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Adaptive Learning for Complex Thinking: A Systematic Review of Users' Profiling Strategies

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Abstract

Adaptive learning strategies applied to e-learning have become a relevant approach towards diversity and inclusion. They bring several benefits to learners in the role of digital platform users, related to the user experience, primarily in the learning process optimization. It aims to provide mediation, tailored content, and adequate channels for users' capabilities and learning styles. The OpenEdR4C is a digital open educational platform designed to expand complex reasoning skills in students and lifelong learners of higher education. The platform addresses five types of learning obstacles: sensory limitations, learning styles, sociodemographic and socioeconomic contexts, and certain kinds of neurodiversity. All these considerations require a dynamic and assertive user profiling strategy to provide compelling adaptive learning experiences. This paper presents a Systematic Literature Review of user profiling strategies published in the last five years in SCOPUS and Web of Science databases. The findings allowed us to identify successful and applicable strategies that the OpenEdR4C research and development teams might use to select and shape the suitable strategy for the platform in two levels: a) procedures that favor the user to self-declare their profile and preferences; and b) profiling based on the system's detection of patterns and behaviors shown by the users. The results and discussion presented are valuable insights for educators, developers in the context of open educational resources design, and decision-makers of HiEd institutions or training centers. There is a suitable strategy for every type of profiling necessity; here is a combination of many to be used and developed collectively.

Keywords: *Adaptive learning, complex reasoning, educational innovation, higher education, user profile, digital platforms.*

Introduction

Adaptive strategies applied to e-learning have become a popular and practical resource for promoting diversity inclusion and optimizing the learning process. It allows learners to take the most advantage of the resources at their reach (Demartini et al., 2020) by adapting the pace and the delivery channels to learners, improving the overall user experience (UX) across the delivery learning methods, content, feedback, and support (Crompton et al. 2020). As an assistive service

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embedded in educational platforms, Adaptive Learning (AL) strategies enable offering "effective personalized experience for every student, creating customized resources and activities that address each student's unique learning needs" (Muñoz et al., 2022, p. 222). The aim is to mediate (Riofrio-Calderon & Ramírez-Montoya, 2022) between the user capabilities and conditions and the system's functionalities (Alvarez-Icaza et al., 2023) all throughout customized content and appropriate channels for users' capabilities and learning styles. A profiling strategy is necessary to select learning paths based on learning types and establish the users needing these adjustments.

According to Martin et al. (2020), the pedagogical model (Instructional Model in their article) assists in defining the types of adaptations and how and when they must be reached and offered. These considerations require a dynamic and assertive user profiling strategy (Normadhi et al., 2019) to provide compelling adaptive learning experiences. This paper presents a Systematic Literature Review (SLR) of user profiling strategies published in the last five years in SCOPUS and Web of Science (WoS) databases. This study contributes and builds upon other previous reviews regarding the relevance of this topic in specific areas, such as learning styles (Katsaris & Vidakis, 2021), machine learning systems (Khanal et al., 2020), and components and frameworks (Rozi, Rosmansyah & Dabarsyah, 2019). Acknowledging that the one-size-fits-all approach is no longer valid, the search for adaptation strategies is articulated through multiple indicator combinations.

The objective of this study is to identify effective and applicable strategies for the OpenEdR4C platform (Figure 1) research and development teams to select and shape the profiling paths in two dimensions: a) procedures that allow the user to self-declare their profile and preferences; and b) profiling based on the system's detection of patterns and behaviors shown by the users. The differential value of this study is linked to the potential of replicating the identified profiling tasks and applied tools to create customized learning paths in e-learning environments. The results and discussion presented are valuable insights for educators and developers in the context of open educational resources design and decision-makers of HiEd institutions or training centers.

Figure 1. OpenEdR4C Platform. Course selection page. Source: R4C Interdisciplinary Research Group.

