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What is needed to build a personalized recommender system for K-12 students' E-Learning? Recommendations for future systems and a conceptual framework

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Abstract
Online learning has significantly expanded along with the spread of the coronavirus disease (COVID-19). Personalization becomes an essential component of learning systems due to students' different learning styles and abilities. Recommending materials that meet the needs and are tailored to learners' styles and abilities is necessary to ensure a personalized learning system. The study conducted a systematic literature review (SLR) of papers on recommendation systems for e-learning in the K12 setting published between 2017 and 2021 and aims to identify the most important component of a personalized recommender system for school students' e-learning. Recommendations for later studies were proposed based on the identified components, namely a personalized conceptual framework for providing materials to school students. The proposed framework comprised four stages: student profiling, material collection, material filtering, and validation.

Keywords e-learning · Personalization · Recommendation systems · School · Systematic review

1 Introduction

The importance of e-learning has grown since 2020 due to the COVID-19 pandemic. Many countries were compelled to undergo complete lockdown during the crisis, including comprehensive movement control operations, and forcing educational institutions to shift from face-to-face to online learning (Radha et al., 2020; Su et al., 2021). The peak of the pandemic caused school closures that affected approximately

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1.6 billion students in 190 countries and regions, which resulted in the sudden expansion of e-learning (Tadeo, 2021).

The sudden change forced academic institutions to choose between available and affordable tools, such as social media platforms (Facebook and WhatsApp), video conferencing tools (Zoom, WebEx, and MS Teams), and learning management systems, namely Moodle, Blackboard, and Google Classroom. The transformation was poorly received by instructors and students due to the complexity of transitioning from traditional teaching and learning methods to technology (Almaiah et al., 2020; Hong et al., 2022). Furthermore, teachers received insufficient training. In traditional teaching, students' facial expressions are indicators used by teachers to gauge students' understanding of certain topics (Klašnja-Milićević et al., 2018; Zhu et al., 2020). Conversely, online tools complicate follow-up with students, specifically in large classrooms.

E-learning has overcome specific issues, such as following up with teachers and equipping students with the necessary knowledge through greater access to resources at any time and location (Almaiah et al., 2020). Nonetheless, students possess varying levels of learning ability, learning styles, and behaviors, which might lead to varying performance levels despite using the same materials and taught with the same approach (Premlatha et al., 2016).

Students may become distracted by the vast amount of information available online. Additionally, students may be unable to choose acceptable materials or sequences to employ those items (Venkatesh et al., 2020). Several studies have examined the challenges students encounter in e-learning environments (Ali et al., 2018; Almaiah, Al-Khasawneh et al., 2020), specifically lack of content interaction, adaptation to students' requirements, and content relevancy to students' needs and performance levels. Teachers were also unable to provide specialized instruction and tailored materials to each student due to inadequate time. Consequently, the need to offer materials to students that suit their requirements and level of performance has emerged (Rahman et al., 2018). Personalized recommender systems are thus an essential aspect of e-learning systems (Sarwar et al., 2019) to enhance student performance and to be in the hands of teachers.

Personalization has become increasingly popular in recommendation systems and services. Personalization guarantees that the quality of the service provided improves based on consumer satisfaction. Personalization results from suggestions based on user preferences that tend to satisfy their needs, which has been incorporated into various recommendation systems, including healthcare (Rohani et al., 2020), tourism (Missaoui et al., 2019), e-commerce (Dixit et al., 2020), and transportation (Borodinov et al., 2019). Thus, incorporating personalization into e-learning systems can provide learners or students with personalized resources tailored to their requirements and learning styles for high performance (Li et al., 2019).

The study conducted a five-year systematic review of personalized recommendation systems for e-learning in the school environment (PRS-ES) from 2017 to 2021 to determine the PRS-main ES components. The components were identified and the study provided recommendations for future PRS-ES. A conceptual framework was also presented based on the recommendations and addressed the following research questions to determine the main components of PRS-ES:

Q1. What are the “must exist” modules in PRS-ES?

Q2. What are the personalization features that can be used to ensure personalization?

The study contributed to PRS-ES research as follows:

1. Presenting a five-year systematic review focusing on schools.
2. Identifying the primary elements of PRS-ES systems for school dedicated systems.
3. Identifying the personalization features that should be used to ensure personalization and the measurement methods.
4. Proposing a conceptual framework for developing PRS-ES systems for schools.

A tailored framework for proposing materials to school students that is based on a methodical analysis of the works already published has effects on the students, the teachers and the system. (i) Students can increase their productivity, performance level, and knowledge while also developing their self-managed learning style. (ii) It can primarily save teachers’ time and effort. (iii) It might increase usage and efficiency for the system. (iv) The foundation of student profiling is personalization characteristics, which the framework employs to assure customisation.

