

Automatic prediction of learning styles: a comprehensive analysis of classification models

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ABSTRACT

Learning styles are a topic of interest in educational research about how individuals acquire and process information in offline or online learning. Identification of learning styles in the online learning environment is challenging. The existing approaches for the identification of learning styles are limited. This study aims to review the many learning styles characterized by various classification approaches toward the automatic prediction of learning styles from learning management system (LMS) datasets. A systematic literature review (SLR) was conducted to select and analyze the most pertinent and significant papers for automatically predicting learning styles. Fifty-two research papers were published between 2015-2023. This research divides analysis into five categories: the classification of learning style models, the collection of the collected dataset, learning styles based on the curriculum, research objectives related to learning styles, and the comprehensive analysis of learning styles. This study found that learning style research encompasses diverse theories, models, and algorithms to understand individual learning preferences. Statistical analysis, explicit data collection, and the Felder-Silverman model are prevalent in research, highlighting the significance of algorithm improvement for optimizing learning processes, particularly in computer science. The categorization and understanding of various methods offer valuable insights for enhancing learning experiences in the future.

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1. INTRODUCTION

Over the last few decades, the impact of information and communication technologies on education has been enormous, resulting in new forms of learning aided by computers and the internet. E-learning courses can take various forms and employ multiple technologies, typically published online via a learning management system (LMS) [1], [2]. Regardless of the features of each learner's learning style, the current E-learning systems generally offer the material similarly. Learners differ in various ways, including learning preferences, comprehension levels, backgrounds, and other factors. Consequently, students may only sometimes acceptably obtain learning materials [3]. E-learning environments (like Moodle) and massive open online courses (MOOCs) are two examples of the numerous types of web-based learning that have become possible due to tremendous technological change and modern web applications. Recent research in

that area has concentrated on finding ways to make the most of the advantages offered by systems of this kind by capitalizing on learning processes [4]. This is one of the reasons why there has been a shift toward individualized learning in recent years. A personalized learning system can provide additional motivation to develop potential based on a student's talents to meet each learner's unique requirements and learning styles [5], [6]. Learners may benefit from having their knowledge requirements oriented and structured through adaptation. Because of this, adaptive learning environments are constructed on the plurality and diversity of content presentation based on a range of parameters, with the learners' learning styles being one of the most prevalent of these characteristics. The material is conveyed to each student in such a way as to make available to them a wide range of individualized exercises that consider the diversity of learner types and the manners in which they learn.

The personalization of education can be accomplished through several distinct approaches and organizational structures. There has been an increase in both the rate of technological progress and the number of people using the internet, which has led to an emphasis on developing digital platforms and educational systems that facilitate personalized learning for students and teachers. Because they consider the preferences of the individuals being taught, learning styles are quickly becoming one of the most widely used forms of individualized education. Learners are encouraged to become more engaged when using different learning styles. Their motivation can increase in an environment built explicitly for them [7]. Students' preferences on how knowledge is presented, how information is dealt with, and how information is absorbed are called their "learning styles." The learning process can be improved if teachers know their students' learning styles.

Learning styles are of tremendous aid to teachers throughout the learning process; nevertheless, it can be challenging to personalize instruction based on these types. When using traditional teaching methods, the tutor cannot deliver a session that is individualized and tailored to the tastes and requirements of each student [8]. Technology-based applications that may be accessed on a computer or smart device aid in personalized lessons but limit classroom activities [9]. Keefe is credited with creating the most widely accepted definition of learning style. Learning styles are a learner's behavioral, cognitive, and psychological traits that are stable indications of how they perceive, react to, and interact with the learning environment [10]. The individual processes, stores, codes, and retrieves information using their preferred learning technique.

Learning style is an area of interest to many researchers in the educational and non-educational fields. Researchers have been interested in how information is processed by the mind and whether or not it is influenced by the perceptions of each individual, regardless of the various definitions of learning styles that have been proposed. Because they are so prevalent in adaptive learning, we will discuss four learning style models in detail: visual, auditory, read/write, and kinaesthetic (VARK), Felder-Silverman, Kolb's, Honey, and Mumford.

