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TOPICAL REVIEW

Educational Recommendation System Utilizing Learning Styles: A Systematic Literature Review

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ABSTRACT Learning styles, learners' preferred ways to learn, can be applied to design personalized learning courses for the individual learner. One of those applications is the recommender system. This study ran a systematic literature review on the recommender system utilizing learning styles from two dependable academic libraries, IEEE Xplore and ScienceDirect, which included six reviewed topics; research objective, research methodology, educational recommendation, learning styles theory, learning style identification, and recommendation algorithm. Finally, the obtained information was examined and summarized in order to develop a unique strategy for leveraging the utilization of learning style theory for a recommender system to improve learning efficiency.

INDEX TERMS Educational recommender system, learning styles, systematic literature review.

I. INTRODUCTION

This paper is an extension of work initially presented at the 2021 6th International Conference on Business and Industrial Research (ICBIR2021) [1]. Different learners have varying preferred learning styles. Some students may comprehend visually, but others prefer text and reading. Some students may do well with theories, while others may learn more efficiently with experiments and examples. Those examples are proofs to ensure that individual learners have their unique styles of learning which can be called learning styles. Gaining insight into different learning styles will offer a way to design a personalized learning approach that meets learner preferences, which will benefit not only learners but other roles in the field of education, such as educators as well. Understanding own learning style will make a learner learns successfully and confidently. For educators, it helps develop academic courses, learning materials, and teaching strategies. Over 70 studies involving learning styles theory have been published recently due to its significant helpfulness [2].

Learning styles have been commonly measured using a survey and a questionnaire, asking learners to evaluate their behaviors. The method is appropriate for the old-school classroom where a document can be distributed to each student and gathered back after a class, but it seems outdated with the current education environment where students can attend class online and do not need to sit in class together anymore. Furthermore, the progress of technology and innovation in data analytics has increased a significant number of educators and researchers applying learning styles to information technology systems and applications, which allows a computer system to quickly identify and analyze the data and information of each student.

For decades, the recommender system has been acknowledged as an application that can satisfy user preferences through personalization. The system selects and offers the most appropriate services or items for similar users by considering their relevance. There are several studies that apply learning styles theory to a recommender system. The most common approach for the application is to select and offer the most appropriate class environment, teaching method, hints, and guidelines for each student [3]. For example, Latham [4] developed the personalized conversational tutoring system utilizing learning styles, and Limongelli [5] developed the recommender system under the lecomp5 framework provides courses of action, including a resource selection learning sequence that best matches students' learning styles.

The objective of this study is to discover the knowledge by running a systematic literature review on the topic of

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the recommender system utilizing learning styles from two dependable academic libraries, IEEE Xplore and ScienceDirect, which included six review research objectives (RO) to accomplish as follows,

- *RO1: Research Objective*
- *RO2: Research Methodology*
- *RO3: Educational Recommendation*
- *RO4: Learning Styles Theory*
- *RO5: Learning Styles Identification*
- *RO6: Recommendation Algorithm*

The remainder of this study is organized as follows. Related theories and studies are shown in section II, Related Work. Section III, Methodology, details the procedure of this systemic review study. Discovered knowledge and analyses were provided in section IV, Result, Analysis, and Discussion. Finally, section V, Conclusion and Future Work, summarizes the study and provides challenges and opportunities for future work.

II. RELATED WORK

Descriptions and examples of relevant research on "Educational Recommendation," "Recommender System," and "Learning Style" are presented in order to provide a better understanding of the methodology utilized in this investigation.

A. PERSONALIZED LEARNING

According to Ashman [6], personalized learning could mean identifying learning or teaching preferences by considering a student or teacher profile. However, as no teaching strategy is appropriate for every learner, to make the teaching and learning process successful, it mainly depends on how well it can be adapted according to individual differences or how well it can be personalized. There are two approaches to personalize learning: user-centered [7] and technology-centered [8], [9], [10]. With the user-centered approach, personalization focus on a procedure [11], [12]. On the other hand, with the technology-centered approach, personalization focus on a system such as a course management system or an e-learning system [13], [14].

Several results from past studies show that learners participating in a personalized e-learning system are more motivated [15]. For example, results from the research [16] on adopting the learner-centered approach system indicate that almost participants found that the learning experience from the system is more effective than the traditional teacher-centered because they feel ownership due to the teacher's role changed to a coach providing a recommendation instead of telling everything [17].

Those examples show the signs of progress in education, meaning students can achieve knowledge not only by the direct transfer of information from teachers but the consequence of actions from efficient recommendations from an educational coach. Regarding technology usage, teachers' advice is still considered necessary for learning as it is able to motivate learners [18], [19].