The study comprised five sections. The first section presented an introduction while the remaining are organized as follows: Sect. 2 elaborates on the most recent systematic reviews with a comparison, Sect. 3 discusses the methodology used in conducting the systematic review, Sect. 4 presents the results and discussion, Sect. 5 proposes the conceptual framework, and the final section concludes the study.

2 Related work

Several systematic review articles on personalized e-learning recommender systems have been published in recent years, which differ in purpose, the covered range of years, digital libraries (DLs), and queries. This section discusses some of the most recent reviews. The systematic study aims to identify the main components and features of PRS-ES that ensure personalization and prioritizes school students’ characteristics and preferences for personalization.

Bernacki et al., (2021) conducted a systematic review on personalized learning (PL). The current study identified 376 studies that investigated one or more PL design aspects using the ERIC, PsychInfo, and IEEE DLs published from 2010 to 2018. The study compiled a list of the various PL definitions to guide implementation in education and reviewed key educational theories that facilitate design and implementation. However, the study did not focus enough on the learner’s characteristics or knowledge level. The collected papers targeted k12 and higher education learners with varying learning needs and preferences. Although the search query includes words, such as “personalization,” “personalized learning,” and “personalized instruction”, future studies should further examine keyword approaches to capture personalization and adaptivity as they involve human subject research in the learning process and its outcomes to manage challenges with the many relevant keywords.

Raj et al. (2021) examined the customized content recommenders in PL environments in 52 journal papers from the Science Citation Index (SCI) and Scopus-indexed journals. The main goal was to examine and describe the research in PL environments between 2015 and 2020 and identify the various e-learning content recommendation strategies, personalization parameters, models, algorithms, and evaluation measures. Nevertheless, the study did not examine a specific type of learners, such as school students or the specific student characteristic that plays a major role in creating a highly personalized e-learning system. One of the students' features that ensure personalization is the learning path, which presents the sequence of materials that students consider through the learning process. MacHado et al. (2021) reviewed learning path recommendations over five decades of studies ranging from 1971 to 2021 but most included papers were from 2014 to 2020.

Xie et al.'s (2019) systematic review of learners from elementary and higher education involved many topics, including PL parameters, learning aids, learning outcomes, subjects, participants, and hardware. The study collected journal papers from 2007 to 2017, while the concept of personalized e-learning changed during that period. The collected papers were only from one index–the Web of Science, which only included the most reputable journal articles. Sajjad et al. (2021) presented a systematic review of the recommender systems for massive open online courses (MOOCs), which were web-based distance learning programs for large groups of students that were geographically dispersed.

Khanal et al. (2019) focused on the approaches used in the recommendation process and developed machine learning (ML) based recommendation systems for e-learning to develop adaptive or personalized e-learning systems. The study identified 35 papers from 2016 to 2018 from Q1 and Q2 journals and obtained 10 papers as a final set. Nonetheless, none of the aforementioned reviews emphasised K-12 school students. School students differ from higher education students due to different learning systems in most countries with different needs, preferences, abilities, and goals (Emanuel et al., 1992; Tüysüz et al., 2010). Western Sydney University and the University of Adelaide mentioned that universities and schools differ in many aspects. The timetable of school students is fixed while the timetable in universities is flexible as students can control and choose the courses. Additionally, teachers provide regular homework to school students who are often guided towards task completion. Meanwhile, university assignments will be known in the first week and the students are responsible for completing and submitting them within the stipulated time. Regarding the student-teacher relationship, school teachers provide regular and direct guidance and feedback to students while university students obtain feedback through assignments.

The study specifically targeted school students from all levels: elementary, primary, and secondary students. The studies were retrieved from five DLs (ACM, Web of Science, Scopus, Science Direct, and Springer) from 2017 to 6th November 2021.

Table 1 Keywords and digital libraries

Year	2017–2021
Search terms	((personaliz* OR personalis* OR customiz* OR customis*) AND ("e-learning" OR "online learning" OR "distance learning" OR "virtual learning" OR "web-based learning" OR "internet-based learning") AND recomm* AND ("secondary school" OR "elementary school" OR "primary school" OR "k12"))
Digital libraries	ScienceDirect, Springer-Link, Web of Science, ACM, Scopus

3 Methodology

The SLR followed Kitchinham guidelines (Kitchenham et al., 2010). Initially, the SLR has followed a comprehensive review protocol that includes various stages to minimize the likelihood of bias in the literature. First, the SLR research questions and DLs were identified and utilized to retrieve studies. Subsequently, the study specified the search procedure, inclusion and exclusion criteria, and quality assessment criteria to filter the studies most relevant to the phenomenon of interest. Finally, the required data were extracted from the selected studies to address the SLR research questions. The following sections clarify the methodology applied in conducting the SLR.