Felder-Silverman's learning style model (FSLSM) focuses on how learners adhere to learning processes. It has four dimensions and divides people into groups based on their learning: i) processing (active-reflective), ii) perception (sensing_intuitive), iii) input (visual-verbal), and iv) understanding (sequential-global), each of which represents two opposing poles that define each learner's learning style [11]. The utilization of this model is frequently observed in educational contexts involving technology and instructional media. This model provides four dimensions of learning based on the psychological aspects of the learners, which is important in an e-learning environment, so it was utilized by several researchers [7], [12]-[15] who were conducting their studies.

Kolb's learning theory [16] is founded on two pillars: horizontal action and vertical knowledge. Vertical knowledge is comprised of four interdependent constructs: reflective observation (RO), abstract conceptualization (AC), active experimentation (AE), and concert experience (CE). In addition, David Kolb created the learning style inventory (LSI) in 1971 so that people could evaluate their learning styles using the experiential learning theory as a foundation. LSI was used to test the individuals, and the results revealed four distinct types of learners. They are diverging: concrete experience and RO; assimilating: AC and RO; converging: AC and AE; and accommodating: concrete experience and AE.

According to the VARK learning styles model, most people can be categorized according to their preferred learning method: visual, auditory, or kinetic. Some students would find it more beneficial to learn using a combination of two or more learning modalities, such as visual and read/written, auditory and kinesthetic, and so on [17], [18]. They defined learning styles as the learner's preferred method of receiving knowledge, information, experiences, how he organizes, records, integrates, and retains this information in his cognitive repository.

Honey and Mumford's learning style model, this model deals with general behavioral tendencies. The learning style questionnaire of this model is derived from David Kolb's LSI [19]. This model uses questionnaires to probe learners rather than directly asking them to indicate their general behavioral tendencies. According to this model, learners are classified into four types: reflectors, theorists, pragmatists, and activists.

This study aims to analyze the learning styles that are characterized by a variety of classification approaches and are associated with a variety of e-learning issues. The findings of this analysis will be used to inform the design of future research. In addition, it has been discussed what the problem is, what the difficulties are, and where the field of e-learning research is most likely headed in the years to come. This literature review, which focuses on the information that should be collected about learning style models in e-learning, contains papers published between 2015 and 2022. This literature review attempts to answer two critical questions about predicting learning styles from this perspective: i) Q1: what are the most significant learning style theories that have recently been applied in e-learning environments, and how have these theories been used? and ii) Q2: based on the literature that has been selected, into what categories can the information be grouped?

2. METHOD

Preferred reporting items for systematic review and meta-analysis (PRISMA) were used for the analysis of this research. A systematic approach for reviewing the literature on software defect prediction is chosen. Systematic literature reviews (SLR) are now a well-established review method in software engineering. An SLR is defined as a process of identifying, assessing, and interpreting all available research evidence to provide answers to specific research questions [20]. The review steps in PRISMA [21] consisted of the following five steps: i) determining the research question; ii) locating relevant studies; iii) selecting the studies to examine; iv) data mapping and extraction; and v) organizing, summarizing, and disseminating the findings.

2.1. Determining the keywords

This review analyzes papers published from 2015 to 2023 retrieved from electronic databases. The databases used include Scopus, SpringerLink, Science Direct, IEEE Explore, and Google Scholar. The keywords related to our literature review study were used to find the most relevant studies, which were “Learning Styles Model,” “Systematic Review of Learning Style,” “Web-based Learning,” “Adaptive e-learning systems based on learning styles,” and “Automatic Prediction Learning Style.”

2.2. Identifying relevant research processes

Identifying relevant research papers is essential in any academic or scientific endeavour. This process involves a systematic approach to sifting through large amounts of literature to find studies related to the topic. To ensure the selection of the most relevant studies, exclusion criteria were applied, including eliminating duplicate papers, those with irrelevant titles and abstracts, and papers not published in English. Eligible papers were identified through previous literature analyses conducted by various authors, focusing on e-learning methods, challenges, and individual learning styles relevant to diverse e-learning contexts. Excluded were documents such as dissertation theses, textbooks, unpublished working papers, book chapters, and abstract-only papers, besides research papers.

