Adv Mobile Learn Educ Res, 2021, 1(2): 124-145
DOI: 10.25082/AMLER.2021.02.007

REVIEW

Adaptive e-learning systems through learning styles: A review of the literature

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Received: September 3, 2021;
Accepted: October 6, 2021;
Published: October 9, 2021.

Citation: Katsaris, I., & Vidakis, N. (2021). Adaptive e-learning systems through learning styles: A review of the literature. *Adv Mobile Learn Educ Res*, 2021, **1**(2), 124-145.
https://doi.org/10.25082/AMLER.2021.02.007

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Abstract: The domain of education has taken great leaps by capitalizing on technology and the utilization of modern devices. Nowadays, the established term "one size fits all" has begun to fade. The research focuses on personalized solutions to provide a specially designed environment on the needs and requirements of the learner. The adaptive platforms usually use Learning Styles to offer a more effective learning experience. This review analyzes the learner model, adaptation module, and domain module, originating from the study of 42 papers published from 2015 to 2020. As more modern techniques for adaptation get incorporated into e-learning systems, such techniques must be compliant with educational theories. This review aims to present the theoretical and technological background of Adaptive E-learning Systems while emphasizing the importance and efficiency of the utilization of Learning Styles in the adaptive learning process. This literature review is designated for the researchers in this field and the future creators and developers of adaptive platforms.

Keywords: learning styles, adaptive e-learning systems, adaptive hypermedia educational systems, intelligent tutoring systems, personalized learning

1 Introduction

As the field of education has been structured at the beginning of the past century, it was focused on the knowledge and skill that a learner can develop without discriminating between the skills, tendencies, and most importantly, the style that each learner prefers to acquire the knowledge. Through this approach, "one size fits all," many students confront difficulties to conform with the school sessions as they are not adapted to their needs (Graf et al., 2008, 2009; Haider et al., 2010; Kinshuk et al., 2009). This is one of the reasons that led in a different direction towards personalized learning. A learning system adapted to each student's needs, and learning style offers extra motivation to build potential based on their skills (Popescu et al., 2009). An additional challenge faced by teachers is the lack of the technological equipment, as well as the insufficient training to new technologies. Furthermore, teachers do not trust the content of the curriculum as it is competent enough in digital tools, leading to the need of researching for appropriate learning object. This process introduce complications such as time consumption, insecurity, fear that these tools do not fit their teaching subject and more (Poultsakis et al., 2021).

There are many methodologies and frameworks for personalized learning. With the advances of technology and the wide usage of networks, there is an emphasis on creating digital platforms and educational systems that assist teachers and students in gaining access to personalized learning (Coffield et al., 2004; Thaker et al., 2018; Vidakis et al., 2019). Learning Styles consist of one of the most popular personalized learning methods, as they can consider the learners' learning preferences. Using Learning Styles helps the learners be more active. As they are in an environment created based on their needs, their motivation can be elevated (Alshammari et al., 2015).

Learning Styles offer significant assistance to the teacher during the learning process, but there are difficulties in personalization. The tutor cannot offer a personalized and adapted lesson based on the preferences and needs of each student by following the traditional methodologies (Maravanyika et al., 2017). Applications that capitalize on technological platforms that can be accessed from a computer or smart devices can help with personalized learning but restrict the activities utilized in the classroom (El Guabassi et al., 2018; Kurilovas, 2016).

2 Literature review

2.1 Adaptive e-learning systems

World Wide Web and information technologies have played a crucial part in the differentiation of the educational process, particularly in universities where the focal point was more personalized learning (Hurtado et al., 2018). Platforms adapt the content, the means of presentation, and the difficulty level depending on the concerned learner each time. In this way, there are not suitable lessons for everyone, but a more suitable lesson for every student (Brusilovsky & Nejdl, 2004). Learning platforms usually are organized based on the Learning Style, as the data from educational psychologists have shown that Learning Styles have a significant impact on the learning process (Popescu, 2010).

New technologies have aided in developing systems that embed the Learning Styles and consequently direct and assist the learners. Some of the developed systems are the Learning Management Systems (LMS), Adaptive Hypermedia Systems (AHS), and Intelligent Tutoring Systems (ITS). Furthermore, in recent years have appeared the Learning Style Based Adaptive Educational Systems (LSAES). The differentiation between previous systems is that they form personalized learning systems based on learning, suggesting the most suitable methods and techniques (Halawa et al., 2016; Nongkhai & Kaewkiriya, 2015).

In this way, the employment and connection of Learning Styles in the educational routine is actualized essentially and practically. There are three significant domains for the Personalized E-Learning Architecture, which are the following (Brusilovsky, 1998):

(1) User module: Store and manage user profile;

(2) Adaptation module: Analyze the best learning object;

(3) Domain module: Store and manage learning objects.

Research reveals that Adaptive E-learning Systems based on Learning Styles are more efficient and reduce the learning time, increase the completion level of a subject, and improve academic performance (Graf et al., 2009). New methods have been developed to provide a more reliable and performant personalized learning process to the learners (Fasihuddin et al., 2016). So, such systems have been developed that the most significant of them are the following:

(1) AHS (Adaptive Hypermedia Systems). This system can provide a personalized experience to a user. This is achieved from hypertexts and hypermedia (Brusilovsky & Peylo, 2003).

(2) AEHS (Adaptive Educational Hypermedia Systems). These systems have been created to aid the learners in education, focusing on their needs and adapting the learning material depending on the prior knowledge and the learning goals that a tutor chooses. In this way, the system can offer a learning experience that best suits the learner's needs (Al-Azawei & Badii, 2014).

(3) AES (Adaptive Educational Systems). The differentiation with the systems mentioned above is that the Learning Style factor is added. Learning Styles are based on educational theories, and in this manner, the navigation and the material that is provided to the learners is not only adapted to their needs but also their learning preferences (Mulwa et al., 2010; Papadimitriou et al., 2012; Popescu et al., 2009). The learning experience becomes more pleasant and interactive, resulting in fulfilling the learning goals and the active participation of students. In contrast, the satisfaction of the learning process is increased.

(4) ITS (Intelligent Tutoring System). This system is developed to take advantage of the data that a user produces during the usage of the system, and based on that data and the resulting outcomes, navigate the user in the right direction. The system records data concerning the mouse movement, required time, resulting in grades, and the type of errors that the user made. Analyzing such data leads to creating a profile that will refer to provide appropriate content to the user. This way, an adaptive learning environment is provided to the user (Abueloun & Naser, 2017; Akkila & Naser, 2017; Aleven et al., 2016; Vidakis et al., 2020).

2.2 Adaptation & mining techniques

Fuzzy Logic (FL)

Lotfi Zadeh introduced it to describe the partial truth of a subject. By classical logic, we can only conclude true or false for a topic. That is an absolute value that might not be the best to describe the result or conclusion. Fuzzy logic allows us to describe this partial truth by assigning degrees of truth, meaning how true an expression is; this partial truth can have values from 0 to 1. Fuzzy logic follows a process of Fuzzification which assigns the numerical values of inputs into fuzzy sets. Then rules get executed to compute the outcome. Finally, Defuzzification gets performed to assign a value to the linguistic outcome from the rules before.

Rule-based systems (RBS)

Rule-based systems manage a system's knowledge and perform/handle actions based on that knowledge. It is used primarily on artificial intelligence, especially in expert systems. Rule-based systems comprise a list of rules, that is, a specific type of a knowledge base, a semantic reasoner which is responsible for performing an action based on an input, working memory that stores the content to be matched in the semantic reasoner and a user interface which is used for sending and receiving input and output signals. Semantic reasoner has its cycle that is: match, conflict-resolution, and act.

K-means

Firstly, introduced by James MacQueen and Stuart Lloyd Bell Labs first proposed the standard algorithm. K-means is an algorithm categorized in unsupervised learning, and it is used for clustering problems. This algorithm allows to group items from an unlabeled (unknown) set of data. K is the number of sets/ clusters that need to be created. Given an initial set of k means, this method assigns each observation to a cluster with the nearest mean calculated from the Euclidean distance. After that, it recalculates the means for the observations in each cluster. The algorithm stops when the clusters do not change.