3.1 The DLs and keywords

Five leading databases were chosen for the SLR as they contained studies on state-of-the-art personalized e-learning recommendations. The DLs are ScienceDirect, Springer, Web of Science, ACM, and Scopus. The study identified relevant keywords to retrieve research from 2017 to 2021 with the Boolean operators AND/OR used interchangeably on the keywords (see Table 1).

3.2 Inclusion and exclusion criteria

The study initialized different inclusion and exclusion criteria to determine the relevant studies within the research boundaries. The study applied the identified inclusion and exclusion criteria for retrieving English publications from peer-reviewed conferences and journal articles. Each article was scanned based on the inclusion and exclusion criteria. The article was included if it matched all the inclusion terms and none of the exclusion terms. The retrieved articles were related to computer science, engineering, and educational technology domains. Moreover, the duplicated articles or book chapters, discussion notes, or reports were excluded from the study. Table 2 lists the eligibility criteria applied in the study.

3.3 Study selection and data analysis

The study performed various steps to select the most relevant studies aligned with the SLR objectives using the above-mentioned inclusion and exclusion criteria. Figure 1 depicts the steps undertaken to select related studies. First, 780 articles were retrieved

Table 2 Inclusion and exclusion criteria

Inclusion criteria
IC1: Publication date 2017 to 2021 (both years inclusive).
IC2: Conference proceedings AND Peer-reviewed journal articles.
IC3: In English and accessible.
IC4: The study proposes PRS.
IC5: The study targets primary school, secondary school, or elementary school students.
Exclusion criteria
EC1: Gray literature.
EC2: Not in the English language.
EC3: The study that proposes a recommendation system BUT does not focus on personalization or e-learning.
EC4: The subject is personalization BUT in fields other than recommendation systems.
EC5: The study that targets populations other than school students, such as teachers, training, disability students, group students, post-graduate or undergraduate students, and researchers.
EC6: A duplicated study published in different venues (reporting similar results).
EC7: Conference papers that extended to journal papers.

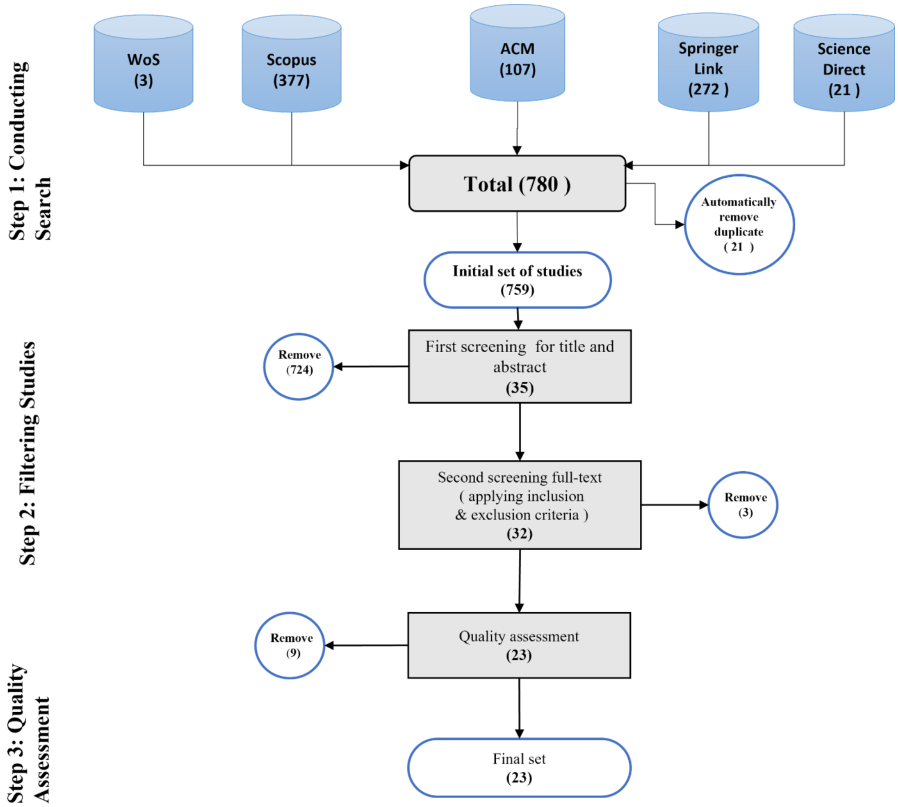


Fig. 1 The SLR phases and study selection

Table 3 Quality assessment criteria

Study ID	QA1	QA2	QA3	QA4	QA5	Total	Include/exclude
1	1	1	1	1	1	5	Include
2	1	1	1	1	1	5	Include
3	1	1	0.5	1	1	4.5	Include
4	0.5	1	0.5	1	1	4	Include
5	1	0.5	0.5	0.5	1	3.5	Include
6	1	1	1	1	1	1	Include
7	1	0.5	0.5	0	0.5	2.5	exclude