2.3. Study selection process

Initially, our search yielded 484 articles. After removing duplicate and irrelevant articles (n=109), we carefully assessed the titles and abstracts of the remaining articles (n=375). Subsequently, 108 articles were selected for a comprehensive review to determine their eligibility. Among these, 56 articles were excluded as they were not fully accessible for review and did not provide relevant insights into the guiding question. So, the remaining 52 papers were used in the paper review analysis process. The identification, screening, eligibility assessment, and inclusion processes are visually represented in Figure 1 of the PRISMA flowchart.

2.4. Data mapping and extraction

After producing 52 papers used for a SLR, the mapping and paper extraction processes continued. In this process, we summarise each paper with the following details: year of publication, publisher, author, learning style model used, data set, feature of the data set, data collection technique, algorithm used, scientific field, research results, conclusions, and further research. All extracted paper information was collected in detail and put into a Microsoft Office Excel file for systematic analysis.

2.5. Organizing, summarizing, and disseminating the findings

Utilizing Microsoft Office Excel for managing data facilitated a comprehensive evaluation, categorization, and comparison of results with efficiency. This structured format enabled data grouping based on the assessment instrument used to evaluate learners' styles and by features such as classification techniques and the theoretical frameworks or models employed to support these groupings. Such systematic organization enhanced the analysis process, allowing for deeper insights into the relationships and patterns within the data.

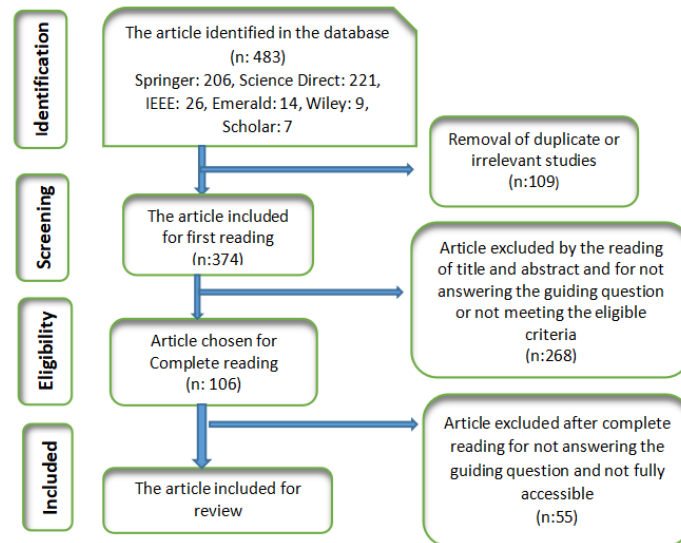


Figure 1. PRISMA flowchart

3. RESULT

The results of a paper review study on applying learning style models to online learning systems have been divided into five review categories. The five categories include classification of learning style models, learning styles based on aggregated datasets, learning styles based on curriculum fields, learning style research objectives, and analysis of learning styles. A detailed discussion of each category can be seen in the sub-discussion section.

3.1. Classification of learning style model

Learning styles have been a long-standing concept utilized in education for several years. Various approaches exist to understanding learning styles, leading to the development of numerous models. Research suggests that these learning styles can enhance students' knowledge and engagement in the learning process. Extensive literature studies have identified learning style methods commonly employed in research conducted at higher and lower educational levels.

The results of the literature study conducted on 52 papers are presented in Table 1. With 45% of the studies, the Felder-Silverman model is the most widely used. The VARK model, Kolb's model, and Honey and Mumford model are next with 23%, 21%, and 11% of the studies, respectively. The popularity of the Felder-Silverman model can be attributed to its simplicity of implementation. This model classifies learning styles based on four primary dimensions: information processing, sensory perception, learning orientation, and learning preferences. As a result, it offers a comprehensive framework for understanding the diverse learning styles exhibited by individual students. Moreover, the mode comes with an assessment instrument, enhancing its practicality and usefulness in educational settings.