Decision Trees

These algorithms can be described visually as a tree-shaped flowchart. It starts with a single node and then splits into two or more branches. Each of these branches contains a different decision. The main parts of a decision tree are the decision nodes that represent a decision that needs to be made, chances nodes that represent a probability or uncertainty, and finally, the end nodes that represent the outcome that is the action that should be made based on the tree.

Machine learning (ML)

Are computer algorithms that can be improved automatically using data acquired over time. It is a subset of artificial intelligence and a related field of study to data mining. Nowadays, machine learning is used in many areas like medicine, computer vision, and more. Machine learning can be approached through supervised learning, unsupervised learning, and reinforcement learning. Common machine learning algorithms include Artificial Neural Networks, Decision trees, Support-Vector Machines, Genetic algorithms, and more.

Genetic algorithms (GA)

Genetic algorithms are biologically inspired by the process of natural selection and rely on operations like mutation, crossover, and selection. Genetic algorithms are a subtype of a larger class called evolutionary algorithms that are also a subset of evolutionary computation. Those algorithms are mainly used for optimization and search problems. The primary process of executing such algorithms is the following: First, an initial population is generated randomly, then each individual of the population is checked against some predefined criteria, and the individuals that suit those criteria better are selected for reproduction. Then, new individuals are created from the selected individuals before. Finally, the least-fit individuals of the population get replaced with the new individuals.

Bayesian networks

These are probabilistic models that represent relationships between variables and their dependencies through a graph. These networks are used to predict the likelihood that an event will happen based on the possible causes that can trigger that event.

Recommender systems

A recommender system is a subclass of information filtering systems that tries to predict a user's preference. These systems are used in many areas, such as video services, social media platforms, and more. There are many approaches to create recommender systems, such as collaborative filtering, content-based filtering, session-based and more. Most systems use collaborative filtering and content-based filtering or both. Collaborative filtering uses models of user behavior and uses that to predict what the user might like. The content-based filtering assigns characteristics on the items to recommend to the user items with similar characteristics.

Software Agents (Intelligent agents)

Software agents in computer science are programs that can act on their own on behalf of a user. Software agents are widely known as bots. Agents can be autonomous or work alongside other agents or people. There are many types of agents, each type referencing a specific characteristic of the agents. Such types may be intelligent agents, autonomous agents, mobile agents, and more.

k-NN

The k-NN algorithm is applied chiefly on classification problems. It was developed by Evelyn Fix and Joseph Hodges in 1951. It is a distance-based algorithm that, by assigning the distance length as k, counts the number of each class label of the training examples found within the k distance from the input.

3 Literature review methodology

This literature review followed (Abyaa et al., 2019) inspired by (Kitchenham et al., 2009). The process consists of the following steps: 1) identifying the need for a literature review, 2) identifying the research questions, 3) identifying research databases, 4) assign inclusion and exclusion criteria as well as the article gathering process, 5) evaluation of the selected studies, 6) data extraction clarification from each study, 7) classification of data exported from the selected studies and 8) extraction and interpretation of the results.

3.1 Research necessity

The paper comprises the foundation for further research of Adaptive E-learning Systems, which can embed various Learning Styles to provide a personalized learning process for the users. Given that the adaptation of Learning Style has been considered a significant factor of success in personalized learning, the development of adaptation rules for the educational systems is a requirement to improve Adaptive Educational Systems further. The research tries to expand the literature in respect of the research questions.

3.2 Research questions

A. Learner factors in adaptive systems

(1) Which learning style model and prediction techniques are used in adaptive e-learning systems?

(2) Which factors are considered for a learner model based on learning styles and Learner Modeling Data Resources?

B. Adaptation

Which are the adaptation elements and techniques in e-learning systems?

C. Domain module

Which are the most studied User Group, Educational Level & Curriculum and which are the Educational and ICT Impacts?

3.3 Research strategy

The process consists of six levels of classifications. In the first level, research was conducted on the databases such as Scopus, SpringerLink, Science Direct, IEEE Explore, and Google Scholar between 2015 and 2020. This research aimed to discover new trends and strategies in a continuously evolving domain, such as Adaptive E-learning, combined with models of Learning Styles that adapt the learning process to profit the user. Specifically, the research was realized using keywords such as "adaptive e-learning," "adaptive hypermedia educational systems," "intelligent tutoring systems," "personalized learning," "learner model" according to "learning styles."

3.4 Criteria for inclusion and exclusion

Inclusion criteria

(1) Papers focusing on personalization and adaptive e-learning based on learning styles;
(2) Theoretical and empirical works on adaptive e-learning systems based on learning styles;
(3) Theoretical and empirical works on a recommender system based on learning styles.

Exclusion criteria

(1) Papers that were not written in English;
(2) Papers to which there was no full access;
(3) Papers that focus on Prediction-detection learning style;
(4) Papers that had not a Learning Style model;
(5) Papers that were not performing adaptation on at least one factor;
(6) Papers that lacked detailed explanation and evaluation of the topic;

(7) Papers with vague methodology, implementation, or results.

3.5 Paper selection process

In the first stage, 935 research articles and publications were gathered. In the second stage, after removing duplicated articles, articles that were not accessible through the web and the articles that were not able to download remained 643 articles. Moving on to the third stage, the titles of the articles written in English were studied to remain only the most suitable for this review, which is 328. In the fourth stage, the abstracts of the selected articles were studied, and publications that are not in the research domain of this review were removed, resulting in 122 articles. Finally, those 122 articles were studied in detail and concluded in 42 articles that covered in full the research questions of this research (Figure 1). The rest were also removed.

As presented in many literature reviews, a common problem is the possibility of missing publications for the desired domain. This might be due to the selected keywords that the authors searched to detect as many papers as possible. The combination of keywords used and their synonyms might not extract articles with the same content. Furthermore, articles might exist on databases that are out of reach for the authors.

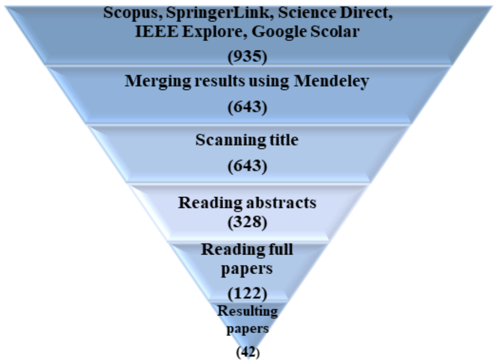

Figure 1 Paper selection process

3.6 Classification of results

The current study has as main goal to research Adaptive E-learning based on Learning Styles. Through the analysis of the selected studies, the extracted information was classified into the following categories:

(1) Learning style models used in adaptive systems include Felder-Silverman, VARK, Honey and Mumford, Gardner's Theory of Multiple Intelligences, and Entwistle's Theory. Additionally, multiple techniques have been used to predict the learner style of users, such as Questionnaires, Fuzzy Logic, Evolutionary Algorithms, Artificial Neural Networks, Decision Trees, Statistics, Content-based Filtering.

(2) Learner model factors in adaptive systems. The learner model is composed of a multitude of user traits. Such factors are the following: learning style, prior knowledge, learning goals, cognitive style, personality traits, learner's device, learner tracking, and working memory capacity. Furthermore, it is of great importance the type of model. Namely, if the model is implicit, it is constantly updating based on the usage data or explicit, meaning that the model is static.

(3) Adaptation elements and techniques in e-learning systems. Elements have been classified into content, navigation, presentation, and assessment. Adaptation Techniques are Rule-Based, Evolutionary Algorithms, Intelligent Agents, Decision Tree, k-NN, Machine Learning, Recommendation System, and Fuzzy Logic.