from the specified DLs using the identified keywords. Subsequently, independent researchers meticulously scanned the article titles and abstracts. Some articles were irrelevant to the state-of-the-art and excluded from the SLR (724 studies), thus minimizing the number of articles to 35. The small number of articles was due to most articles being related to the field of recommendation systems for e-learning dedicated to universities or MOOCs. The study critically scanned the full content of each included article in the second step of filtration. Thus, three studies were categorized as irrelevant and included 32 studies with strong relevance to the SLR objectives. Finally, the study applied quality assessment criteria to assess the quality of each selected article and obtained 23 selected articles. Figure 1 illustrates the filtration of articles and selection procedure.

3.4 Quality Assessment

The quality assessment stage is crucial as it assessed the included studies to analyze the findings and interpretations (Kitchenham et al., 2010; Nidhra et al., 2013). The study identified Zayet and Al-Madi's five quality assessment (QA) criteria to assess the relevant studies.

QA1: Are the study objectives and goals clearly defined?

QA2: Does the study clearly state the research methodology?

QA3: Are the study contributions and limitations clearly stated?

QA4: Are the data collection procedures and results clearly explained?

QA5: Does the study mention how the personalized recommendation system is built?

The quality assessment procedure was conducted through three quality rankings: "high", "medium", and "low" and applied to each QA criterion (Nidhra et al., 2013). A score of 1 is given to the study that comprehensively satisfied the quality criterion. Similarly, 0.5 is assigned to a quality criterion that partially satisfied the study. A score of 0 is assigned to the quality criterion that has not been satisfied. Thus, 5 is considered the highest score, while 0 score is the lowest. Depending on the coding scheme, the assessed study with a score of >4 is considered high quality. The assessed study with a score of <3.5 to >2.5 is considered medium quality, while the study is considered low quality if the score is <2.5. Table 3 presents various examples of quality assessment results for seven studies. Ultimately, 32 studies were high, medium, and low quality, while nine studies were excluded for being low quality.

3.5 Data extraction

The data extraction stage extracted the required data from the selected studies. The study created a form to record the data extraction of 23 articles for data collection completeness (Kitchenham et al., 2010). Several critical elements were identified for data extraction: study ID, types of system modules listed in the study, types of personalization features, students' characteristics, and type of recommended items or context. Finally, the content of the remaining studies was carefully reviewed and analyzed to accurately extract the data for each identified element.

4 Results and discussion

The systematic review findings are presented and discussed in this section with recommendations for further study and the development of recommendation systems. Table 4 summarizes the final collection of papers and the proposed system and personalization feature that was used. Each personalization feature is associated with the students' characteristics to ensure its usage and measurement. The discussion focused on the main modules and features employed to ensure personalization following the study theme. Section 4.1 and 4.2 addressed the research questions (Q1 and Q2) mentioned in the introduction section, respectively. Section 4.1 presents the identified primary modules of the PRS-ES system and Sect. 4.2 demonstrates the identified personalization features used in the articles. Improvement issues concerning future systems were identified and presented as suggestions for later systems during the analysis process in Sect. 4.3. Figure 2 displays the trend of final papers set over the last five years.

4.1 The PRS-ES: main modules

Each system is formed from modules that are in charge of a set of duties usually tied to one of the system actors. Three primary elements (see Table 4) are needed to ensure personalization in the e-learning recommendation system: student profiling, collection and processing of materials, and recommendation generator.

I. Student profiling module: The module is considered the most crucial as it determines which items are recommended. Students' attributes are defined and assessed in the student profiling module, which describes students' interests, needs, performance level, knowledge points and level, learning style, and other individualized aspects. The qualities were utilized to suggest appropriate materials or learning paths to each student to improve their performance and understanding. The module is present throughout the publication, as presented in Table 4.
II. Material collection and processing: The resources for the module are the recommended objects for the students gathered from various sources, including teachers, the internet, and the students. Teachers will usually supply pupils with at least the most basic materials, such as textbooks, syllabuses, notes, and previous tests.

