Revista Latinoamericana de Tecnología Educativa, 23(2)
https://doi.org/10.17398/1695-288X.23.2.69

RELATEC
Revista Latinoamericana de Tecnología Educativa

Received: October 25, 2022
Reviewed: June 10, 2024
Accepted: July 1, 2024

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ARTICLE / ARTIGO

Indicators of adaptive learning in virtual learning environments: Systematic Literature Review

Indicadores da aprendizagem adaptativa em ambientes virtuais de aprendizagem: Revisão Sistemática da Literatura

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Abstract: Digital Information and Communication Technologies act as partners in the educational context, making it more dynamic through Virtual Learning Environments (VLEs). The adaptive system is based on technological solutions/tools, which allow the customization of teaching processes according to the student's singularities. Therefore, we conducted a systematic literature review (SLR) to elucidate which educational performance indicators best guide adaptive learning in virtual learning environments. To this end, we adopted the principles of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) as a systematic review protocol, and as operational support, we used the online tool Parsifal. The initial database search - IEEE, ACM, and Scopus - returned 276 articles. After filtering based on the protocol, 16 articles remained part of the analysis and discussion corpus. The RSL results indicate that most of the indicators used to guide activities are based on the correctness and error of the questions. This shows that there is still much to be implemented in learning adaptability in virtual environments; for a more holistic assessment of learning, it is necessary to consider an integrated set of these indicators and not just individualized analyses.

Keywords: Adaptive Learning, Learning Indicators, Virtual Learning Environments, Personalized teaching, Adaptive environment

Resumo: As Tecnologias Digitais da Informação e Comunicação atuam como aliadas ao contexto educacional, tornando-o mais dinâmico por meio dos Ambientes Virtuais de Aprendizagem. O sistema adaptativo baseia-se em soluções/ferramentas tecnológicas, que permitem customizar os processos de ensino de acordo com as singularidades do estudante. Diante disso, realizamos uma Revisão Sistemática da Literatura (RSL) para elucidar quais indicadores de desempenho educacionais são mais utilizados para guiar a aprendizagem adaptativa em ambientes virtuais de aprendizagem. Para tanto, adotamos os princípios do Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) como protocolo de revisão sistemática, e como suporte operacional utilizamos a ferramenta online Parsifal. A busca inicial nas bases de dados - IEEE, ACM e Scopus - retornou 276 artigos. Após a filtragem baseada no protocolo, restaram 16 artigos que fazem parte do corpus de análise e discussão. Os resultados da RSL indicam que a maioria dos indicadores utilizados para direcionamento das atividades se baseia no acerto e no erro das questões. Isso mostra que ainda há muito a ser implantado no que tange a adaptabilidades de aprendizagem em ambientes virtuais, pois para uma avaliação da aprendizagem mais holística, é necessário considerar um conjunto integrado desses indicadores, e não apenas análises individualizadas.

Palavras-Chave:: Aprendizagem Adaptativa, Indicadores de Aprendizagem, Ambientes Virtuais de Aprendizagem, Ensino Personalizado, Ambientes Adaptativos.

1. Introduction

Technological advances have provided new communication possibilities that minimize geographic barriers and become part of everyday life. Thus, digital information and communication technologies are present in all areas of knowledge, starting to act as allies in the educational context and making it more dynamic through virtual learning environments (VLEs). For Moresco and Behar (2003), VLEs are computational environments with technological resources that provide a place for students to exchange information, reflect, establish relationships, and develop projects and research. These spaces must have " a structure composed of functionalities, interface, and pedagogical proposal, enriched with symbolic codes, representations, images, sounds, movements, and synchronous and asynchronous communication devices" (Moresco and Behar, 2003).

In this way, a virtual learning environment is an online platform used for educational purposes. It encompasses environments that supplement the course, whether they are reading resources, informational websites with autonomous skills assessments, or other forms of virtual learning focused on the student. In student-centered learning, the teacher gives students more control over what, how, and when they learn a particular topic. This degree of personal interaction makes students more active in their own learning process and has demonstrated significant results (Behar, 2013).

