies available.

Additionally, there is a possibility that the current review may not fully encompass the culture-related differences in learner models as we only included the studies published in English. However, we believe such bias is limited as notably, the studies on AeLSs conducted in non-English speaking countries may also be published in English. For instance, in exploring the social/emotional dimension of the advanced FSLSM, Hamada et al. (2013) found that a higher percentage of boys preferred social learning over girls, who favored emotional learning in Japan. The researchers considered the potential gender-biasing effects of Japanese culture on social behavior as a possible factor, indicating that these findings might be culture-specific.

5. Conclusions

This systematic review aimed to delineate the trends in research on AeLS through the synthesis of 57 studies. The results underscore a scarcity in reporting the development of a learner model, though interest in AeLS is generally increasing. We also found that learning styles and knowledge levels remain the two most frequently applied learner characteristics in these models, with three learning style theories commonly used by researchers. Although fuzzy logic emerged as the predominant technique among the studies we reviewed, researchers have also explored a variety of other methods, including Bayesian approaches, decision trees, and neural networks, each with distinct strengths.

While a majority of studies used only a single type of learner characteristic in adaptation, we recommend that future AeLS research designs incorporate multiple, well-justified learner attributes. Specifically, researchers should consider incorporating additional learner characteristics, beyond learning style and knowledge to enhance adaptation. In addition, researchers should also select adaptive techniques whose strengths align with the available data and the intended purpose of the adaptation to make accurate personalization and improved learning outcomes. For that purpose, comparing the effectiveness of different adaptation methods will help identify the most suitable approach for the given learning contexts.

By adopting appropriate methodologies and incorporating relevant learner characteristics, AeLSs can better address the diverse needs of learners, thereby enhancing educational outcomes and fostering an engaging learning environment. We hope this systematic review can serve as a valuable resource for researchers and developers involved in the design, implementation, and enhancement of AeLSs.

CRediT authorship contribution statement

Xiyu Wang: Writing – original draft, Methodology, Investigation. **Yukiko Maeda:** Writing – review & editing, Supervision. **Hua-Hua Chang:** Conceptualization.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2024.105184.

Data availability

No data was used for the research described in the article.

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