Table 4 The final set of papers

Reference	Modules	Personalization features	Students' characteristics	Recommended Item
(Kopeinik et al., 2017)	material repository, tags repository, frequent tags extractor, domain modeling, tags recommender	tagging	used tags by the student	suitable tags for the uploaded materials
(Mutahi et al., 2017)	user manager, content manager, attention manager, context manager, notification manager	performance	content interaction patterns, comments, questions, affective state	resource and activity
(Wongwatkit et al., 2017)	learning diagnostics module, learning style diagnostics module, mastery learning-based guided-inquiry learning mechanism module	learning problems, learning styles	current understanding	learning activities
(Gong et al., 2018)	knowledge component recognition, knowledge graph, exercise generation	proficiency level	time spent on exercises, score, the ability of memory	exercises with a suitable degree of difficulty
(Hongthong et al., 2018)	mobile application with four main modules, including interfacing, content repository, student assessment, and student feedback response modules	performance and preferences	score	guidance to cyber security awareness
(Klašnja-Milićević, Ivanović, et al., 2018)	learner module, domain module, application module, adaptation module, the recommendation module	interests and knowledge	needs and previously acquired knowledge	learning content
(Klašnja-Milićević, Vesin, et al., 2018)	learner-system interaction module, recommendation module [tags recommendation - recommendation of resources - reports generator], data storage module [tag repository - learner model]	educational goals, learning history	used tags	learning resource, tags

Table 4 (continued)

Reference	Modules	Personalization features	Students' characteristics	Recommended Item
(Perišić et al., 2018)	learning object module, student module, user interface module, adaptation module, visualization module, and reporting module	learning style	general information (name and surname, date of birth, email, interest), learning progress (average grade, learning style, time spent in the course, action), information about the student's actions (viewed, loaded, deleted, graded, submitted, posted), duration of the sessions, learning object attendance, time spent on the learning object, and number of visits of the learning object	learning material, semantic report
(Lee et al., 2018)	contents registration, management, and recommendations	learning history	video contents data, types of similar contents, sharing subjects, contents log, satisfaction, and comment data	learning video contents
(Guan et al., 2019)	personal information management, learning course plan management, course selection, assessment, achievement management, learning ability identification	learning ability	knowledge points, length of course learning, number of the learned courses, course credits, specialty	personalized curriculum
(Troussas et al., 2019)	students' repository, students' modeling, materials generator, recommender, hints, and trophies repository	knowledge level, learning style	age, (pre-existing knowledge on a domain, current knowledge level, knowledge level on previous concepts (scores and concepts)), preferred learning styles and techniques	individualized hints, possible collaborators, learning material, trophies

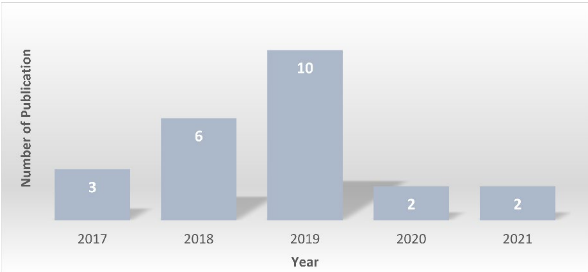
Table 4 (continued)

Reference	Modules	Personalization features	Students' characteristics	Recommended Item
(Mimis et al., 2019)	students' repository, students' modeling, rank prediction, the recommendation module	performance level	score (national baccalaureate score, first-year score, score of class council of the second year), students ranking in accordance to other students, quarterly rank in each subject, (age, social motivation)	guidance to a career path
(Jagušt et al., 2019)	communication (server communication, lesson delivery, group work delivery, and progress monitoring modules), central (database, multimedia content repository, event log), adaptivity and aggregate data calculation, (lesson authoring and conducting, and lesson management (for teachers))	performance level, knowledge level	relative score to other students, time spent on tasks, activities solved	activity, visual representation of a lesson, suitable time to finish an activity
(Ch et al., 2019)	sentence reformation, summarization, factual sentence identification, trial test generation and evaluation, identification of the less confident portion	performance level	score (of the provided trial exams)	sections to revise
(Bhaskaran et al., 2019)	System interaction module, Off-line modeling, Recommendation engine	learning style and knowledge level	personal data, preferences, dominant meaning words, behavior	courses
(Fakooa et al., 2019)	student ontology, English verb ontology, admin panel, ANN module	learning style, level of knowledge	A score of quizzes, time spent on the quiz, text, and visual contents	quizzes and verb ontology
(Segal et al., 2019)	difficulty ranking module, the recommendation module	student performance	grades, number of retries, and time spent solving questions.	suitable problem sets or exams to student's ability, topics to strengthen
(Nian et al., 2019)	recognition module of expression information, the personalized recommendation module	performance, emotions	score, expression	courses
(Troussas et al., 2019b)	students' module, domain knowledge adaptation module, assessment adaptation module, advice provider module	knowledge level and preferences	scores	personalized guidance and questions
(Saito et al., 2020)	clustering module, prediction module, the recommendation module	submission history, ability chart	scores, current knowledge, goal	learning path recommendation
(Ma et al., 2020)	advanced automated assessment module, peer tutor recommender module	learning performance	scores	peer tutor