Table 1. Classification of learning style model

Learning style model	Number of article (52)	References
Felder-Silverman	23	[7], [12]-[15], [22]-[39]
VARK	12	[40]-[51]
Kolb's	11	[52]-[62]
Honey and Mumford	6	[63]-[68]

3.2. Learning styles based on collected dataset sources

Based on an extensive analysis of 52 papers, the authors categorized the learning style models based on their data sources. The data collection methods distinguished these categories: explicit questionnaires, implicit data from online activities, and a hybrid approach that combined both. Table 2 highlights that most of the literature study's results relied on data obtained through questionnaires (explicit) at 56%. Subsequently, 31% of the data originated from student activities on the LMS platform, while 13% utilized a hybrid model.

Table 2. Learning styles based on collected dataset sources

Dataset resources	Number of article (52)	References
Questionnaire (explicit)	29	[7], [14], [22], [25], [26], [30], [32], [38], [41]-[44], [46]-[52], [54], [57]-[59], [64]-[68]
Database logserver (implicit/automatic)	16	[12], [13], [15], [23], [24], [27]-[29], [31], [33], [34], [36], [60], [62], [63], [39]
Hybrid	7	[35], [37], [40], [45], [53], [58], [61]

Due to their standardization and simplicity, researchers prefer explicit models like questionnaires. However, these models have weaknesses, such as potential respondent bias, errors in completion, misinterpretations, or refusal to answer specific questions, which can affect data accuracy and validity. Furthermore, their lack of flexibility poses challenges in modifying or adding new questions once the questionnaires have been collected, hindering researchers from obtaining more comprehensive information or tracking the topic's developments over time. To overcome the limitations of the questionnaire, this study chose online data collection from the LMS log server. This method provides more accurate and reliable data, automatically generated from real-world user behavior and interactions with the learning platform. LMS log servers enable real-time and continuous capture of learning style data from user interactions, enabling up-to-date analysis and a thorough understanding of individual preferences and learning styles.

An advantage of obtaining data via the LMS log server is that it does not disrupt users' learning processes and the data collection process remains transparent. Additionally, the data is quickly processed automatically and can be analyzed using specialized algorithms or software, benefiting from a diverse and large user population. With such a broad user base, the analysis can encompass various learning styles exhibited by different groups of individuals.

3.3. Learning style based on the curriculum area

Based on the comprehensive collection of 52 references, the research domains were categorized into four scientific fields: social sciences, programming, computer science, health, and engineering. Table 3 shows a clear preference among researchers, with computer science ranking highest at 34%, health at 29%, programming at 25%, engineering at 6%, and social sciences at 6%. Table 3 shows the highest subdomains in the field of computer science. This is due to several reasons, such as building computer-based learning systems, which is a much-needed research subject because understanding individual learning styles helps design and develop more effective learning systems that suit user needs [7], [33].

The prominence of computer science can be attributed to its technical and practical learning aspects. Understanding individual learning styles in software development, programming, and information technology, in general, holds significant value for researchers, educators, and practitioners seeking to develop more effective teaching methods and learning designs. Research on learning styles enables the identification of optimal learning methods for specific individuals or groups, ultimately reducing the time and effort required to grasp new concepts. The ability to adapt quickly to technological advances can be a competitive advantage, and knowledge of learning styles has proven to be important in computer science. Furthermore, exploring learning styles can offer insights into how software developers can create more intuitive and user-friendly learning products, benefiting end users in their learning journey. This understanding can lead to the development of highly accessible and user-friendly educational tools and software products in the computer science domain.

Table 3. Learning style based on research domain

Research domain	Number of article (52)	References
Social	3	[22], [56], [39]
Programming	13	[15], [23]-[25], [27], [28], [32], [40], [51], [58], [60], [62], [38]
Computer science	18	[7], [12], [13], [26], [29]-[31], [33], [34], [36], [37], [42], [52]-[54], [61], [63], [67]
Health	15	[35], [41], [43]-[50], [57], [59], [64], [66], [68]
Engineering	3	[14], [55], [65]

3.4. Learning style research objectives

Based on the literature study's findings, the research objectives have been categorised into four distinct groups: enhancing higher learning performance or achieving a positive impact on learning outcomes, developing improved technical algorithms, facilitating the learning process, and increasing overall process efficiency. The results of this objective classification are presented in Table 4. Table 4 shows that learning styles often improve learning performance or outcomes, resulting in 55% of study objectives. Following this, 21% of the objectives aimed at strengthening technical algorithms, while 12% focused on facilitating the learning process and enhancing process efficiency.