The purpose of the OpenEdR4C educational platform is to offer personalized routes and content for participants for their complex thinking sub-competencies scaling-up: scientific thinking, systemic thinking, critical thinking and innovative thinking. Complex thinking as a mega-competence allows the visualization of scenarios to find solutions to complex problems affecting the world and societies' wellbeing (Ramírez-Montoya et al., 2024). As each person might have different levels of this sub-competencies development, it becomes relevant to provide learning alternatives and adaptive features to foster efficient processes in the abilities and skills acquisition.

Framework

Adaptive Learning Benefits

Today, "technology is heavily utilized in education in terms of the tools and methods employed to enhance teaching and learning" (Muratbekovna et al., 2009, 113). As a part of the growing technology used in education, e-learning systems aim to facilitate learning online through online technologies (Garrison, 2017). To accomplish this task requires interrelations among critical elements, such as pedagogical practices and information technologies, resulting in highly complex systems. Providing more effective and pleasant cooperation between person and machine (Medina-Medina & Garcia-Cabrera, 2016) is vital to promote learning. Let's assume that a large number and diversity of users utilize these systems. In that case, their satisfaction can be achieved by employing flexible processes that adjust the learning system's appearance and functionality to the specific features of each user.

Adaptive learning systems aim to provide individualized and differentiated instruction for diverse learners (Chien-Chang et al., 2023). There is much agreement on the benefits of adaptive learning (Liu et al., 2017), which include increased efficiency and efficacy of the learning process (Imhof, Bergamin & McGarrity, 2020), improved student performance and engagement (Mahesa, 2023), as well as automated tracking and reporting (Harrigan et al., 2009). Furthermore, due to the progress of technology, adaptive learning systems are becoming ubiquitous, and they contribute to reducing inequalities in education due to poor geographic access, rural-urban disparities, and socioeconomic inequity (Wang et al., 2023).

The benefits of adaptive learning systems are made possible by their capacity to dynamically adjust how content is delivered to students (Osadcha et al., 2020). A key element for achieving this dynamic personalization is the user profiling strategy for understanding the specific characteristics of learners (Altun, 2016). The profiling strategies can differ in the tool used to extract the data, the type of data collected, and its source, whether it comes from the student's behavior or context, learning styles, capabilities, or preferences.

Self-Declared Profile

One functionality of adaptive learning systems is the self-declared profile, which refers to users or learners voluntarily providing information about themselves in a digital educational context. From the learner model point of view (Alshammari et al., 2015), the adaptive learning environment should incorporate knowledge and personal traits of the learner, such as learning styles and cognitive level characteristics. Likewise, in order to build an optimal learner profile, the information provided by the user should consider aspects such as their interests, learning strengths, preferences, and motivations (Peng et al., 2019) so that the learning system can adapt to their needs (Afini Normadhi et al., 2019). Thus, the characteristics provided by the user will define the learner as an individual and distinguish them from others concerning how they use sensory information to generate learning.

The ways of learning, or learning styles, have been approached from many different theoretical perspectives and proposed by other authors. It is possible to recognize the influence of Howard Gardner (2000) in education with his proposal of multiple intelligences; however, the VARK model (Fleming, 2001) is one of the most widely used in such a context as well as other areas (Luangrungruang & Kokaew, 2022). The VARK model classifies students according to their learning preferences: visual, auditory, reading/writing, and kinesthetic (Fleming, 2001; Cabual, 2021). According to this model, those who consider themselves visible will prefer materials such as maps, graphs, illustrations, or diagrams; auditory learners will most enjoy being part of discussions, debates, and stories; readers/writers will prefer essay-type activities, reports, print readings, and note-taking; and finally, kinesthetic learners will select activities where they can "do" things directly, such as field trips or laboratory activities that stimulate their senses (Subagja & Rubini, 2023). While the literature on learning styles has been under discussion, the consideration of individual differences in teaching and learning processes highlights the importance of pedagogical strategies to meet the varied needs of learners in a personalized manner.