B. EDUCATIONAL RECOMMENDATION BY THE RECOMMENDER SYSTEM

A recommender system can offer learners appropriate learning resources and guidance in many possible learning materials [20], thus increasing the success of learning something properly [21], [22]. The principal beneficiaries of educational recommendations generated by a recommender system are students who lack prerequisite knowledge or expertise in a particular discipline or who lack time to evaluate the vast number of available learning materials. Some examples of recommendation system capabilities in education are shown as follows [23], [24],

1) Respecting roles, tasks, and degrees of expertise, the system is able to provide proper knowledge to learners in collaborative study group settings.
2) The system can aid students in arranging their learning schedule by identifying courses that correspond with their choices and imposed regulations.
3) The system can propose instructional materials and resources.

According to Shute [19], an educational suggestion is a constructive guidance expressing information to a student that aims to adjust the learner's specific behavior to enhance learning, concluding that the recommender system is the best suitable technology to enable educational recommendations. The type of educational recommendations is identified as follows,

1) Recommendations are connected to qualities that address the attributes or contents of the goal concept or taught skill, such as recommendations for the learning materials.
2) Suggestions are pertinent to the topic being studied, such as course recommendations, that are topic-dependent.
3) Response-contingent recommendations focus on the learner's unique response, such as a discussion of why the incorrect response is incorrect and why the correct response is correct, without employing mistake analysis.
4) Hints/cues/prompts advise directing the student in the proper direction, such as a strategic tip on what to do next.
5) Recommendations for bugs/misconceptions comprise error analysis and diagnosis, such as an explanation of what is wrong and why.
6) Tutoring suggestions that provide recommendations that are a blend of prior recommendations.

C. RECOMMENDER SYSTEMS UTILIZING LEARNING STYLE

The user model is the basis of the personalization system, as it has been referred to as "The core of all automated personalization systems" [25]. In education, the user model consists mostly of learner-specific information, such as prior knowledge, learning experience, education, learning objectives, and learning styles. The issue for researchers is to determine the appropriate learner model structure for a given application. The learning style is regarded as the most influential influence on e-learning and academic proficiency [26].

According to Kurilovas [27], "Learning styles are strategies, or regular mental behaviors, habitually applied by an individual to learning, particularly deliberate educational learning, and built on her/his underlying potentials." There are several learning style descriptions and classifications proposed by various theories [28]. Those theories were usually called the "Learning Style Model," for example, Felder-Silverman's Learning Style Model. Coffield [2] officially identified 71 learning style models, becoming the standard for many past studies. Different theories of learning styles have been the subject of a number of recent research. For instance, between 1985 and 1995, 2,000 papers were written about the Myers-Briggs Type Indicator Learning Style Model [29], and more than 1,000 articles referenced the Kolb Learning Style Model [30] and the Dunn and Dunn Learning Style Model [31].

Numerous research [32], [33], [34], [35] examined the association between learning style and various learning scenario components. Kurilovas [27] discovered interrelationships between learning style and preferred learning activities, learning object kinds, and suitable teaching/learning approaches, for instance, in his study. However, research suggests that a person's learning style might differ based on the activity or learning material. Consequently, it appears counterproductive to lock the student into a set learning style profile following the initial evaluation. Consequently, it appears counterproductive to lock the student into a set learning style profile following the initial evaluation. Regarding the use of learning style data in system adaption design, there are still several unanswered concerns. For instance, questions pertaining to how learners with different learning styles respond to assessment tests, exercises, activities, Etc., navigation traces followed by learners with different styles, common characteristics of learners of the same style, and evidence pertaining to how learners of a specific learning style select and to use educational resources deemed advantageous for their style, Etc. [36].

III. METHODOLOGY

This study adopted the systematic literature review procedures from the Guidelines for Performing Systematic Literature Reviews in Software Engineering [37]. The procedures consisted of three phases which are shown in Figure 1.

A. IDENTIFICATION OF THE OBJECTIVES OF THE REVIEW

The first process of the planning phase was identifying the review research objectives (RO) as the guidelines for the review.