(4) User groups that participated in empirical studies are learners, learners and teachers, high education experts. Educational levels are Students of Higher education, Secondary education, and Primary education. The scientific domains where the adaptive e-learning systems were tested are Computer Science & Engineering, Mathematics, Social sciences, Chemistry, English, Earth Science, and various disciplines. Finally, concerning the Educational and ICT Impacts that referred in the literature are: Higher learning performance or Positive impact on learning outcomes facilitates learning processes, enhance learning satisfaction, effective communication with teachers, enhancing the learning self-efficacy, suitability of learning materials, improved algorithms/techniques, improved data mining results.

4 Results

4.1 Learner module

The procedure for a correct and complete user profile underlines a key point of adaptive platforms. Through a user profile, not limited to suitable content and knowledge, the optimal order of such materials will be provided to achieve as high performance as possible (Kaplan & Haenlein, 2016). To accomplish such a task, there is the need to collect information according to the user preferences, knowledge, interests, and more (Brusilovsky & Peylo, 2003; Henning et al., 2014).

There are many different methods for data retrieval, some of them using explicit (or collaborative) modeling such as questionnaires or rate satisfaction, and other methods using implicit (or automatic) modeling such as the mouse movements or the period for completing a task (Gauch et al., 2007; Sweta & Lal, 2017). The challenge for creating a compelling user profile lies in the correct assessment and the determination of fair values (weights) so that the algorithm can utilize those values appropriately (Alshammari et al., 2014; Bouneffouf, 2013; Kanoje et al., 2014).

4.1.1 Learning style used in Adaptive e-learning systems

Every person learns in a different style. This ascertainment can be described as trite, but most educational systems today still use the principle of “One size fits all.” The most popular and acceptable definition for the learning preferences, or as there are referred to in the international literature, “learning styles,” has formulated by Keefe (1979), who described them as the characteristic cognitive, affective and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment (Keefe, 1979), while Felder (1988) primarily focuses on the means that a student can receive and process the information (Felder & Silverman, 1988; Keefe, 1997).

The technology in recent years has allowed developing systems that aid the tutors to design learning objects notably adapted to the students’ preferences (Feldman et al., 2016). In this direction, the systems promote the improvement of the learning process. At the same time, the students learn their subjects more effectively in their preferred style and way (Bernard et al., 2017; Supangat & Bin Saringat, 2020). However, these aspects require more research to culminate in the exact profits of the learning process based on Learning Styles (Kirschner, 2017; Truong, 2016).

4.1.2 Classification of Learning Styles

The development and the application of Learning Styles in education have been present for many decades. Approaches about the style that people prefer to learn are very different. For this reason, many Learning Styles have been developed. According to Coffield et al. (2004), 71 Learning Style models have been formulated, which tried to group the following five categories considering the similarities between such models. The “Families of learning style” as Coffield et al. (2004) names them are:

(1) Learning styles and preferences are constitutionally based, including four modalities: visual, auditory, kinaesthetic, and tactile; (Dunn and Dunn, Gregorc, etc.);

(2) Learning styles reflect features of the cognitive structure, including ability patterns (Riding, Gardner, etc.);

(3) Learning styles are one component of personality type; (Myers-Briggs, Apter, Jackson, etc.);

(4) Learning styles are flexible learning preferences; (Kolb, Honey & Mumford, Felder & Silverman, etc.);

(5) Move from learning styles to learning approaches, strategies, orientations, and conceptions (Entwistle, Vermunt, etc.).

Some of the most known Learning Styles are those of Felder and Silverman (1988), Kolb (1984), Honey and Mumford (1986), Pask (1976). In the studied articles that associate Learning Styles with Adaptive Learning, the following were found: Felder and Silverman, VARK, Honey and Mumford, Gardner’s Theory of Multiple Intelligences, Entwistle’s Theory.

Felder-Silverman Learning Style Method (FSLSM). Engineering prof Dr. Richard Felder and educational psychologist Dr. Linda Silverman collaborated and implemented a taxonomy to help students in the engineering field. The processed and implemented method primarily concerned higher education, but it can be used in the lower education levels. The taxonomy is based on the four different learning Style categories: Sensing/Intuitive, Visual/Verbal, Active/Reflective, Sequential/Global (Felder & Silverman, 1988).

The Index of Learning Styles questionnaire includes 44 questions. After the supplementation of the questionnaire, the suggested Learning Style has been acquired, and the system can be adapted to the learner. Over time, this procedure has been differentiated, shaped, and automated (Ahmad et al., 2013; Chang et al., 2009; Dorça et al., 2013).

According to Vark Learning Style, students' preferences are Visual, Aural, Read/Write, and Kinesthetic learning (González, 2012; Leite et al., 2010). According to Fleming (1995), it would be preferred for visual students to receive the information through graphs, charts, and flowcharts. Aural students prefer to receive information through hearing. As for the students who fall into the read/write subcategory, receiving information through reading or writing scripts is preferred. Finally, the students in the kinesthetic category prefer the learning process to be through experiential learning using all the previous senses (Fleming, 1995).

Honey and Mumford, whom Kolb highly influenced, created a Learning Style Questionnaire (LSQ) to arrange students into Activists, Theorists, Pragmatists, Reflectors based on their preferences.

H. Gardner created a theory suggesting that human intelligence is not uniform but can be divided into sectors. So, eight intelligence types were surveyed. This Theory has a significant impact on the education community. Based on the introduced types of intelligence came the Learning Styles related to each type(Gardner, 1983; Sanchez-Martin et al., 2017).

Entwistle worked on the concept that each student learns better when a specific learning process is designed based on that student's characteristics. Through this Theory, three categories of students emerged. Surface learners focused on data acquisition, strategic learners aimed at attainment, and deep learners concentrated on personal progress (Entwistle, 1997).

4.1.3 Advantages of Learning Styles

Studies have proven that Learning Styles can assist the students on the knowledge level and improve their activity during the learning process. The conclusion mentioned above is reached through comprehensive research on higher education and lower education levels. Students in an environment that suits their needs and learning style can stay focused for a higher amount of time and show better performance (Graf et al., 2009; Papanikolaou et al., 2003; Triantafillou et al., 2004).

Another significant contribution of Learning Styles in personalized learning is that students are equipped with the appropriate means for tuition attendance. Nowadays, tutors and designers of learning platforms have at their disposal a wide range of tutoring mediums, of which only a few are selected in each subject (Coffield et al., 2004). However, the advancement and diffusion of Learning Styles provide the possibility of full utilization through appropriately designed platforms (Dorça et al., 2016). Felders' labeling is remarkable that learning difficulties are likely to be introduced when a student is not treated through the manifested Learning Style (Felder & Silverman, 1988).

4.1.4 Critique on Learning Style usage

Despite studies suggesting that the learning procedure is significantly improved by using Learning Styles on e-learning platforms, there are challenges in their application (Van Zwanenberg et al., 2000). Questionnaires that have to be filled during the initial state of the process are extensive, with many questions. Thus students are often discouraged from correctly completing them (Felder & Spurlin, 2005). Additionally, the possible answers often express subjective opinions, and questions might be challenging to comprehend or ambiguous(Coffield et al., 2004). In order to provide a solution to these challenges, efforts are made to reduce the number of questions, at least in the questionnaires for the younger age groups, so that the process of completing them is easier and faster (Halawa et al., 2016). The questionnaire is only used once to initialize the procedure. Then specially designed algorithms undertake the student's navigation on the platform (Watkins, 2016).

From Table 1, most adaptive systems utilized the Felder-Silverman model, n = 34 ($\simeq$ 79%). The next most used model is VARK, n = 4 ($\simeq$ 10%). Next, we identify the Honey and Mumford model, n = 3 ($\simeq$ 7%). At the same time, Gardner's (Theory of Multiple Intelligences) and Entwistle's Theory are sparsely used, with only n=1 and $\simeq$ 2% each.