The purpose of a personalized learning experience is, as far as possible, to meet the needs of each learner engagingly. Therefore, the personalization of the learning environment starts with an appraisal of one or more aspects of a learner and should guide how a learning environment adjusts the learning experience by implementing one or more modifications (Walkington & Bernacki, 2020; Zheng et al., 2022). This personalized learning approach, in addition to interests, strengths, and needs, favors content mastery, and allows users to influence what, how, when, and where they learn (Bernacki et al., 2021), achieving a combination of automated and learner-centered pedagogies (Lokey-Vega & Stephens, 2019). By receiving content selected for each profile, users increase their motivation and engagement and become more aware of their strengths and weaknesses in the learning context.

Correspondingly, personalized learning based on the self-declared profile takes on greater importance regarding inclusion. Although the attention of students with disabilities is increasingly considered, their proportion in schools is small, and their information is often subject to privacy protection (Basham et al., 2016). Therefore, it is necessary to consider the development of a framework that considers vulnerable and disabled users for the personalization of learning processes and, thus, avoids digital exclusion (Alshammari, 2020; Basham et al., 2016; Pérez-Escolar & Canet, 2023). By fostering self-determination and customization, a self-declared profile is a valuable tool to optimize personalized learning in higher education, contributing to an inclusive and equitable student-centered educational environment.

Method

Research Design

This study employs a Systematic Literature Review (SLR) to identify and analyze user profiling strategies for adaptive learning systems, focusing on those strategies that potentially would aid in the development of complex thinking skills. The SLR methodology follows the PRISMA guidelines (Moher et al., 2009) ensuring a comprehensive and unbiased review of the literature. According to the PRISMA statement, it can address questions for a specific intention within a research field, thus allowing a correct problem formulation through research questions (Page et al., 2021). For this study, we followed the protocol proposed by Kitchenham (2004), following a five-step process: (1) identification of research terms in databases; (2) selection and filtering of studies; (3) quality assessment; (4) data extraction and monitoring; and (5) data synthesis.

Data Collection Tools

The primary sources of data for this review were the Scopus and Web of Science (WoS) databases. These databases were selected due to their extensive coverage and relevance to contemporary research, both databases are positioned as the most comprehensive sources and have corresponding metadata (Pranckutė, 2021). These databases are complementary yet not mutually exclusive. Therefore, the search showed some duplicates, but the entire database was completed in terms of span and number using the two sources.