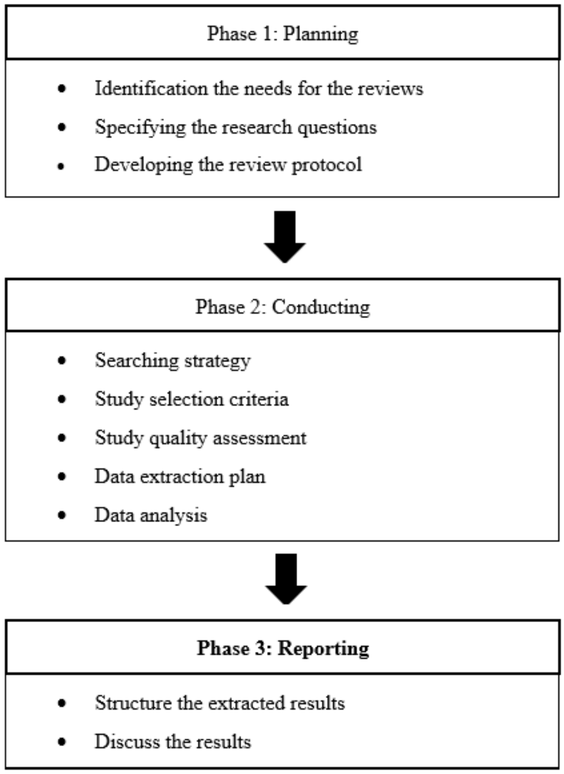

FIGURE 1. Systematic literature review process phases.

B. SPECIFYING THE REVIEW RESEARCH QUESTIONS

The review research questions (RQ) were specified to clarify the RO. Each RQ explains each RO as follows,

- *RQ1: What is the most common procedure for utilizing a learning style in a recommender system?*
  This RQ clarifies the RO1: Research Objective, the RO2: Research Methodology, and the RO3: Educational Recommendation. Despite the fact that learning styles have been applied to a variety of applications, including recommender systems where classes are organized and teaching methods, hints, and guidelines are provided in a way that fits different individual students [3], a recommender system has not been the most common application for systems utilizing learning styles over the past several years. Therefore, to understand the research progress, this question directs the review to analyze and summarize information about the procedure of the reviewed studies, including the objective, the methodology, and the applied educational recommendation.
- *RQ2: What is the recommender system's most commonly utilized learning style theory?*
  This RQ clarifies the RO4: Learning Styles Theory and the RO5: Learning Styles Identification. As drill-down information after the research procedure is the applied theory, this question directs the review to analyze and summarize information about the utilized learning

TABLE 1. Search keywords.

Topic	Set of keywords		
Learning styles	Learning style(s) OR	Mind Style(s) OR	Cognitive Style(s) OR
	Type Indicator OR	Motivational Style(s) OR	Brain Dominance OR
	Study Skill(s) OR	Thinking Style(s)	
Recommender system	Recommender system(s) OR	Recommendation system(s) OR	Recommendation OR
	Recommender		

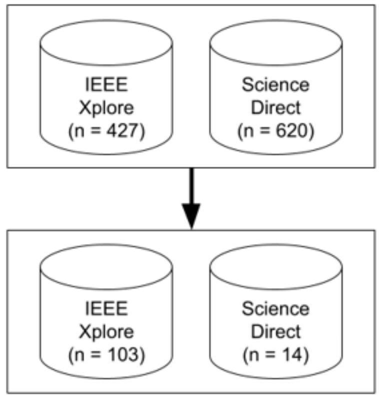

FIGURE 2. Process of study selection criteria.

theory of the reviewed studies, including the theory and the identification of the style.

- *RQ3: What is the recommender system utilizing learning styles' most commonly used algorithm for recommending?*
  This RQ clarifies the RO6: Recommendation Algorithm. Another drill-down information after the research procedure is the used algorithm of the system to offer a recommendation. This question provides another insight into the recommender system utilizing learning styles, not in how to use the learning style but how to make the recommendation system based on it, and directs the review to analyze and summarize information about the algorithm that uses the identified learning style to make a recommendation.

C. DEVELOPING THE REVIEW PROTOCOL

The review protocol adopted from the guideline [37] was used for structuring the procedure. The protocol is shown in Figure 1.

D. SEARCH STRATEGIES

The reviewed studies were collected through two dependable academic libraries, IEEE Xplore and Science Direct, using the advanced search on several search keyword combinations.

E. SEARCH KEYWORDS

This study's search strategy was developed by following the RO and expanding on the RQ to filter reviewed studies. First, search keywords were identified and then separated into three groups based on the topic of keywords. Most of the keywords were extracted from the previous study. Then, synonyms, plural forms, capital forms, and alternative spellings were manually identified. Finally, search strings were generated by combining each group of keywords. The Boolean operator 'OR' was used to add synonyms and alternative spellings, while the Boolean operator 'AND' was used to connect the keywords. The search keyword combinations are shown in Table 1.