Table 4 (continued)

Reference	Modules	Personalization features	Students' characteristics	Recommended Item
(Nurzaman et al., 2021)	students modeling, learning style identification, material repository, assessment, recommender	performance level, learning style	score (from teacher and systems)	learning resource
(Y. Zhang, 2021)	students' repository, resources repository, model generator, recommender	Students' history	Students' evaluation score for each resource	auxiliary English teaching resources

Fig. 2 The trend in the selected publications over the past five years



The system can automatically collect resources from the internet using scraping techniques and students may share such resources with their peers. The material collector sub-module is where the collection takes place. Subsequently, the materials were treated and examined. The scraped and shared resources must be screened and validated as the internet provides a great number of resources and students may upload or share irrelevant resources, thus necessitating the use of a sub-module known as material validation. Finally, material profiling determines the material topic. The material profile may also include information, such as the number of views, average rating, average time spent on the material, frequently asked questions about the material, the average difficulty level of the material, the performance level of students who typically view it, a summary of the material, and sub-subjects of the material. The information improves individualized recommendations for each student in the future.

III. Recommendation generator: The stage determined which items were recommended to each student based on their needs and preferences, hence making it a "must" in the recommendation system (see Table 4). The step involved the use of data mining (DM) and ML techniques and one or more recommendation approaches, such as collaborative filtering, content-based filtering, context-based filtering, knowledge-based filtering, and hybrid approaches.

4.2 The PRS-ES: personalization features

Personalization features are features that the system uses to ensure personalization and are the core of student profiling. The system determined the most suitable material or task for the specific student based on the personalization features. Figure 3 displays the trend of the main used personalization features over the reviewed literature.

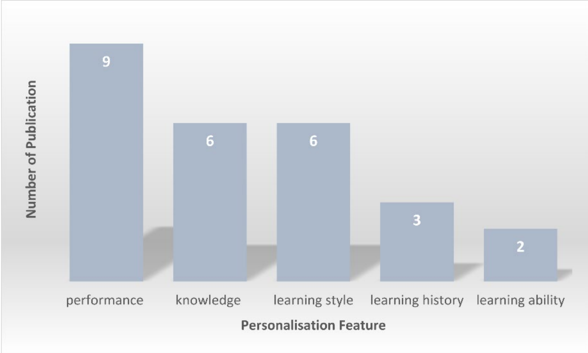


Fig. 3 The distribution of the personalized features over the publications

I. Performance level: The degree of students' performance is a typical personalization characteristic utilized in e-learning recommendation systems as the primary goal of the systems is to improve students' performance. Students' scores are a frequent individualized feature utilized to assess their performance level. Nonetheless, utilizing scores as a single indicator of students' performance is inaccurate due to the student's psychological state during the tests (Mudenda et al., 2020). Other personalized characteristics should be used to obtain a more precise performance levels measurement, such as students' content interaction patterns, comments, questions, affective state (Mutahi et al., 2017), time spent on activities or materials, number of solved materials (Jagut et al., 2019), and students' expression (Nian et al., 2019).

II. Learning style: Learners' preferred learning strategies and styles often vary. The type of content (visual, textual, and aural) is usually related to learning style where some students prefer to learn through images, hearing, demonstrating, or a combination of the methods (Troussas et al., 2019a). Two approaches determine a student's learning style (Fakooa et al., 2019): manual and automatic. Students submit input on their learning style via a form or questionnaire in the manual technique, while the system updates the students' learning style based on their learning behavior in the automatic method. Researchers have employed a human method to determine the preferred learning style of the initial students and used an automatic method to update and confirm the original learning styles (Bhaskaran et al., 2019; Perišić et al., 2018). Others relied solely on the automated way to obtain the information (Fakooa et al., 2019).

III. Learning ability: Multiple elements, such as overall performance level, knowledge level, and achievement rate or level interfere with determining the learning ability (Guan et al., 2019). Hence, the number of items learned over time is a significant determinant.

4.3 The PRS-ES: recommendations for later Systems

The study provided suggestions for developing new recommendation systems to ensure the delivery of more tailored resources based on two categories: recommendations on student profiling and recommendations on material processing.