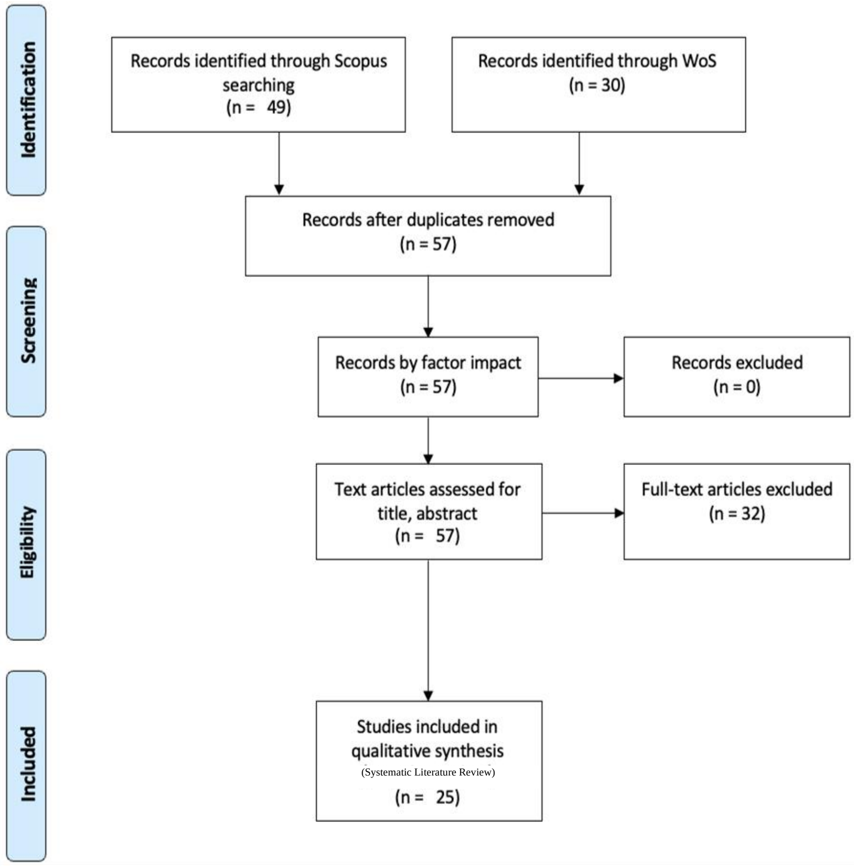

Figure 2. PRISMA 2009 flow diagram for the systematic literature review (Moher et al., 2009).

The search strings in the fields Title, Keywords, and Abstract included the keywords "profile" and "adaptive learning" for both databases. Documents from 2019 to 2023, only articles in English or Spanish, were selected.

Data Collection

The data collection process involved multiple steps to ensure the relevance and quality of the included studies. Initially, 79 articles were retrieved: 49 of them in Scopus and 30 in WoS. The PRISMA flow diagram (2009) shown in Figure 2 explains the exclusion of 22 documents due to duplicate extraction; it also indicates that 32 papers were eliminated after reading and analyzing the abstracts or the entire document. It was found that 26 studies did not combine adaptive learning and educational environment, and there were still three reviews among the filtered documents. Additionally, one article was unretrievable, and two of them were in a language other than Spanish or English.

The results from the Selection and Filtering of Studies phase resulted in 25 documents selected for the Quality Assessment phase. As shown in Figure 3, the studies were conducted by researchers from 15 countries: 10 from Europe, 10 from Africa (eight from Morocco, one from Egypt, and one from Tunisia), and five more from America (North and Latin America). Some of the studies were a collaboration between several institutions in different countries. Notably, the search did not show studies developed in Asia or Oceania, and there was only one study from Mexico, which presents an opportunity for the authors of the present review and the project related to it.

Figure 3. Geographic distribution of the reviewed studies. Own elaboration.

Data Analysis

Data analysis was conducted through a thematic approach, focusing on the definition of five research questions RQs, presented in Table 1. RQs were formulated to define the user's profiling strategies applied to the studies. This study aims to use the synthesized results in creating categories and the most suitable profiling strategy for an inclusive and adaptive open educational platform: the OpenEDR4C project.

Table 1

Research questions and the expected outcome to retrieve.

Research Questions	Expected information to be retrieved	Treatment of results
RQ1 What is the object of study?	Types of systems that used the profiling strategy	Categories building
RQ2 Who is the potential user in the system?	Types of users: Can the system be used for learners, educators, or developers?	Categories building
RQ3 Which tools were used for the users' profiling?	The tools, algorithms, and strategies applied for the profiling.	List of strategies.
RQ4 Which indicators were analyzed for the users' profiling?	Variables and characteristics retrieved from the sample.	Categories building
RQ5 What were the outcomes obtained from the study?	Declared results from the study, the strategy's effectiveness, and the application scope.	List of strategies.

Content Analysis

The analysis primarily relied on content and thematic analysis. This approach allowed for an in-depth examination of the qualitative data extracted from the reviewed articles. The themes and categories were developed iteratively, ensuring that the analysis captured the nuances and complexities of user profiling in adaptive learning contexts. The RQs guided the search for relevant data as detailed in the following section. Throughout this process, categories were established based on the findings outlined in the subsequent section.

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Findings

RQ1 What is the object of study?

The focus of the studies was found to differ in two main, almost equal categories (Figure 4): the studies were focused on the students' attributes or the system's performance. From the first group, the observed qualities allowed researchers to apply diverse processing or data gathering techniques; some developed specially, and others combined existing ones. It was also found that while the majority focused on student qualities, the study only applied to college students, while the few focused on other ages and conditions.