F. STUDY SELECTION CRITERIA

Numerous papers found using the search strings in Table 3 were selected based on specified criteria to verify their relevance and ability to address all RQ. Relevant studies were those that satisfied all inclusion criteria, such as title, abstract, and keywords. The inclusion criteria are listed as follows,

- *Studies that are written in English*
- *Studies that were published between 2011 and 2020*
- *Studies that presented the learning style theories*
- *Studies that presented the including recommender or recommendation system*
- *Studies whose title, keywords, and abstract do contain the following words: "recommend," "system," "learn," and "style."*

Studies that satisfied any exclusion criteria were excluded. The exclusion criteria are listed as follows,

- *Course*
- *Encyclopedia*
- *Book chapters*
- *Editorials*
- *Correspondence*
- *Others (type of literature except for article)*
- *Articles whose full text was not accessible*
- *Duplicate articles that reported the same study from different academic databases*

G. ASSESSMENT CRITERIA FOR STUDY QUALITY

The inclusion-exclusion criteria-filtered studies will be evaluated based on the quality evaluation criteria. The quality evaluation checklist for this study was adapted from Papamitsiou's study [39] due to the similarities of the studies, as it was used to evaluate articles included in the systematic literature review study of technology utilization in education. The adopted checklist will be modified to evaluate and describe articles more accurately, as shown in Table 2. Every question on the quality evaluation checklist was rated on a three-value Likert scale with varied descriptions, and the findings were utilized to summarize and describe the included research.

TABLE 2. Quality assessment (QA) checklist.

Item	Assessment Criteria	Description of Checklist
QA1	Does this article clearly describe the aim of the studies which propose the recommender system for usage in the field of education?	No, the aim is described but was not for the usage in the field of education.
		Partially, the aim is described as proposing the system for usage in the field of education but not the system that can give the recommendation.
		Yes, the aim is clearly described as proposing the recommender system for usage in the field of education.
QA2	Does the article clearly present the usage of learning style theory?	No, the usage of learning style theory is not clearly presented.
		Partially, the usage of learning style theory is not clearly presented and described.
		Yes, the usage of learning style theory is clearly presented and described.
QA3	Does the article clearly present the development of the recommender system?	No, the recommender system was not developed or there is no evidence of the system being developed.
		Partially, the developed system can give recommendation, but it is not actually the recommender system.
		Yes, the recommender system was clearly developed.
QA4	Does the article present the implementation of the proposed system?	No, the proposed system was not implemented or there is no evidence of the system being implemented.
		Partially, the proposed system was tested or simulated by feeding the created data.
		Yes, the proposed system was clearly implemented.
QA5	Has the article been cited by other authors?	No, not at all.
		Partially, 1-5 other articles cite this article.
		Yes, more than 5 articles cite this article.

H. DATA EXTRACTION PLAN

This study employed a standard information form derived from Kitchenham's study [39] to obtain the information required for analysis from a selection of publications. The Mendeley application was used to extract vital information and publishing characteristics, and the original study was utilized to collect particular data from each article based on the classification of the first study. The Microsoft Excel program was used to create a spreadsheet concluding finalized and summarized information as follows,

- *Research Objective*
- *Research Method*
- *Learning Style Theory*
- *Style Identification Techniques*
- *Recommendation Algorithms*
- *Educational recommendations addressed by the study*
- *Number of studies that cited the study*

IV. RESULT, ANALYSIS, AND DISCUSSION

1) DATA ANALYSIS: RESULT OF QUALITY ASSESSMENT

Not all selected studies were considered for analysis; only some that passed the assessment criteria were analyzed as the criterion was used to filter out the irrelevant, for example, studies that were not for usage in the field of education. The result of quality assessment was shown in Figure 3.

In the first criterion (QA1), the objective of each selected study was evaluated. Among 117 selected studies, only 57 were found to clearly describe the objective of proposing the recommender system for usage in the field of education. 15 studies partially propose the system for usage in the field of education but cannot give a recommendation. Although 45 studies have the word "recommend," "system," "learn," and "style" in their title, keyword, and abstract, their aim was not for usage in the field of education. For example, the study titled "Clothing Recommendation System based on Visual Information Analytics" does have "recommend" and "system" in the title and has "style" and "learn" in the abstract and keyword due to referring to fashion style and deep learning. This article aims not for usage in the field of education. Therefore, these 45 studies were excluded from the reviews.

After considering the study's usage in the field of education, the second criterion (QA2) examined whether the studies present or describe the usage of learning style theory. 18 studies did not present or describe the usage of learning styles theory and were excluded. On the other hand, 8 studies presented the usage of learning style theory but did not clearly describe the usage, like how to identify each person's learning style. However, these studies were still acceptable.

Regarding the third criterion (QA3), the result discovered that 13 articles were excluded due to this review study focusing on developing the recommender system or the system that can give the recommendation. Examples of the excluded articles were "Developments in Educational Recommendation Systems: A systematic review," which involved the recommender system for usage in the field of education but was not focused on in this review study. On the other hand, 17 articles were acceptable as they proposed a system that could give recommendations even though it was not the recommender system.

The fourth criterion (QA4) examined whether the studies implemented the proposed system. Only 18 studies were clearly implemented and evaluated the proposed system. The others were only the framework or the prototype system.