Researchers are drawn to research to enhance learning performance or positively impact learning outcomes due to its ease of implementation and the immediate visibility of results through simple statistical analysis. This goal allows for swift assessment and evaluation of the effectiveness of implemented learning styles. In conclusion, there are a variety of research objectives, with the majority of researchers aiming to improve learning outcomes or performance, then efforts to enhance technical algorithms, simplify the learning process, and increase overall process efficiency.

Table 4. Advantages of implementation learning style prediction

Goal	Number of article (52)	References
Enhancing higher learning performance or achieving a positive impact on learning outcome	29	[7], [22], [26], [28], [35], [38], [41]-[52], [55]-[58], [60], [61], [63], [65]-[68]
Developing improved technical algorithms	11	[13]-[15], [30], [31], [33], [34], [36], [39], [54], [62]
Facilitating the learning process	6	[23], [25], [40], [53], [59], [64]
Increasing overall process efficiency	6	[12], [24], [27], [29], [32], [37]

3.5. Learning styles analysis

Learning style research involves using algorithms to analyze and identify individual learning preferences. Various algorithms have been categorized in the 52 collected references, and their results are summarized in Table 5. Statistical analysis is the most widely used method, accounting for 48% of the cases. Additionally, 10% of the studies employed the fuzzy logic algorithm, 10% used neural networks, and the rule base and K-nearest neighbor (KNN) methods were utilized in 6% of the cases. The K-Mean and decision tree (DT) methods accounted for 4% each. In comparison, the support vector machine (SVM) and naive bayes (NB) methods were used in 2% of the studies; additionally, 10% of the studies needed to describe the algorithms employed clearly.

Table 5. Classification method of learning style analysis

Classification method	Number of article (52)	References
Rule-based	3	[7], [26], [29]
K-means	2	[27], [36]
Fuzzy systems	5	[13], [23], [24], [39], [65]
Descriptive statistics	25	[32], [38], [40], [42]-[52], [55]-[59], [61], [63], [64], [66]-[68]
Neural network	5	[28], [34], [35], [60], [62]
KNN	3	[31], [33], [53]
SVM	1	[37]
NB	1	[54]
DT	2	[15], [41]
Others	5	[12], [14], [22], [25], [30]

As shown in Table 5, researchers prefer statistical analysis methods because of their structured and standardized framework, which enables a clear interpretation of relationships and differences between variables concerning learning styles. Popular statistical methods, such as hypothesis testing, regression analysis, and analysis of variance, provide a systematic understanding of how certain variables influence learning styles [48]. These statistical analyses are well-suited for structured data, and various software tools are available to analyze learning style data.

Despite their advantages, statistical methods do have limitations. The information gathered may limit them. If the measurement of learning styles needs to be improved or more adequate to include essential aspects, statistical analysis may not completely understand individual learning styles. Additionally, statistical analyses often focus on relationships or differences between variables, which might not comprehensively understand the underlying mechanisms or reasons behind individual learning preferences [69]. Qualitative analysis or algorithm-based approaches can help researchers overcome these limitations and identify learning styles. By using a variety of methods, researchers can better understand learning preferences. The choice of method or algorithm should be based on the research objectives, the data's complexity, and the research's specific context. Combinations or modifications of algorithms can provide a more complete picture of learning styles.

4. DISCUSSION

Research on learning styles has been conducted extensively, utilizing various learning style models and algorithms. The results of these studies have demonstrated the potential to assist students and educators in determining learning styles that align with individual preferences. Among the theories linking learning styles to adaptive learning, notable ones include Felder-Silverman's theory of multiple intelligences, VARK, honey and mumford's theory, gardner's theory of multiple intelligences, and Entwistle's method of FSLSM.