4.3.1 Recommendations on student profiling level

Considering that student profile is the most important aspect of the recommendation system, the feature requires more improvements to ensure that students are provided with the most appropriate materials. The aspect has potential for development. Many proposals have been researched but require further efforts and improvements as the followings:

I. Identifying the difficulty level of each task or material by each student: The difficulty level of each task or material cannot be generalized due to the diversity of students' abilities, performance levels, and knowledge levels. The difficulty level should be tailored to each learner instead of generalization (Segal et al., 2019; Yaqian Zhang et al., 2021).
II. Identifying the performance level by considering more factors other than scores: As stated in Sect. 4.2, scores may not be a precise indicator of a student's performance level as the score can be influenced by anxiety and other psychological issues. Therefore, other factors should be used to measure student performance, such as knowledge level, time spent on a task or material, number of views of the material, rating of the material, and students' questions and comments (Mutahi et al., 2017; Perii et al., 2018; Fakooa et al., 2019; Chang et al., 2022).
III. Diagnosing the students' ability: Ability is a broad term that refers to critical thinking ability, ability to comprehend a topic, and ability to memorize (Burin et al., 2021; Supriyatno et al., 2020; Yaniawati et al., 2020). Thus, recommendation systems detect students' talents automatically and make individualized suggestions to improve them (Gong et al., 2018; Saito et al., 2020).
IV. Diagnosing student learning style: Various materials, including text, audio, interactive games, and video are available. Different students prefer to obtain information through various types of materials. "Automatically" identifying the desired and appropriate materials for each student improves the recommended resources. Hence, the process enhances students' performance and knowledge levels (Rasheed et al., 2021).

4.3.2 Recommendations on the material processing level

Material processing prepares resources recommended to pupils. Material profiling is the most important process in material processing. The following suggestions are made to improve material profiling and recommendation results:

I. Creating the materials graph: Gaining information through learning is an accumulative process, hence many materials can be a prerequisite for others. The relationships between the topics of the materials should be recognized (Su et al., 2020) and presented in the form of a directed graph.
II. Assigning the general difficulty level of the material: Identifying the material difficulty level determines the target group of students for material recommendations. Teachers can manually determine the general difficulty level or automatically via

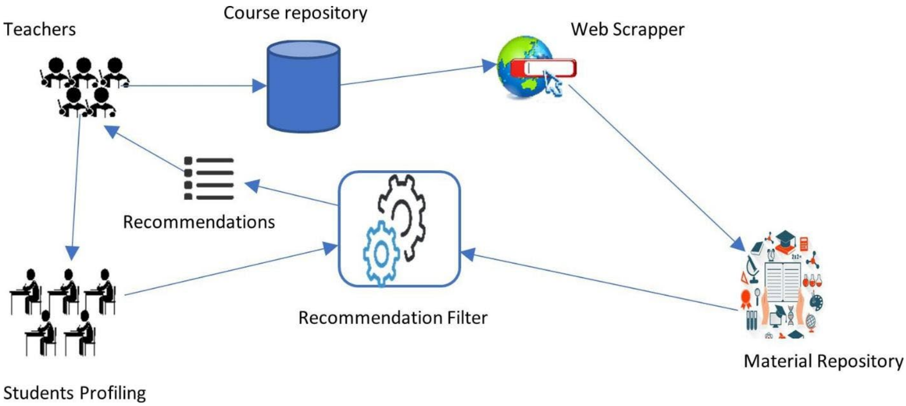


Fig. 4 General Architecture of the proposed system

systems. Comments, reviews, ratings, number of views, content, inquiries, and other factors can be used to automatically assign a difficulty level.

III. Using augmented reality technology: Many courses and classes require practical experience, specifically science-related ones, such as physics and chemistry. Students cannot undertake experiments in most e-learning environments given that experiments require specialized equipment and usually involve experimenting without the teacher's direct supervision, which could be unsafe. Students can conduct experiments safely and interactively using augmented reality (El Kabtane et al., 2018; Marienko et al., 2020; Rongting et al., 2016; Wu et al., 2019).

5 Proposal of material recommendation system architecture

The study proposed the overall design of the material recommendation system for the school by considering the prior proposals. The technology personalizes the learning experience for students by offering appropriate content depending on their performance and needs. The suggestion procedure is semi-automated as the process involves teacher monitoring. Figure 4 depicts the overall module architecture as follows:

I. Course repository: data provided by teachers, such as course syllabus, basic materials, exams, and grades.
II. Students profiling module: The module provides student information, such as material history, performance level (updated by the system regularly), material rank, and grade. Part of the information was provided by students while others by teachers.
III. Material repository: The module contains the materials retrieved from the internet and recommended to the students. The module also contains reviews and ranks from other reviewers and students.

IV. Recommendation module: The module is responsible for producing the recommended materials for each student using DM and artificial intelligence approaches.
V. Validation module: Validation of the recommended materials to each student by teachers.