According to the conducted literature review, the main reason behind the preferences of most researchers for the Felder Silverman model concerning the rest lies mainly in the fact that a questionnaire has been developed that is very effective and easy to use for adaptive

Table 1 Learning style is adaptive systems

Learning style	No. of articles (n = 42)	References
Felder Silverman	33 (79%)	(Abech et al., 2016), (Ali et al., 2019), (Almeida et al., 2019), (Alsobhi & Alyoubi, 2019),(Anantharaman et al., 2019), (Andaloussi et al., 2019), (Apoki et al., 2020), (Araújo et al., 2020), (Arsovic & Stefanovic, 2020a), (Alshammari et al., 2015), (Alshammari & Qtaish, 2019), (Bendahmane et al., 2019), (Boussakuk, 2020), (Budiyanto et al., 2017), (Christudas et al., 2018), (Dwivedi et al., 2018), (El Guabassi et al., 2018), (Elkot, 2019), (Fasihuddin et al., 2016), (Hurtado et al., 2018), (Karagiannis & Satratzemi, 2020), (Kolekar et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019), (Lakkah et al., 2017), (Rani, Vyas, et al., 2017), (Sunil & Doja, 2019), (Supangat & Bin Saringat, 2020), (Sweta & Lal, 2017), (Tarus et al., 2017), (Tortorella & Graf, 2017), (Vaidya & Joshi, 2018)
VARK	4 (10%)	(Aeiad & Meziane, 2019), (Bradáč & Smolka, 2020), (Hassan & Qureshi, 2018), (Nalintippayawong et al., 2017)
Honey and Mumford	3 (7%)	(Baharudin et al., 2017), (Drissi & Amirat, 2016), (Papanikolaou, 2015)
Gardner's Theory of Multiple Intelligences	1 (2%)	(Hafidi & Bensebaa, 2015)
Entwistle's Theory	1 (2%)	(Siddique et al., 2019)

environments, especially in the age group that includes university students. The questionnaire contains closed-ended questions related to the respondent's preferences.

The VARK and Honey and Mumford models follow significantly lower percentages, as they do not offer the same level of usability. Lastly, H. Gardners Theory of Multiple Intelligences is only utilized in one study. Thus we understand that it is hard to adapt it for digital systems. It promotes a holistic approach instead of a differentiation of intelligence. Entwistle's Theory is also only utilized once.

4.2 Learning style prediction techniques

Defining students' learning styles is one of the most crucial factors in the success of a platform. Quality and quantity of appropriately scoped information offer better grounds for the algorithms and improve their outcome (Graf et al., 2009). When designing such systems, there are two approaches to choose from: an initial evaluation, often named Explicit or Collaborative modeling, usually consisting of a questionnaire, or a gradual identification through choices and actions, often referred to as Implicit or automatic Modeling. Implicit modeling might initially use an evaluation method as a basis. However, the critical difference is that it will collect information through usage to update the learning style and create more accurate models. Both methods have their benefits as well as their drawbacks. (Anantharaman et al., 2019; Karagiannis & Satratzemi, 2020).

The usage of questionnaires can be captured with high fidelity the traits and preferences of the learners. However, there are cases where questions cannot be clearly stated for everyone resulting in unpredicted answers (Bendahmane et al., 2019; Truong, 2016). From another point of view, machine learning provides much information that cannot fully describe a learner's preferences. So, great attention is required to clearly state the questions to capture an overall image of the user profile (Almeida et al., 2019).

As expressed by Table 2, a large majority uses explicit modeling, while only a quarter of the studies utilized implicit modeling. This can be due to many difficulties in realizing a system with implicit modeling or the expected validity of questionnaires recently utilized in the field. However, questionnaires come with a few drawbacks that can harm this validity. As stated earlier, learners often do not understand questions correctly, leading to an answer that does not reflect the students' true nature, resulting in an erroneous profile. Additionally, due to the long list of questions, some students might get tired and lack the motivation to give the needed attention to all questions. Furthermore, there is the argument that learners evolve and might have slight, or even quite dramatic, changes in their learning style during courses or school years. Thus the results of a single questionnaire cannot be the only source of truth in a system for an extended period.

From the studies that chose the implicit approach, we observe a scattered selection of prediction techniques with a pretty even distribution. Content-Based filtering was selected in most studies, 3, while Fuzzy Logic, Decision Trees, and Statistics all had two studies using them. Lastly, evolutionary algorithms and artificial neural networks were utilized in one study each. However, apart from the prediction techniques selected, these studies do not share much in their approaches.

Table 2 Learning style prediction techniques

Learner Modelling	Learning Style prediction technique	No. of articles (n = 42)	References
Explicit or Collaborative Modelling (Static)	Questionnaire	31	(Abech et al., 2016), (Ali et al., 2019), (Aljojo et al., 2016), (Almeida et al., 2019), (Alsobhi & Alyoubi, 2019), (Apoki et al., 2020), (Araújo et al., 2020), (Arsovic & Stefanovic, 2020a), (Alshammari & Qtaish, 2019), (Baharudin et al., 2017), (Bendahmane et al., 2019), (Boussakuk, 2020), (Bradáč & Smolka, 2020), (Budiyanto et al., 2017), (Dwivedi et al., 2018), (Drissi & Amirat, 2016), (El Guabassi et al., 2018), (Elkot, 2019), (Fasihuddin et al., 2016), (Hafidi & Bensebaa, 2015), (Hassan & Qureshi, 2018), (Hurtado et al., 2018), (Lakkah et al., 2017), (Nalintippayawong et al., 2017), (Papanikolaou, 2015), (Rani, Vyas, et al., 2017), (Siddique et al., 2019), (Supangat & Bin Saringat, 2020), (Tarus et al., 2017), (Tortorella & Graf, 2017), (Vaidya & Joshi, 2018)
Implicit or automatic modeling (Dynamic)	Fuzzy Logic	2	(Sweta & Lal, 2017), (Kolekar et al., 2018)
	Evolutionary/Genetic Algorithms	1	(Christudas et al., 2018)
	Artificial Neural Networks	1	(Anantharaman et al., 2019)
	Decision Tree	2	(Karagiannis & Satratzemi, 2020), (Kurilovas, 2019)
	Statistics	2	(Aeiad & Meziane, 2019), (Kurilovas, 2019)
	Content-Based Filtering	3	(Andaloussi et al., 2019), (Sunil & Doja, 2019), (Kolekar et al., 2019)

It becomes pretty clear that there is a need to move into implicit techniques, providing greater flexibility and allowing the learner to change and evolve along with her skills. However, even the studies that have been made that way have differing outlooks on how this automation should be achieved, resulting in multiple approaches with no standard anchors. Thus, we need to discern the most important aspects of human behavior regarding learning styles and how they are expressed in digital systems to create a shared roadmap for any attempts towards implicit learning style detection.

4.3 Factors comprising the Learner model

The selection of the relevant factors that will need to be considered in an adaptive system is difficult for researchers due to the abundance of personal information (Normadhi et al., 2019). As mentioned above, personalized learning based on Learning Styles offers a multitude of benefits to the students. Combining Learning styles with prior knowledge facilitates learning even more (Alshammari & Qtaish, 2019). This, however, does not mean that personalization could or should be based only on those two factors. Other factors that can be considered include Knowledge, Background/ Experience, Preferences, Interests, Goals/Tasks, Personality Traits, Cognitive Traits, Learning Styles, Personal Data, Geographic Data, Demographic Data, Abilities/ Disabilities, Behavior, Emotion, Social/ Group, and Environment/ Work (Abdo & Noureldien, 2017). From those 16 factors that can be a basis for intelligent tutoring systems, Abdo and Noureldien (2017) decided to utilize four factors, not including the Learning Styles, Knowledge, interests, goals/tasks, and behavior. With these factors, the effectiveness of the adaptation model is maximized. In other words, they decided that the construction of adaptation models that utilize multiple factors is not efficient. Therefore the increase of adaptation factors is not a panacea.