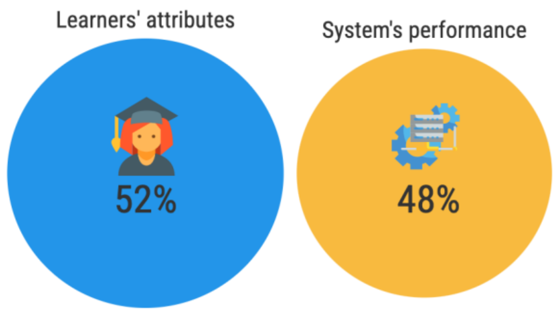

Figure 4. Distribution of documents' object or subject of study. Own elaboration.

When observing the system, it was identified that when the object of study was systems, some were the Learning Management Systems (LMS) or educational platforms in which diverse types of ontologies, or data collecting or processing systems, were applied. The systems reported could be used in a variety of moments in the learning process, whether it could be used to select or recommend learning paths, offer tutoring, or measure performance. Those systems that focus on learner's attributes rather than in system's performance set and approach towards measuring and validating student's abilities and competences, a much valuable feature when addressing complex thinking or any other competence in digital educational environments.

RQ2 Who is the potential user?

The performed analysis comprises a revision of who can benefit from the reposted studies. Among the possible beneficiaries are every type of user involved in creating educational platforms and systems and those who would use them for learning, teaching, or managing educational systems. During the review, it was discovered that almost half of the studies considered HiEds (learners) as the potential users of their innovations, closely followed by educators. Developers were only considered in a third part of the studies, and just six of the documents directed their efforts to students of all ages. Figure 5 shows the distribution of the population addressed and those studies aimed at more than one segment of users.

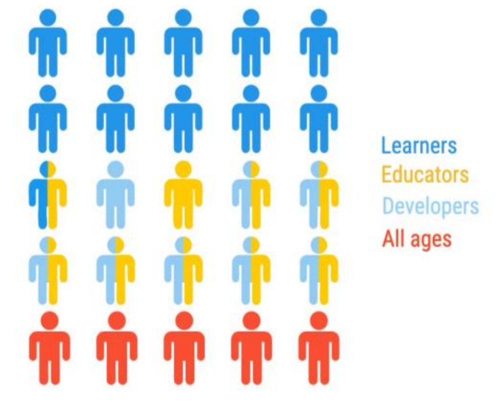

Figure 5. Potential users of the innovation described in the studies. Own elaboration.

To the best of the research team's knowledge, it is essential to highlight that no documents were reporting the educational managers or policymakers as beneficiaries of such technology development. Therefore, there is a relevant gap in shaping databases at a large scale that potentially might be used to build strategies for inclusive education regulation. Additionally, the profiles reported on the reviewed documents do not address populations with specific learning needs, therefore, to design strategies differentiating learning profiles it is relevant to perform a profiling prior to the digital platform usage or through data collection on behavior, preferences, learning styles and rhythms.

RQ3 Which tools were used for the users' profiling?

Regarding the tools and systems reported in the reviewed documents, there are numerous possibilities, as the word cloud in Figure 6 presents. Some of the identified tools were used for data collection from students. In contrast, some were applied in the processing stage, and a third group utilized different systems after profiling users for the adaptive learning strategy. The recommender system was the highest number of tools found, which offers educational resources according to the student's preferences and characteristics.

From the many possibilities of collecting data, the documents describe that data could be generated from different sources; thus, the system corresponds to the type of information to retrieve. If the information came from the students, instruments were used to collect facial micro-expressions, heart rate, language, learning styles, learning preferences, student performance, and previous knowledge. If the data came from other sources, such as the context, demographics, or students' opinions on the educational content.