The sole study that met all acceptable requirements out of a total of 40 will be evaluated based on the fifth criterion (QA5), which involves citations of the study in other articles. The number of citations was verified using Google Scholar (citation checking on 3 March 2021). According to Google Scholar, of the 40 selected studies, 23 were cited

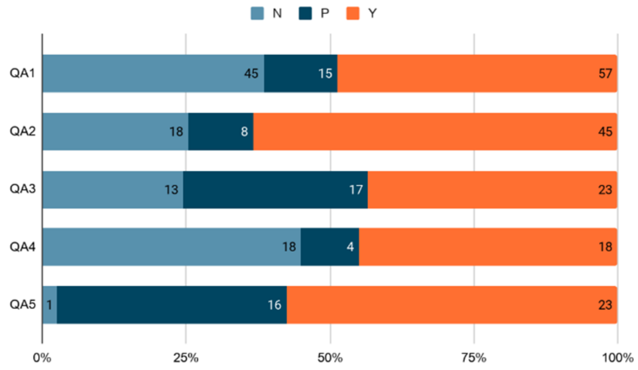

FIGURE 3. Result of quality assessment.

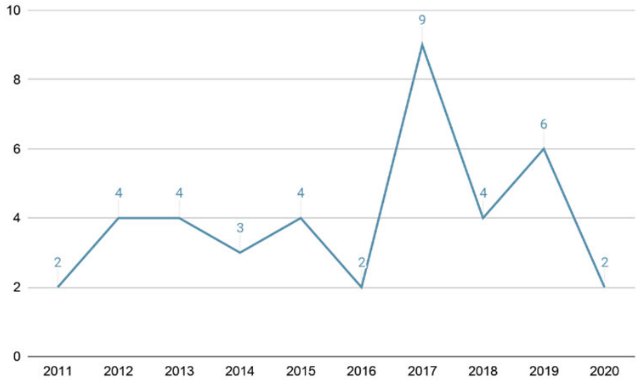

FIGURE 4. Distribution of articles based on publication year.

more than five times by other studies, 16 were quoted seldom (1-5 times), and only one had no citations as of the date of citation verification. Due to the frequency with which the citation is changed, the QA5 outcomes may differ at various times.

Figure 4 shows the distribution of studies based on the publication year. The trend of recommender systems utilizing learning styles increased significantly from 2016 to 2017. This trend occurred because, in 2017, many researchers were encouraged to publish the system studies as a proposed framework, with no need to implement or develop the actual system as it can be seen that among 9 studies about the development of the educational system in 2017, there were only 4 studies that implemented the system. The other 5 studies only propose the framework. This amount of research was soaring from the last year, 2016; there were only 2 studies. Only 1 study implemented the system, and another just proposed the framework.

2) RESEARCH OBJECTIVE ANALYSIS

The findings distribution of the analyzed papers on research objective is presented in Table 3. Among 40 studies, there are only two proposed objectives. Most of the selected studies, 90%, propose to design a system that considers the learner's learning style to give an educational recommendation. Klanja-Milievi [33] described in 2011 a suggestion module of the ''Protus'' ''programming tutoring system,

TABLE 3. Overview of the studies' objective.

Research Objective	Number of studies	%	Reference
System that consideres the learning style to give educational recommendation development	36	90%	[33] [35] [41]-[55] [57]-[70] [72]-[76]
Research to provide insights into detail for personalizing learning	4	10%	[28][41][56][71]

which can automatically adjust to a learner's interests and knowledge levels by identifying patterns of learning methods. This study is the most well-known educational recommender system research and became a reference for many later studies in this field. Many later studies adopted its system architecture and design, such as learner and recommender modules. Another 10% of the studies provide detailed insights for personalizing learning to improve learning quality and efficiency. Kusumawardani's enhanced idea mapping between student traits and categories by Felder-Silverman Learning Style Model and relevant material inside Moodle-based e-learning was the most referenced study [40]. This study produced a number of ideas that constitute the fundamental definition of learning styles and e-Learning material, as well as a number of rules used to integrate content suggestions from the fundamental definition.

3) RESEARCH METHODOLOGY ANALYSIS

The findings distribution of the analyzed papers on research techniques is presented in Table 4. Among 40 studies, the majority of the methodology, 97.50%, is studies that actually develop a system or plan to develop a system which is distributed as studies that developed a system along with the present of evaluation, 52.50%, and the study which developed the system with no evaluation presented or just proposed the system framework, 45%. The most cited study that developed the system was ''Protus'' [33]. The most recognized research for the creation of the framework was ''Protus 2.0,'' [35] which suggested a new version of the system framework of the ''Protus'' tutoring system that will rely only on Semantic web standards and technologies. The main objective of this kind of study was only to present the advantages and new functionalities of the system. The implementation of the framework system is usually presented as future work.