In Table 3, it is clearly illustrated that from the total 42 studies of our review, 32 have combined Learning Styles with prior knowledge for their adaptation factors. Secondly, several studies (15) have utilized Behavioural data, recording data from user behavior within the system and utilizing resulting data as adaptation factors to better suit the learner in his learning process. Studies that utilized learning goals provided by the educator or the learner follow (6), and then there are studies (4) that utilized cognitive styles or information about the device currently in use. Finally, only one (1) study used Dyslexia type or working memory capacity as a factor for adaptation.

In a more detailed analysis, with the numbers shown in Table 3, fourteen (14) studies combine Learning styles and prior knowledge as the only factors for adaptation. Five (5) studies add behavioral data to the mix, while 4 combine them with learning goals. Two (2) studies combined Learning Styles, prior knowledge, learning goals, cognitive style, and two (2) other studies combined Learning style, Prior Knowledge, Learner's Device Information, Behavioural data. Lastly, the following combination was only adopted by one (1) paper each, a) Learning style,

Table 3 Learner factors

Factor Combination	No. of articles (n = 42)*	References
Learning style only	3	(Alshammari et al., 2015), (Kolekar et al., 2018), (Vaidya & Joshi, 2018)
Learning style & Prior Knowledge	14	(Ali et al., 2019), (Alshammari & Qtaish, 2019), (Anantharaman et al., 2019), (Arsovic & Stefanovic, 2020a), (Bendahmane et al., 2019), (Bradáč & Smolka, 2020), (Budiyanto et al., 2017), (Drissi & Amirat, 2016), (Karagiannis & Satratzemi, 2020), (Lakkah et al., 2017), (Rani, Vyas, et al., 2017), (Supangat & Bin Saringat, 2020), (Sunil & Doja, 2019), (Tarus et al., 2017)
Learning style & Behavioral data	7	(Elkot, 2019), (Fasihuddin et al., 2016), (Hurtado et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019), (Nalintippayawong et al., 2017), (Sweta & Lal, 2017)
Learning style, Prior Knowledge & Behavioral data	5	(Andaloussi et al., 2019), (Baharudin et al., 2017), (Christudas et al., 2018), (Hafidi & Bensebaa, 2015), (Papanikolaou, 2015)
Learning style, Prior Knowledge & Learning goals	4	(Aljojo et al., 2016), (Apoki et al., 2020), (Boussakuk, 2020), (Dwivedi et al., 2018)
Learning style, Prior knowledge, Learning goals & Cognitive style	2	(Aeiad & Meziane, 2019), (Almeida et al., 2019)
Learning style, Prior knowledge, Learner's Device Information & Behavioral data	2	(Abech et al., 2016), (Araújo et al., 2020)
Learning style, Prior Knowledge & Cognitive style	1	(Hassan & Qureshi, 2018)
Learning style, Prior Knowledge & Learner's Device Information	1	(Tortorella & Graf, 2017)
Learning style, Prior Knowledge & Dyslexia type	1	(Alsobhi & Alyoubi, 2019)
Learning style, Prior Knowledge & Working memory capacity	1	(Siddique et al., 2019)
Learning style, Prior knowledge, Cognitive style, Learner's Device Information & Behavioral data	1	(El Guabassi et al., 2018)

Notes: * Articles per Learner Adaptation factors: Learning Style (42); Prior knowledge (32); Behavioural data (15); Learning goals (6); Cognitive style (4); Learner's Device Information (4); Dyslexia type (1); Working memory capacity (1)

Prior Knowledge & Cognitive style, b) Learning style, Prior Knowledge & Learner's Device Information, c) Learning style, Prior Knowledge & Dyslexia type, d) Learning style, Prior Knowledge & Working memory capacity and e) Learning style, Prior Knowledge, Cognitive style, Learner's Device Information & Behavioural data.

From a total of fifteen (15) studies that utilized Behavioral data, seven (7) combined it with learning style only. At the same time, the rest used prior knowledge and/or learner's device information. Lastly, three (3) studies considered Learning Styles as their only factor for adaptation.

It is important to note that in most studies, thirty-nine (39), to be precise, have combined at least two adaptation factors, which highlights the fact that surveys are multi-dimensional.

The main outtake from this review is the combinations that were utilized by the studies. In most cases, they utilized multiple factors to improve the learner's adaptation. This reinforces the view that learning is a complex and multifactorial process. Therefore, to create an effective adaptive system, many factors need to be taken into account. These factors are then analyzed by the algorithms and facilitate the personalization of the educational process. Each factor is an input for the algorithms, and researchers determine the weight and emphasis that each shall be given.

4.4 User Model information retrieval

Building the Learner model for any system begins with the identification of the factors mentioned above. This procedure may be conducted in two different manners, with explicit modeling, meaning that the information is gathered once to initialize the learner model, or implicit modeling, which is continually gathered through various pipelines. The learner model is kept up-to-date with the latest available data. Explicit modeling is used widely, based on reviews, questionnaires, and other tried and proven methods over a long period. On the other hand, implicit modeling is a newer concept that arose due to new technologies. Gathering data for implicit modeling can be done through almost any digital platform or even with analog methods (like the questionnaires) that are then imported to the system through data entry. Adaptive e-learning systems will either use the explicit model or use a questionnaire as an initial "cold start" data resource but continue with data collected through the adaptive platform, the assessments, or third-party platforms.

Table 4 allows us to get meaningful insight into the correlation of learner modeling types and the data resources used. Having explicit modeling will mean no data source past the initial data

Table 4 Learner model Data Resources

Learner Modelling	Learner Modelling Data Resources	No. of articles (n = 42)	References
Explicit or collaborative modeling	Questionnaires	23	(Ali et al., 2019), (Aljojo et al., 2016), (Almeida et al., 2019), (Alsobhi & Alyoubi, 2019), (Apoki et al., 2020), (Arsovic & Stefanovic, 2020), (Alshammari et al., 2015), (Araújo et al., 2020), (Bendahmane et al., 2019), (Baharudin et al., 2017), (Boussakuk, 2020), (Bradáč & Smolka, 2020), (Budiyanto et al., 2017), (Drissi & Amirat, 2016), (Elkot, 2019), (Fasihuddin et al., 2016), (Hassan & Qureshi, 2018), (Lakkah et al., 2017), (Papanikolaou, 2015), (Siddique et al., 2019), (Supangat & Bin Saringat, 2020), (Tortorella & Graf, 2017), (Vaidya & Joshi, 2018)
Implicit or automatic modeling	learning process tracking	11	(Abech et al., 2016), (Aeiad & Meziane, 2019), (Anantharaman et al., 2019), (Andaloussi et al., 2019), (Christudas et al., 2018), (El Guabassi et al., 2018), (Hurtado et al., 2018), (Kolekar et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019), (Nalintippayawong et al., 2017)
	Assessment	4	(Aeiad & Meziane, 2019), (Sunil & Doja, 2019), (Hafidi & Bensebaa, 2015), (Dwivedi et al., 2018)
	Data Mining (social media etc.)	4	(Andaloussi et al., 2019), (Sweta & Lal, 2017), (Karagiannis & Satratzemi, 2020), (Tarus et al., 2017)

used to create the learner model. In the implicit case, we were able to identify three different resources. Learner behavior within the system, assessments taken within the system, and, lastly, data mining from third-party platforms, such as social media. Tracking the learner behavior within the system was the most utilized method, possibly since the data are already there to be used. Assessment data and third-party data were used equally by four studies each.

The source plays an important role, as different data are found, with various implications. Learner behavior within the system offers data on the way the learners study and learn. The assessment offers data on how well the learner has understood the material given and ultimately how good of a grasp she has on the subject. Lastly, Data Mining from third-party platforms can contain any possible information and needs to be considered. For instance, data from social media might be inappropriate for an educational platform.

In contrast, data from a different learning platform might offer valuable insight into prior knowledge or even learning styles. However, it can be challenging to employ such information appropriately since there is no Standard, and the data can be misinterpreted. Again, most studies have chosen the straightforward approach. However, the argument for implicit modeling, made above, applies here as well: Learners evolve as they learn, so should the learner model. Additionally, adaptive feedback allows better platform evaluation as feedback can be given after a course or a test or even during the learning process as interaction data and more (Hurtado et al., 2018).