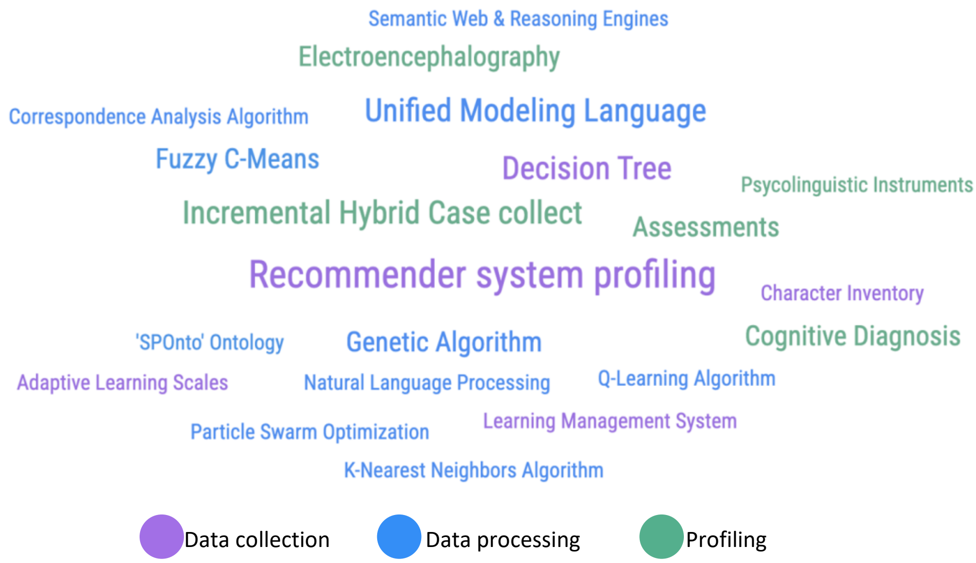

Figure 6. Tools and strategies for data collection or analysis are described in the reviewed documents—own elaboration.

The type of adaptation to the learning process of each student varies depending on the tools used. In the case of the Recommender Systems, and the Decision Tree, the adaptation consists in the suggestion of content that might be interesting to the learner. Another possibility is the starting point of the mastery level which will be determined by Cognitive Diagnosis, Assessments, Adaptive Learning Scales or Psycholinguistic instruments. Additionally, Genetic Algorithm, Swarm Optimization, Natural Language Processing, or Semantic Web would be used for specific cases in each platform, depending on its purpose and providing different tools to optimize the learning environment and experiences.

RQ4 Which were the indicators analyzed for the users' profiling?

The reviewed documents exhibit diverse sources of information for the users' profiling. The findings allowed a set of seven categories presented in Table 2, showing different combinations to assemble the system's user profiles according to the desired approach for each study. The most common indicator is the student's performance, which was recovered from the activities and tasks completed on the platform or, in other cases, retrieved from the academic record provided by the HiEd Institutions.

Table 2

Categories of indicators applied to the study samples

ID	ARTICLE	DEMOGRAPHICS	FEEDBACK	PERFORMANCE	EMOTIONS	BEHAVIOR	LEARNING STYLE	PREFERENCES
1	Belarbi et al. (2019)	✓	✓			✓		
2	Hssina et al. (2019)	✓		✓				
3	Nihadet al. (2019)						✓	
4	Opincariu (2019)				✓			
5	Petersen, Gundersen (2019)			✓				
6	El Ghouch, En-Naimi, Kouissi(2020)			✓				
7	El Kerdawy et al. (2020)			✓	✓			
8	Ennouamani, Mahani, Akharraz (2020)			✓			✓	
9	Heras et al. (2020)	✓				✓	✓	
10	Rodionov et al. (2019)			✓				
11	Villegas-Ch et al. (2020)			✓				
12	El Emrani, El Merzouqi, Khaldi (2021)	✓		✓				
13	Islam et al. (2021)			✓				
14	Matzavela & Alepis (2021)	✓		✓				
15	Missaoui & Maalel (2021)	✓		✓				
16	Moreira et al. (2021)			✓				✓
17	Paquette, Marino & Bejaoui (2021)			✓				
18	Boscardin et al. (2022)	✓		✓				
19	Ferilli et al. (2022)			✓				✓
20	Ouatiq et al. (2022)			✓				✓
21	Rincon-Flores et al. (2022)			✓	✓			
22	Sabeima, Lamolle &Nanne (2022)			✓			✓	✓
23	Smaili et al. (2022)			✓				✓
24	Lhafra & Abdoun (2023)			✓				✓
25	Mustapha et al. (2023)	✓					✓	