4) EDUCATIONAL RECOMMENDATION ANALYSIS

Following the objective and methodology analysis, the last analysis performed to answer the RQ and lead to exploring challenges and opportunities is the utility or value proposed system can be used in the field of education.

As mentioned in the related work session, formative feedback represents information communicated to the learner that is intended to modify the learner's thinking or behavior in

TABLE 4. Overview of the studies' methodology.

Research Methodorogy	Number of studies	%	Reference
Discussion or experiment about techniques, methods, or algorithms to improve or acquire knowledge	1	2.5%	[41]
Developing the system to conduct an experiment or de-ploy a prototype system then evaluate its performance	21	52.5%	[28] [33] [45] [46] [50]-[53] [55] [57] [59] [63] [64] [66] [67] [69]-[73] [75]
Design the system framework for an experiment or a proto-type system	18	45%	[35] [40] [42]-[44] [47]-[49] [54] [56] [58] [60]-[62] [65] [68] [74] [76]

order to improve learning. Six types of formative feedback were identified as ''Educational Recommendation and are described below.

- *Attributed-related*
- *Topic-contingent*
- *Response-contingent*
- *Hints/cues/prompts*
- *Bugs/misconceptions*
- *Tutoring recommendations*
- *Number of studies that cited the study*

The proposed system would deliver one kind of these educational recommendations so it can be helpful in the field of education. Table 5 presents the results distribution of the reviewed studies regarding the educational recommendation.

Among 40 reviewed studies that proposed the system, the majority of 75% was attributed-related because most of the systems proposed to help recommend the learning materials as recommender system algorithm mainly calculated by the user's preference to an item, so it is most convenient to build. The most cited article was also the most famous one, Protus 2.0 [40]. The system that provided tutor educational recommendations is the most advanced one, which was also the challenge many researchers want to try to study and develop. Kurilovas's work [53] is the most-cited paper that provides the results of employing the adaptive ant colony optimization approach to identify appropriate learning routes for students depending on their learning styles. This research focused on building a new approach for customizing learning units by modifying and expanding the Ant Colony Optimization (ACO), making it the ideal source for generating a novel method or algorithm.

5) LEARNING STYLES THEORIES ANALYSIS

The first stage in creating or constructing an adapted system is selecting a learning theory, which may be a problem for researchers since it determines the data collection technique and recommender algorithm employed. The landscape of learning styles and theories is clustered. In the past thirty years, nearly seventy hypotheses have been produced. Several of them may overlap. For instance, Felder-model

TABLE 5. Overview of the studies' educational recommendation.

Topic	Number of studies	%	Reference
Attributed-Related	30	75%	[33] [35] [40] [42] [45]-[48] [50] [52] [54] [55] [57]-[60] [62] [64]-[68] [70]-[76]
Response-Contingent	2	5%	[51] [69]
Hints / Cues / Prompts	2	5%	[49] [61]
Tutoring Recommentations	6	15%	[41] [43] [44] [53] [56] [63]

Silverman's [2] shares similar dimensions with models by Kolb and Riding. Also, according to Coffield [2], the majority of theories describing learning styles have validity and/or dependability difficulties.

Therefore, no theory is superior to others. In the modified recommender system, few hypotheses have been implemented. Table 6 displays the outcomes of the content analysis according to the learning modes utilized. Article references are also supplied. 72.5% of the data fit the Felder-Silverman model. [80] The Felder-Silverman model distinguishes between learning styles along four dimensions: perception (Sensory/Intuitive), information input (Image/Verbal), information processing (Active/Reflective), and comprehension (Sequential/Global). The same number of other theories, such as Kolb's Learning styles inventory [77] and Honey and Mumford's Learning styles [78], were also utilized. These theories might be regarded as alternatives to the Felder- Silverman's model since the researcher wants to examine alternative ways. According to Germanakos et al. [79], a theory such as Kolb's was complicated and highly connected with personality theories; hence, it was neither sufficient nor easily quantifiable.

As a result, they advocated employing the Felder-Silverman model, which consists of a discrete scale that corresponds to various parts of the learning process. Feldman [81] defended their decision to focus on perception style on the grounds that it is intricately intertwined with other crucial variables such as profession inclinations, aptitudes, and management styles. Dorca et al. [82] claimed that Felder-Silverman's model stood out due to the fact that it incorporated many major learning styles and concepts. The fact that the custom theory ranked second, at 10%, indicates that several studies are still attempting to produce a new theory that can deliver the greatest performance of the current ones by merging various theories, Etc.