5.1 Conceptual framework of the proposed architecture

The previously presented architecture conceptual framework involved four primary stages: student profiling, material collection, material filtering, and material validation. The student profiling stage oversees the generation of information about students' needs, performance levels, and academic history using ML and DM approaches.

In the material collection stage, DM was used to produce the keywords of courses. The keywords were used to create the queries that were utilized in the material search process. Subsequently, all of the retrieved materials were gathered in a repository. The DM and ML play the most important role during the material screening stage. The ML techniques were utilized primarily to filter the materials in the repository at the stage to select the most appropriate materials for each learner. The chosen materials were validated by teachers who determined whether they benefit the identified students. Each stage is explained in detail in the sub-sections below.

5.1.1 Students profiling

The stage is primarily responsible for profiling information on students, such as their level of performance, subjects chosen, and material history. Some data were entered by students or teachers, while others were identified through DM and ML techniques. The three types of student information are presented as follows:

I. Personal information: Includes students' gender, name, and grade (level of study). The students entered the information through a separate form or read from the school database.
II. Session information: The recommendation system heavily relies on session information. The system provides information about any activity that the student engages in, such as the materials that each student has used, ratings, comments, and the number of views. Summarily, the system contains information on the student's history.
III. Performance information: Students' performance information was divided into two parts: explicit and learned. The explicit part was entered by teachers or the system through the generated exams and quizzes and includes data, such as students' marks for each question, exam, and course. Meanwhile, the learned performance utilized the session information apart from the data of the studied materials to learn the student performance through DM and ML approaches.

5.1.2 Material collection

The materials indicated each course-related item including visual materials, such as videos, reading materials, such as reports, articles, and books, or interactive materials, such as games. The materials were suggested to the students and gathered from the following two sources:

I. Materials provided by teachers: Teachers provided materials to students in the study framework, namely basic materials, such as textbooks, lecture notes, additional questions, and exam samples.
II. Materials collected from the internet: The teachers' materials and course information were used to generate queries, which were used to search the internet for similar resources. Finally, a web scrapper was used to collect the materials and their associated data and placed in the materials database. The DM techniques were used to extract keywords from the material provided to develop queries.
III. Materials generated by the system: The exams, quizzes, and other materials were generated by the system to suit each student.

5.1.3 Material filtering

The filtering stage entailed the production of the recommendation. The outcome of the stage is a list of recommended materials for each student, which contains four modules as follows:

I. The content-based module: The module is responsible for analyzing the contents of the materials and representing each material with a set of keywords and assigning them to topics and courses.
II. The collaborative module: The module used the ratings, reviews, and number of views of the materials in the student's history.
III. The contextual module: The module used the students' marks and level of performance.
IV. The serendipity module: The module used the publicity of the materials and their reviews in the material database.

The DM and ML approaches were used in all of the above-mentioned courses. The first three modules shaped students' study habits and performance and generate sequential study patterns for each student. The sequential patterns included a list of materials that the student should consider.

5.1.4 Validation of the recommended materials

Teachers recognized students' weaknesses and strengths and the material filtering stage is useful in finding suitable materials for individual student use by checking the materials beforehand. Therefore, students can view only the materials approved by teachers. Teacher approval of the materials was considered feedback to the system to periodically enhance the recommendation list.

6 Conclusion

The study conducted an SLR on PRS-ES. The study identified the system primary components in providing recommendations for developing individualized e-learning recommendation systems. The review was based on articles published between 2017 and 2021 with a focus on publications related to the school setting. The total number of papers reported in the study was 23 based on the screening and quality assessment of the papers.

The study suggested a personalized conceptual framework to recommend materials to school students based on the proposed recommendations. The framework operates in a semi-automated mode with certain activities requiring human intervention and others being completed automatically. The four primary stages of the framework are student profiling, material gathering, material filtering, and result validation.

The proposed personalized framework can improve student engagement, performance, and knowledge as student behavior, requirements, preferences, background, learning style, and ability are considered. Furthermore, the study focused on school students and presented recommendations for future research directions, hence paving the way for more research.

Future research should adopt and test the proposed framework with the aid of teachers and students in Malaysian high schools. The goal of the implementation is to determine the effectiveness of the proposed framework in assisting students' e-learning. The results are limited based on the review of past literature, thus the study proposed data collection using survey forms and interviews with students and teachers to improve the proposed framework. Additionally, the technique will provide an avenue to identify real needs and preferences and understand the real situation in teaching and learning systems.

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Data availability "The data that support the findings of this study are available from the corresponding author upon reasonable request".

Declarations

Conflict of interest The authors have no conflicts of interest to declare.

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