The less explored variable was the feedback from the learners in the role of a platform user; this could be because one can only provide input from a known experience. Hence, this source of information can only be used in specific cases where the profiling is generated after the learning experience. Furthermore, in a couple of studies the behavior of the students was also recovered, and in both cases linked to the type of response or preference that the students show according to their experience on the educational platform. Finally, fewer studies used students' emotions as a profiling indicator; some used a facial expression reader, while others used a survey about the current emotional state of students.

RQ5 What were the outcomes?

The analysis showed that the outcomes described in the reviewed documents relate to three main categories: (1) the learning experience in a given system, (2) the student's learning performance after the learning experience in a given system, and (3) the system's effectiveness concerning the creation of personalized learning paths and recommendations. As expected, the difference between categories, presented in Figure 7, relates to the object/subject of study; however, our focus is on combining the categories associated with the learning outcome, which comprises more than two-thirds of the reviewed documents.

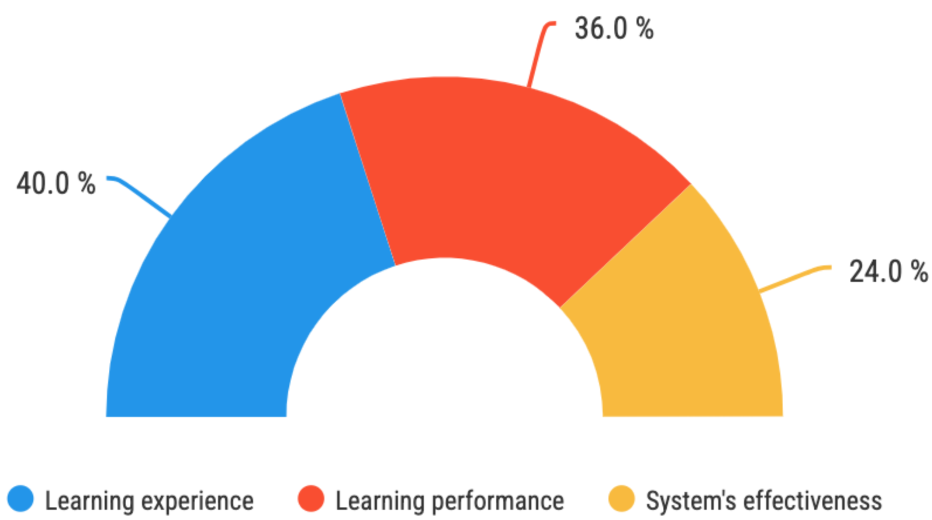

Figure 7. Studies' outcomes. Own elaboration.

Notably, the profiling strategies were assembled with data collected from the students' characteristics and, in a few cases, the conditions of their culture, context, or potential disabilities; this is an opportunity area that can be taken into account in the strategy building for the OpenEdR4C educational platform. Lastly, another relevant finding is that no studies described the relation between each profile and the most suitable learning path for each student class or type. This opens the possibility for this research team to explore the construction of a framework that links the student’s profile with a set of learning resources as components of a learning path.