5 Adaptation module

5.1 Which are the adaptation elements and techniques

On Adaptive Hypermedia Systems, three basic adaptation techniques: adaptive content, adaptive navigation, and adaptive presentation. When the students search for information that is appealing to them, the system chooses and prioritizes the content that is most suitable to the student's interests (Brajnik et al., 1987; Brusilovsky, 1992). Content adaptation considers pedagogical criteria, such as prior knowledge, educational level, student preferences, and more relevant data to provide the most suitable content based on the user's needs and preferences (Knutov et al., 2009). The system's goal is to present the same learning object with variations. A teacher can teach a notion with various learning objects (Kolekar et al., 2019). These objects in adaptive systems are called Learning objects, corresponding to students' learning styles (Liyanage et al., 2016).

Adaptive navigation enables the user to follow his learning path by adapting the presentation of links to objects, knowledge, and student preferences (Brusilovsky & Nejdl, 2004). Some of the techniques used for adaptive navigation include adaptive link sorting, live guidance, adaptive link generation, adaptive link, adaptive link hiding, annotation, map adaptation, etcetera (Supangat & Bin Saringat, 2020).

Adaptive presentation modifies the design and the visual appearance of learning objects following the preferences and needs of the learner. This method provides different media, which

Table 5 Adaptation elements

Adaptation Elements*	No. of articles (n = 42)	References
Content only	9	(Aeiad & Meziane, 2019), (Almeida et al., 2019), (Baharudin et al., 2017), (Budiyanto et al., 2017), (Christudas et al., 2018), (Elkot, 2019), (Sweta & Lal, 2017), (Tarus et al., 2017), (Vaidya & Joshi, 2018)
Content & Navigation	9	(Ali et al., 2019), (Alshammari & Qtaish, 2019), (Anantharaman et al., 2019), (Apoki et al., 2020), (Araújo et al., 2020), (Bradáč & Smolka, 2020), (Lakkah et al., 2017), (Rani, Vyas, et al., 2017), (Supangat & Bin Saringat, 2020)
Navigation only	6	(Alshammari et al., 2015), (Bendahmane, Falaki, et al., 2019), (Dwivedi et al., 2018), (Fasihuddin et al., 2016), (Hafidi & Bensebaa, 2015), (Hurtado et al., 2018)
Content, Navigation & Presentation	5	(Andaloussi et al., 2019), (Boussakuk, 2020), (El Guabassi et al., 2018), (Kolekar et al., 2019), (Papanikolaou, 2015)
Content & Presentation	4	(Abech et al., 2016), (Kolekar et al., 2018), (Kurilovas, 2019), (Tortorella & Graf, 2017)
Navigation & Presentation	3	(Aljojo et al., 2016), (Alsobhi & Alyoubi, 2019), (Karagiannis & Satratzemi, 2020)
Content & Assessment	2	(Nalintippayawong et al., 2017), (Siddique et al., 2019)
Navigation & Assessment	2	(Hassan & Qureshi, 2018), (Sunil & Doja, 2019)
Content, Navigation, Presentation & Assessment	1	(Arsovic & Stefanovic, 2020a)
Content, Navigation & Assessment	1	(Drissi & Amirat, 2016)

Notes: * Articles per adaptation elements: Content (31), Navigation (27), Presentation (13), Assessment (6)

present the same content leaving the system to choose the most relevant to the user at the given node (Brusilovsky, 2001). Researchers report that a student's Learning Style is one of the most valuable factors for the adaptive presentation because of the ability to distinguish learners (Bernard et al., 2017). Some researchers have experimented on adapting the presentation based on the learning environment collecting data from the sensors found on mobile devices. Such adaptations can better adapt the presentation of a course so that the learner can better keep track of the lesson. Such adaptations can be the presentation of the lesson in audio if there is too much light in the environment that the learner cannot watch the screen (Abech et al., 2016; Alsobhi & Alyoubi, 2019; Tortorella & Graf, 2017).

Adaptive assessment is a set of assessment tests, which give the user the appropriate material to test his knowledge after a chapter has been completed. Such tests can be exercises, multiple-choice questions, crosswords, the question to matching, etcetera (Drissi & Amirat, 2016).

According to Table 5, thirty-one (31) studies accomplished content adaptation, twenty-seven (27) adaptive navigation, thirteen (13) adaptive presentation, and six (6) assessment.

Further analysis results in nine (9) from forty-four (42) studies of this review adapt the learning process only based on content, while nine (9) combine the adaptive content with the appropriate learning path (adaptive navigation). Six (6) of the studies created only appropriate learning paths for the users. Five (5) accomplished adapting content, navigation, and presenting the information to the users. Four (4) studies adapt content and presentation, three (3) combined adaptive navigation and presentation. In four (4) studies performed adaptive navigation or content together with an assessment, one (1) study succeeded in adapting the assessment with content and navigation. Finally, one (1) succeeded in the addition of adaptive presentation on the previous three adaptations.

Table 6 illustrates the adaptation techniques utilized from the studies. One-third of the studies chose Rule-Based techniques, making it the most popular technique, possibly due to the proven efficiency of problem modeling and reaching a solution. A considerable amount (7) chose to utilize their custom solutions, referred to like others in the table. These were unique systems that cannot easily be categorized into one of the techniques identified through all the studies and would be beyond the scope of this study to assess and categorize them. Additionally, some (2) studies did not consider the techniques within the scope of their study. They did not mention what techniques were utilized. Lastly, many studies have mentioned utilizing machine learning. However, they failed in reporting the exact technique within the field due to the same reason.

From the educational scope, there is no interest in examining these techniques. They all offer educational benefits that depend on the available learner model and learning material rather than the algorithms or techniques used. Their differences are engaging on a technical level, such as run-time and model scales. However, it is essential to note that more sophisticated techniques can accept more complex inputs from the users and their environment and thus have a more

Table 6 Adaptation techniques

Adaptation Technique	No. of articles (n = 42)	References
Rule-Based	14	(Abech et al., 2016), (Aeiad & Meziane, 2019), (Aljojo et al., 2016), (Alsobhi & Alyoubi, 2019), (Arsovic & Stefanovic, 2020), (Alshammari & Qtaish, 2019), (Baharudin et al., 2017), (Budiyanto et al., 2017), (Drissi & Amirat, 2016), (El Guabassi et al., 2018), (Fasihuddin et al., 2016), (Kolekar et al., 2019), (Nalintippayawong et al., 2017), (Siddique et al., 2019)
Evolutionary Algorithms	2	(Dwivedi et al., 2018), (Lakkah et al., 2017)
Intelligent Agents	1	(Apoki et al., 2020)
Decision Tree	3	(Hafidi & Bensebaa, 2015), (Kurilovas, 2019), (Vaidya & Joshi, 2018)
k-NN	1	(Bendahmane et al., 2019)
Machine Learning	4	(Andaloussi et al., 2019), (Ali et al., 2019), (Anantharaman et al., 2019), (Christudas et al., 2018)
Recommendation System	3	(Hurtado et al., 2018), (Sunil & Doja, 2019), (Tarus et al., 2017)
Fuzzy Logic	4	(Bradáč & Smolka, 2020), (Kolekar et al., 2018), (Rani, Vyas, et al., 2017), (Sweta & Lal, 2017)
Others	7	(Almeida et al., 2019), (Araújo et al., 2020), (Boussakuk, 2020), (Hassan & Qureshi, 2018), (Karagiannis & Satratzemi, 2020), (Supangat & Bin Saringat, 2020), (Tortorella & Graf, 2017)
Not Mentioned	2	(Elkot, 2019), (Papanikolaou, 2015)

holistic approach and result (Abdo & Noureldien, 2017).

Lastly, a final observation is that the field is shifting since recent studies are more likely to utilize techniques other than Rule-Based, meaning that there is a move towards new technologies regarding big data and machine learning that might generate more reliable and accurate results based on more comprehensive datasets.