6) IDENTIFICATION TECHNIQUES ANALYSIS

Table 7 presents the results distribution of the reviewed studies about the learning style identification technique. The most popular method is a questionnaire which was according to the theories. For example, the study using the Felder- Silverman model also used ILS, the questionnaire for analyzing Felder-Silverman's learning style, as the most comfortable and accu-

TABLE 6. Overview of learning styles theories applied in adaptive learning system.

Theory	Number of studies	%	Reference
Felder-Silverman	29	72.5%	[33] [35] [39] [40] [43] [45] [46] [48]-[50] [52] [54] [56]-[58] [60]-[64] [66]-[74] [76]
Honey & Mumford	2	5%	[53] [65]
Kolb	2	5%	[41] [55]
Reid Perceptual Learning Style Pereference	1	2.5%	[47]
GRLSS	1	2.5%	[51]
VAK	1	2.5%	[59]
Custom	4	10%	[28] [42] [44] [75]

TABLE 7. Overview of identification technique applied in adaptive learning system.

Technique	Number of studies	%	Reference
Questionnaire	27	73%	[33] [35] [40] [42]-[44] [46] [47] [49]-[54] [56] [58]-[60] [62]-[66] [69]-[74]
Data Mining	7	18.9%	[41] [45] [48] [57] [61] [75] [76]
Rule-Based	2	5.4%	[55] [67]
Fuzzy C Mean	1	2.7%	[68]

rate method to gather the data. The other option is to use data mining to analyze the log data or store transaction data from the learner. This method seems not to hinder the learner and does not put too much effort into the learner as the user, but this method needs a lot of stored data to analyze. Most of the study that used this technique was the study that developed the education system that was already implemented.

7) RECOMMENDATION ALGORITHMS ANALYSIS

The results distribution of the examined papers on recommender strategies is shown in Table 8. The recommendation algorithm is the engine that enables the recommender system to create recommendations. However, the recommendation algorithms used in the education data are diverse, as this sector is still relatively young, and the optimal base algorithm has not yet been established.

In 42.5% of the examined research, the most prevalent approach is appropriate. Appropriate refers to applying to the learner the most effective method for learning based on their learning style description. Kolekar's study [68] is the most referenced study that describes the method for identifying learning styles by adopting Felder-Learning Silverman's Style Model (FLSM); each learner with a specific learning style would then be allocated a corresponding theme and component. This recommender idea appears useless since it is based only on the learning style theory, yet it was the most popular approach because it is the most convenient way to apply suggestions tailored to the learning style. Collaborative-Filtering was the second most popular method for recommender systems, accounting for 27.5% of all instances.

TABLE 8. Overview of the article's recommendation algorithm.

Algorithm	Number of studies	%	Reference
Suitable	17	42.5%	[40] [41]-[44] [47] [48] [55] [56] [58] [61] [65] [67] [68] [70] [74] [76]
Collaborative-Filtering	11	27.5%	[33] [35] [45] [49] [50] [52] [54] [63] [64] [72] [75]
Hybrid	4	10%	[46] [57] [66] [73]
Rule-Based	2	5%	[62] [71]
Other	6	15%	[28] [51] [53] [59] [60] [69]

8) DISCUSS THE RESULT

Multiple results from each data extraction analysis were organized to address all RQs. The results of the systematic literature studies reveal a number of intriguing advancements, prospects, and obstacles. Knowledge gained from analyzing educational suggestions indicates that numerous established educational recommender systems have offered a comprehensive view of how learning styles might be utilized when making recommendations. They also answer RQ1. Same for research objective analysis and research methodology analysis. It showed that although recommender systems have provided several types of educational recommendations, most of the systems were developed to provide an attribute-related recommendation as it is the simplest type of educational recommendation because the primary purpose of a recommender system is to recommend an item or attribute in the field of education, so this is the direct adaptation, the simplest one. Analysis of recent trends revealed that educational recommendation-related research is still in its infancy and requires additional investigation and growth. A second concern revealed by the methodological analysis is that not all of the evaluated publications contain an assessment of the systems, which classifies them as framework studies that cannot be utilized as a reference for future research.

The findings from the learning styles theories analysis were used to answer RQ2. Felder-Silverman's model is the most widely employed theory in recommender systems. Due to the fact that a substantial amount of research has utilized this theory, it will be possible to compare and assess the findings. Recommender systems employing other learning theories are underexplored; hence, future research should develop models for measuring and integrating additional theories. On the basis of their influence on students' learning outcomes, it is possible to compare the performance of such systems to that of the Felder- Silverman's model.