Discussion

First, we acknowledge that to be successful, adaptive learning requires determining the best segmentation strategy aligned with each particular goal and target group. As found in the analysis (Figures 4 & 5), most studies are student-centered, and addressing other types of stakeholders in the learning experience was not considered. Understanding that one relevant part of the segmentation is understanding the target group through tracking and reporting (Harrigan et al., 2009), it might be valuable to include segmentation strategies for students and visual dashboards for the other involved parties in the learning process and planning. The definition of an integrative segmentation system can lead to a quicker evolution of a particular system through data collection from students, educators, and administrators.

Second, regarding the data sources, to set a profile and the corresponding learning route for each class, they must relate to the learner's characteristics and depend on the collecting data tool (sensors, questionnaires, predictions, etc.). As shown in Table 2, the majority of the studies, an 80%, use the performance of the digital platform, 32% use student sociodemographic data, 24% are based on user preferences, 20% use the learning style of the students, 12% use the emotional state of the users, and 8% are based on the behavior of the users and only 4% use feedback aspects. To achieve better solutions regarding digital educational platforms, it must provide a balance to improve the learning process (Imhof et al., 2020) and offer a system that adapts to the learner's needs (Afini Normadhi et al., 2019). Therefore, it would be necessary to gather data from the students in their roles: platform user and learner with a background and a specific context.

Third, based on the analysis, we can observe an opportunity to explore the collection of data on students' behavior to create new learning pathways and improve understanding of their needs over time. Table 2. Shows that only two of the papers analyzed collected this data. Fruitful and unpleasant interactions can elicit a variety of responses from the user (Medina-Medina & Garcia-Cabrera, 2016). The analysis of these effects could lead to the development of different ways to keep or attract students' attention, creating engagement according to personality traits and behavior (Regmi & Jones, 2020). Therefore, there is an opportunity to innovate in the type of data to be collected and even in the definition of desirable behavior when interacting with e-learning to promote a better and more efficient learning experience.

Finally, the segmentation strategies will offer a biased profile of a student that must improve their learning experience and performance. As discovered and presented in Figure 7, most study segmentations were assembled with data about students, disregarding other aspects such as culture, context, or potential disabilities. As some researchers recommend, such as Xie et al. (2019), to reduce the bias in the profile, it is convenient to include data related to students' emotions, behavior, and correlations with their surroundings. Although combining as much information as possible in the profile could be essential, technical, privacy, and specific conditions may prevent this, so it is crucial to evaluate the impact of the profile on the overall learning outcome..

At the end of this section, the result(s) obtained in the study should be re-stated and related implications should be explained. Implications should be based on and limited to the findings of the study.

Conclusion and Implications

The present study found characteristics and patterns in user segmentation applied to adaptive learning on digital education platforms. Primarily focused on student attributes and system performance, most studies limit their scope to college students, overlooking other age groups and educational conditions. This narrow focus calls for broader research to encompass diverse educational contexts. A critical gap identified is the lack of attention to educational managers and policymakers as beneficiaries of technological advancements. Most studies focus on students and educators, with developers included in only a third of the cases. Addressing this oversight is essential to facilitate comprehensive and inclusive educational strategies that involve all key stakeholders.

The tools and indicators used for user profiling reveal a strong emphasis on student performance and demographics, with limited consideration of feedback, emotions, and behavior. Expanding the range of profiling indicators to include these factors is crucial for developing more holistic and effective adaptive learning strategies. This could lead to a better understanding of learners' needs and enhance personalized learning experiences. The outcomes predominantly relate to learning experience, student performance, and system effectiveness, with a strong interest in optimizing learning through personalized paths and recommendations. However, the limited use of behavioral and emotional data indicates a significant opportunity to innovate and improve the profiling process.

This work underscores the need for more inclusive and comprehensive research in educational technology. Expanding the focus to include a wider range of students and educational contexts, integrating additional profiling indicators, and involving educational managers and policymakers can significantly enhance the development and implementation of effective adaptive learning systems. Addressing these gaps will lead to more personalized and impactful learning experiences.

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Appendix

The complete dataset with the search strings and the categories resulting from the defined process are available and open at the following link: https://hdl.handle.net/11285/651641