6 Domain module

Adaptive e-learning systems have been designed to assist the students as much as the teachers in their work. Their creation is intended to help students find themselves in a learning environment specifically designed for how they prefer to learn. However, it is an educational tool that the teachers themselves should be the ones who manage and use it. Thus, their attitude and perspective play a crucial role in how to utilize this tool. The platforms are created mainly by university teams, directly related to the content and presented. The goal is to gradually and after an in-depth investigation of their results, the platforms should be integrated with the rest levels of education, helping the learning process even more.

Table 7 Experiments' participant type

Exp. Participant type	No. of articles (n = 42)	References
Learner	33 (79%)	(Abech et al., 2016), (Ali et al., 2019), (Aljojo et al., 2016), (Alsobhi & Alyoubi, 2019), (Alshammari et al., 2015), (Alshammari & Qtaish, 2019), (Andaloussi et al., 2019), (Araújo et al., 2020), (Arsovic & Stefanovic, 2020), (Baharudin et al., 2017), (Bradáč & Smolka, 2020), (Budiyanto et al., 2017), (Christudas et al., 2018), (Dwivedi et al., 2018), (Drissi & Amirat, 2016), (Elkot, 2019), (Fasihuddin et al., 2016), (Hafidi & Bensebaa, 2015), (Hassan & Qureshi, 2018), (Hurtado et al., 2018), (Karagiannis & Satratzemi, 2020), (Kolekar et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019), (Nalintippayawong et al., 2017), (Papanikolaou, 2015), (Rani, Vyas, et al., 2017), (Siddique et al., 2019), (Supangat & Bin Saringat, 2020), (Sweta & Lal, 2017), (Tarus et al., 2017), (Tortorella & Graf, 2017), (Vaidya & Joshi, 2018)
Teacher	0	
Learner & Teacher	1	(Almeida et al., 2019)
Higher Education experts	1	(Aeiad & Meziane, 2019)
No experiment, theoretical study	7 (17 %)	(Anantharaman et al., 2019), (Apoki et al., 2020), (Bendahmane et al., 2019), (El Guabassi et al., 2018), (Lakkah et al., 2017), (Sunil & Doja, 2019), (Supangat & Bin Saringat, 2020)

From Table 7, it appears that out of forty-two (42) surveys, thirty-five (35) conducted an empirical survey, while seven (7) did not. The majority of the systems with thirty-three (33) studies are addressed to students. In contrast, only one (1) study has been proposed to ICT experts and combined with students and teachers. Finally, in seven (7) articles, no experimental or theoretical study has been done.

From this part of the research, it appeared that there is a need to further explore the field of teachers (of all levels) in terms of adaptive systems. The reason is that through research, both the material and the proposed activities and the general functionality of the platform can be improved.

Table 8 Educational level

In classroom Experiments & Case studies	No. of articles (n = 42)	References
Students of Higher education	32	(Abech et al., 2016), (Aeiad & Meziane, 2019), (Aljojo et al., 2016), (Almeida et al., 2019), (Alsobhi & Alyoubi, 2019), (Alshammari et al., 2015), (Alshammari & Qtaish, 2019), (Andaloussi et al., 2019), (Araújo et al., 2020), (Arsovic & Stefanovic, 2020), (Baharudin et al., 2017), (Bradáč & Smolka, 2020), (Budiyanto et al., 2017), (Christudas et al., 2018), (Dwivedi et al., 2018), (Drissi & Amirat, 2016), (Elkot, 2019), (Fasihuddin et al., 2016), (Hafidi & Bensebaa, 2015), (Hassan & Qureshi, 2018), (Hurtado et al., 2018), (Karagiannis & Satratzemi, 2020), (Kolekar et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019), (Nalintippayawong et al., 2017), (Papanikolaou, 2015), (Rani, Vyas, et al., 2017), (Supangat & Bin Saringat, 2020), (Sweta & Lal, 2017), (Tarus et al., 2017), , (Vaidya & Joshi, 2018)
Secondary education	3	(Ali et al., 2019), (Siddique et al., 2019), (Tortorella & Graf, 2017)
Primary education	0	

From Table 8, it is clearly stated that most studies have been conducted on higher education. More specifically, out of thirty-five (35) surveys, thirty-two (32) relate to higher education while only three (3) relate to secondary education. No research has been done in primary education, which shows the need to investigate this level of education. One of the main reasons many higher education surveys appear is that students have easy and direct access without further bureaucratic procedures.

Table 9 Curriculum area

Curriculum Area	No. of articles (n = 42)	References
Computer Science & Engineering	27	(Abech et al., 2016), (Almeida et al., 2019), (Alsobhi & Alyoubi, 2019), (Alshammari et al., 2015), (Alshammari & Qtaish, 2019), (Andaloussi et al., 2019), (Araújo et al., 2020), (Baharudin et al., 2017), (Budiyanto et al., 2017), (Christudas et al., 2018), (Dwivedi et al., 2018), (Elkot, 2019), (Fasihuddin et al., 2016), (Hafidi & Bensebaa, 2015), (Hassan & Qureshi, 2018), (Hurtado et al., 2018), (Karagiannis & Satratzemi, 2020), (Kolekar et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019) (Nalintippayawong et al., 2017), (Rani, Vyas, et al., 2017), (Supangat & Bin Saringat, 2020), (Sweta & Lal, 2017), (Tarus et al., 2017), (Vaidya & Joshi, 2018)
Mathematics	1	(Aljojo et al., 2016)
Social sciences	1	(Arsovic & Stefanovic, 2020)
Chemistry	1	(Drissi & Amirat, 2016)
English	2	(Bradáč, 2020), (Siddique et al., 2019)
Earth Science	1	(Tortorella & Graf, 2017)
Variety of disciplines	2	(Ali et al., 2019), (Papanikolaou, 2015)

Out of the thirty-five studies of Table 9 conducted empirically, twenty-seven (27) are related to Computer Science. It is easier to create courses in this area and check the participants' performance through tests. The rest of the Domain Areas are concerned with sciences such as Mathematics that appear in one (1) study, Chemistry in one (1), Earth Science in one (1). A minor part of the research includes Social sciences referring to one (1) and English to two (2). Finally, there are two (2) studies that refer to a variety of disciplines.

Adaptive e-learning systems offer significant advantages in the educational process, not only in knowledge acquisition but also in other areas. In this way, they change the learning process and upgrade it towards smart learning (Andaloussi et al., 2019). At the same time, students with learning difficulties can help effectively (Alsobhi & Alyoubi, 2019).

In detail, as shown in Table 10, twenty-one (21) studies have reported that higher learning performance or positive impact on learning outcomes have been achieved, showing that the students can learn more effectively within a personalized environment tailored to their needs.