Nevertheless, regardless of the selected theory, the strengths and limitations must be acknowledged in full. Finally, there is a possibility to combine theories of learning styles since they may complement and enhance one another, hence enhancing flexibility and recommendation capacity. This discovery is also the opinion of scholars such as the research of Ocepek [28]. Identification methods analysis was also employed to answer RQ2 since it provides a complicated picture of the relationship between a student's learning style and their actual behavior. While the idea may be the same, the mechanism for identifying styles may vary between research. Since none of the articles evaluated yet have been able to analyze the performance of questionnaires in comparison to other methods, questionnaires were the most popular approach. This discovery points out an open question regarding different online attributes' power and performances in identifying or predicting learning styles, and as a result, there is a demand for future studies to tackle the issue. These findings can serve as a reference for e-learning system makers and contribute to the enhancement of the performance and efficiency of classification and prediction models, as each technique has its strengths and drawbacks. Although this categorization adheres closely to the theories and their associated metrics, such as the questionnaire, there is very little or no updating during the course. Besides the questionnaire, some exciting findings show that data mining for the log data can also identify the style. This finding may investigate further by combining many algorithms, as each model has an equal vote. The result, which in this case is the chance that a student belongs to a specific style, will be the proportion of all algorithms.

Findings acquired from Recommendation Algorithms Analysis show that a suitable rule-based approach is mainly used. Follow with the collaborative filtering algorithm. This discovery leads to the assumption that single algorithms or method is the most focused approach. Also, this finding was used to answer RQ3. This finding opens the door for less-explored, more complex approaches, such as hybrid and ensemble algorithms, which mix several algorithms or methodologies to achieve greater accuracy. Ensemble learning, on the other hand, elaborates and integrates the outcomes of a variety of individual algorithms to produce the final output [83].

V. CONCLUSION

Reviewing forty papers and evaluating data extracted from various areas of the studies on recommender systems incorporating learning styles provides insight into current development and research, as well as potential and obstacles. A discussed and analyzed topic and process are structured in the systematic literature method to find the answer to the RO and RQ. Finally, all findings from the analyses were gathered to discuss the recent trends, challenges, and opportunities.

It has been determined that Felder-Silverman is by far the most prevalent theory used in the recommender system. While the philosophy and approach may be similar, they are distinguished in a number of ways. However, the results also highlight a problem: none of the prior research gives information on the performance of various strategies for detecting learning styles. In addition, despite the fact that there are several recommendation algorithms, only rule-based suggestions were nearly implemented. In addition, none of the published works explore the comparison or combination of algorithms. The review also reveals that while attributed-related dominate educational recommendations provided by the system, recently, there has been a trend showing some studies trying to develop more varied educational recommender system such as Hints/cues/prompts and tutoring however it is still in the early stage of development which requires further research and exploration.

1) LIMITATIONS

Despite the fact that the assessment sheds light on several facets, it is essential to note its limits. As is the case for many academics conducting a literature evaluation, it is possible to overlook published pieces of literature on the subject for a variety of reasons. First, a considerable number of search strings and their synonyms can be related to the topic. For example, while there are authors who associate a ''recommender system'' as a ''recommendation system,'' others may denote it as a ''recommending system'' or an ''intelligence system'' (which can provide the recommendation), Etc. A complete list of significant phrases and synonyms was compiled to reduce the likelihood of overlooking crucial research publications. This list and study articles were then continually updated throughout the research process using the ''snowball'' technique, which employs clues from previous research papers. Table 1 displays the final lists of each keyword. This substantial number of individual keywords led to an even greater number of possible keyword combinations. Therefore, it is possible to overlook study material due to the absence of unique keywords and keyword combinations. In addition, with hundreds of thousands of results provided by a search engine such as ScienceDirect and IEEE Xplore, only the most relevant articles were evaluated; hence, the quality of the research is reliant on the effectiveness of the search engine. Consequently, it is possible that there are published articles in other libraries that have not been evaluated.

2) FUTURE RESEARCH OPPORTUNITIES

Various recommendations for future research possibilities have been made based on the findings and debate. Firstly, there is a chance to investigate alternative learning styles to contemporary theories, such as the Felder-Silverman's model is an integration of multiple learning styles theory. However, regardless of whatever learning styles theory is implemented, it is advised that future research highlight the advantages and disadvantages of the chosen learning styles theories. Secondly, one of the future study topics can focus on evaluating the performance of various identification ways of learning styles since this information can be utilized to build novel methods in addition to the use of a questionnaire. In addition, it is possible to use more complex approaches by combining several procedures. This idea can also be adapted for the recommendation algorithm, so there are many more opportunities for studying more advanced algorithms like ensemble and hybrid. Many educational suggestions that the established recommender system exploits learning styles are still in their infancy, necessitating more research and improvement.

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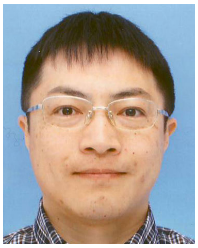

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