Addressing the first research question about significant learning style theories recently applied in e-learning environments and their usage, multiple theories have been employed, including Felder-Silverman, VARK, Kolb's, Honey, and Mumford. These learning style methods can be seen in Table 1. According to the literature study, the Felder-Silverman model is the most widely used model by researchers. Its popularity can be attributed to its comprehensibility and the availability of the index of learning styles (ILS) as a measurement instrument based on this model. The ILS enables researchers and educators to systematically assess individual learning style preferences according to model dimensions [28], [29], [31], [66], [68].

For the second research question, the literature studies have been put into groups based on different factors, including the learning style model classification, the curriculum area, the goals of predicting learning style implementation, and the algorithms used for learning style analysis. This grouping can be seen in Tables 1-5. Research related to learning styles in computer science is more prevalent than research in other scientific fields. The fast-paced nature of computer science, involving both technical and practical aspects, poses unique challenges for researchers to analyze student learning styles, thus striving to enhance learning efficiency [5].

Based on the literature study that has been carried out, conclusions in terms of data collection methods have been drawn. Explicit or static data, obtained through questionnaires, was frequently chosen over online or automatic data derived from student activities in the LMS or through a hybrid combination of explicit and implicit data. How to collect data can be seen in Table 2. While explicit data collection is convenient, it possesses weaknesses such as bias in respondents' answers, limited information, and inflexibility [43], [52], [67], [68]. This study opted for implicit data retrieved automatically from the LMS log server as a remedy. This approach allows for real-time and continuous data retrieval from user interactions with the LMS platform, enabling up-to-date analysis and a comprehensive understanding of students' preferences and learning styles.

Research objectives were divided into four categories: improving learning outcomes or achieving a positive impact, enhancing algorithms for techniques, facilitating the learning process, and enhancing process efficiency. These categories are shown in Table 4. Most studies focused on improving student learning outcomes by creating a learning environment tailored to individual needs. Some articles emphasized facility support to aid the learning process, while a few studies discussed the enhancement and development of algorithms used in learning style research. Although improved algorithms received less attention, they are crucial in optimizing learning by aligning learning materials with individual characteristics and preferences, enhancing learning effectiveness, and reducing computational load during large-scale data implementation [57]. Such research is particularly important in computer science, where optimizing algorithms can significantly improve learning.

Based on the references collected, the methods or algorithms employed in the research were categorized as rule-based, K-Means, descriptive statistics, artificial neural networks (ANN), KNN, convolutional neural network (CNN), SVM, NB, collaborative filtering (CF), and DT. The algorithm used can be seen in Table 5. The study found that statistical methods are the most widely used, particularly in explicitly obtained data models. Additionally, some studies utilized algorithms that were not clearly specified, while others modified algorithms to suit specific case problems. Learning style research employs diverse theories, models, and algorithms to understand individual learning preferences. Statistical analysis, explicit data collection, and the Felder-Silverman model were commonly used in research. Moreover, the study emphasized improving algorithms to optimize learning processes, especially in computer science. Categorizing and understanding the various methods employed in this research field provide valuable insights for further enhancing learning experiences.

5. CONCLUSION

The recognition of diverse learning styles and their integration into adaptive learning environments has grown significantly over time due to their profound impact on the entire learning process. This article highlights the most recent studies (2015–2023) focusing on learner modeling, particularly learning styles and their application within the LMSs framework. Furthermore, the research provides insights into commonly used strategies, analyses their benefits, and limitations. Recent studies predominantly employ a combination of methods, encompassing computer-based and human-based questionnaires, to predict learning styles within online learning environments autonomously. However, it is vital to explore a broader range of parameters

beyond the user's interactions with the system to accurately forecast a user's learning styles. A deeper understanding of learners can be achieved by investigating additional personality traits that align with various learning styles and integrating them into adaptable learning environments. This approach can lead to better learning outcomes by catering to individual preferences and needs.

Automatic online learning style prediction is an essential educational technology advancement. Researchers and educators can use machine learning algorithms and data analytics to predict online learners' preferences and cognitive processes. These predictive algorithms use user interactions, engagement, assessment performance, and demographic data to make personalized suggestions and adapt learning materials. Online learning platforms can better automate content delivery, instructional tactics, and feedback to meet students' learning styles and needs. Automatic prediction of learning styles in online learning can improve learner engagement, educational outcomes, and a more inclusive and prosperous online learning experience for all learners.

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