Nine (9) articles state that adaptive learning facilitates the learning processes. Thus, the advantages in knowledge concerning the traditional teaching methods are shown. One area that

Table 10 Educational & ICT impacts

Educational or ICT Impacts	No. of articles (n = 42)	References
Higher learning performance or Positive impact on learning outcomes	21	(Ali et al., 2019), (Aljojo et al., 2016), (Alsobhi & Alyoubi, 2019), (Alshammari et al., 2015), (Alshammari & Qtaish, 2019), (Andaloussi et al., 2019), (Arsovic & Stefanovic, 2020), (Baharudin et al., 2017), (Christudas et al., 2018), (Dwivedi et al., 2018), (Drissi & Amirat, 2016), (Elkot, 2019), (Hafidi & Bensebaa, 2015), (Hassan & Qureshi, 2018), (Karagiannis & Satratzemi, 2020), (Kolekar et al., 2018), (Kurilovas, 2019), (Papanikolaou, 2015), (Siddique et al., 2019), (Tortorella & Graf, 2017), (Vaidya & Joshi, 2018)
Facilitates learning processes	9	(Aljojo et al., 2016), (Almeida et al., 2019), (Arsovic & Stefanovic, 2020), (Christudas et al., 2018), (Fasihuddin et al., 2016), (Hafidi & Bensebaa, 2015), (Papanikolaou, 2015), (Rani, Nayak, et al., 2017), (Sweta & Lal, 2017)
Enhance learning satisfaction	5	(Arsovic & Stefanovic, 2020), (Alshammari et al., 2015), (Drissi & Amirat, 2016), (Christudas et al., 2018), (Karagiannis & Satratzemi, 2020)
Effective communication with teachers	1	(Arsovic & Stefanovic, 2020)
Enhancing the self-learning efficacy	2	(Elkot, 2019), (Papanikolaou, 2015)
Suitability of learning materials	7	(Aeiad & Meziane, 2019), (Budiyanto et al., 2017), (El Guabassi et al., 2018), (Hurtado et al., 2018), (Kolekar et al., 2019), (Kurilovas, 2019), (Tarus et al., 2017)
Improved Algorithms or Techniques	6	(Andaloussi et al., 2019), (Apoki et al., 2020), (Bendahmane, Falaki, et al., 2019), (Hafidi & Bensebaa, 2015), (Kurilovas, 2019), (Tarus et al., 2017)
Improved Data Mining Results	2	(Aeiad & Meziane, 2019), (Karagiannis & Satratzemi, 2020)

is very important for both students and teachers is learning satisfaction. It can positively affect students and the learning procedure as a whole. In five (5) articles, the participants positively responded regarding the adaptive systems method.

One (1) article states that effective communication with teachers has been achieved, while two (2) seem to have a positive effect on enhancing learning self-efficacy. Seven (7) articles refer to the suitability of learning materials. This illustrates that a platform can offer differentiated learning and a combination of Learning Styles to improve learning outcomes personally for each student. Six (6) articles present Improved Algorithms / Techniques. Two (2) articles present Improved Data Mining Results showing the work done in this area.

7 Discussion

Many types of research support the fact that adaptive e-learning systems using Learning Styles can help learners effectively and in various ways as they learn closer to their desires, needs, and more generally to the way they learn. With the utilization of new technologies and smart devices, more and more platforms and applications use adaptive e-learning.

Answering the first research question about which Learning styles are used in adaptive systems, it seems that Felder Silverman's model appears in the vast majority. Our review also complies with previous research literature (Al-Azawei & Badii, 2014; Kumar et al., 2017; Özyurt & Özyurt, 2015; Truong, 2016). The most crucial difference in the preferences of most researchers in the Felder Silverman model compared to the rest models lies mainly in the fact that it is widely accepted and that a questionnaire has been developed that is very effective and easy to use for adaptive environments. Especially in the age group of university students (Felder & Silverman, 1988b). Future research concerning the other models or a combination of models of learning systems is highly needed to cover a broader range.

The previous context of predicting learning styles indicates that most use explicit modeling, while a quarter uses implicit. This happens because it is easier to implement (Özyurt & Özyurt, 2015). Nowadays, due to a large amount of data, we need more complex algorithms for their processing. Using these methods, the system can be adapted throughout the learning process and the student's development. The review concluded that there is no approved way to implement the learning style prediction, and each researcher followed his approach.

Answering the second research question regarding the factors considered for creating an adequately adapted Learner model, it turns out that the Learning styles in combination with the prior knowledge are the factors that give better results in the adaptation. Furthermore, the results state that user behavior within the system plays an essential role in adapting the model and can help the system dynamically adjust its suggestions to learners.

Previous research shows that using both Learning Systems and prior knowledge is a more efficient combination in the learning process (Alshammari & Qtaish, 2019). Also, it seems that corresponding research results in four Learner adaptation factors (Knowledge, learning style, Interests, Goals / Tasks) (Abdo & Noureldien, 2017). Concluding this research question, it should be noted that modern adaptive systems utilize user behavior to improve the platform's experience (Andaloussi et al., 2019) and provide additional learning motivation (Abyaa et al., 2019). At the same time, these adaptive systems must be combined with learning theories and pedagogical theories to be used more efficiently at the lowest levels of education. In this way, the adaptive systems will become more complete both theoretically and practically wise.

Following the conclusion of the learning style, we should update the data we keep for each apprentice, according to the implicit model. Questionnaires are more useful in traditional learning environments, where there is difficulty in analyzing students' preferences (Kumar et al., 2017). Therefore, there is an opportunity to avoid the traditional data entry method (questionnaires, etc.) and move forward with dynamic methods by implementing new techniques that can be used in digital environments (Normadhi et al., 2019).

The third research question has to do with the adaptation technologies and how they form the course according to the characteristics of the users. Our review indicates that most of the articles adapted the content of the courses to the student and created the appropriate learning path to navigate the student through the sections of the courses. One-third of the studies adjusted how information was presented to users, and only six focused on personalized evaluation. The issue of adjusted assessment needs to be addressed in a meaningful way, especially concerning the overall system operation.

The fourth research question relates to the field in which adaptive systems are addressed. The literature review showed that most of the research was conducted in higher education, while few were lower. No research was conducted in primary education. Thus, there is little data available for younger ages. We consider that adaptive systems can play a particularly essential role. Also, in most research, it seems that the prevailing subject is that of engineering & computer science. The adaptive platforms must be enriched with more learning objects to address them.

Our research shares common ground with the pre-existing literature, including a wide range of research in higher education and computer science or engineering compared to a much smaller percentage dealing with secondary and elementary education levels (Kumar et al., 2017). In addition, our research emphasizes that adaptive systems are tested on students, and there is a significant lack of research on teachers who should make suggestions and evaluate these systems (Özyurt & Özyurt, 2015).

Finally, regarding the results of adaptive systems in the learning process, it emerged that most systems that adapt the learning process to the needs and requirements of students achieve higher learning performance or a positive impact on learning outcomes. In addition, the personalized course facilitates the learning process compared to the traditional course. It achieves greater satisfaction from users, as the learning objects match the students' data. Also, past research has offered significant improvements and innovations in terms of adaptation algorithms and data mining results.

According to similar previous studies, there is a high impact on academic accomplishments, learning performance, and learner satisfaction level with learning style in adaptive systems (Kumar et al., 2017; Sensuse et al., 2020). Özyurt & Özyurt (2015) concluded that learning style affects satisfaction, usability, and preferability, while behavioral data can affect student performance (Al-Azawei & Badii, 2014). Finally, learning styles enable a more flexible and personalized educational process. In this way, the development of the metacognitive ability and self-efficacy of the user is achieved, as students discover their learning needs and preferences (Tsortanidou et al., 2017) which is vital for the modern educational society.

8 Conclusions and future research

(1) The use of adaptive digital platforms with Learning Styles seems to be an effective way to utilize and integrate new technologies in education. In other words, it proves that machine learning techniques can effectively extract, analyze and adapt data to the learning objects (learning objects: video, game, etc.) of the learning platform.

(2) The courses included in the platforms examined are few. They could be increased in the future to cover most of the curricula of the educational levels. In this way, students will be able to use digital learning platforms more often.

(3) The aim is to study other Learning Styles besides Felder Silverman's and to analyze in-depth the many benefits of adaptive platforms, which concern the learning part as research

suggests.

(4) The data evaluation methods of adaptive digital platforms are a subject of study and discussion, a crucial point to capture and analyze the performance and results of their use.

(5) In addition, we need to discern the most important aspects of human behavior regarding learning styles and how they are expressed in digital systems to create a shared roadmap for any attempts towards implicit learning style detection.

(6) We consider that the involvement of teachers on a large scale in the creation and evaluation of adaptive systems is of high importance. Thus, the content of the lessons can be improved. The educational theories can be integrated since the teachers are the experts in the classrooms. They are the ones who can give the most appropriate directions towards a more personalized learning process.

(7) Moreover, it is essential to thoroughly apply and examine adaptive platforms' results at lower levels of education. Through this process, adaptive assessment can be integrated to assess each student in the best way possible.

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