However, the use of technological resources does not necessarily affect mastery learning. To this end, in addition to aligning the components of the Education system (curriculum and its intended results, teaching methods used, assessment tasks), it is necessary to reflect on methodologies that go beyond ready-made formulas, from a perspective in which the methods of teaching and learning are aligned with students' needs.

Traditionally, most VLEs offer the posting of assessment activities to students in a sequential manner, as demonstrated by the flow of content and activities of a teaching module in Figure 1. This module is covered to fulfill an educational objective, and to this end, it has instructional material (which can be hypertext, media, documents, among others) and activities to assess knowledge.

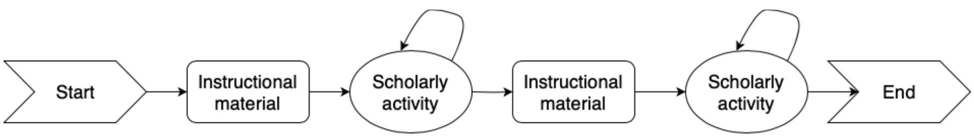

Figure 1. Flow of a Standard Configuration Course in Moodle.
Source: Research data prepared by the authors.

https://doi.org/10.17398/1695-288X.23.2.69

Figure 2 demonstrates a learning trajectory that would adapt to students' difficulties and could be integrated into VLEs. In the same sense, proposals allow adaptive learning implementation (Maravanyika, Dlodlo, and Jere, 2017). Adaptive learning (Zhao & Wang, 2019) uses adaptive models, ranging from technological artifacts to intelligent systems, which can be used in collaboration with traditional teaching environments.

Adaptive learning is a form of personalization of teaching, which includes the development of learning methods that consider students' singularities and preferences to give more meaning to the construction of knowledge. According to Despotovic-Zrakic (2012), adaptive learning can also be called learner-oriented platforms, adaptive environments, adaptive systems, or personalized systems.

Didactic materials with a focus on adaptive learning are designed to adapt to the knowledge levels and needs of students, seeking to increase their learning levels and allowing each student to follow their own path to achieve the objectives of the course or discipline, creating, thus, several trajectories within the same content or course.

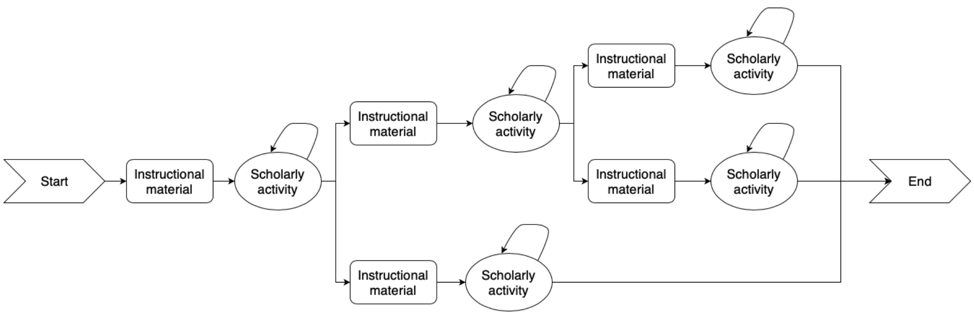

Figure 2. Example of adaptive learning flow.
Source: Research data prepared by the authors.

Some adaptive learning proposals can be observed in the literature. For example, Moodle[1] supports the insertion of plugins that can offer conditional activities[2] mplemented in the format of questionnaires[3], and uses the correctness or error of questions[4] as a learning indicator to define whether the student can advance in the learning level. Hasibuan, Nugroho, and Santosa (2018) propose to predict student learning through a questionnaire parallel to the activity and carry out a mapping of responses based on the VARK model (Visual, Auditory, Read/Write, Kinesthetic) to reveal the strengths and learn weaknesses. Likewise, Pitigala, Gunawardena, Hirakawa, and Liyanage (2013) used a questionnaire parallel to the activities. On the answers, they apply an FSLSM model (Felder-Silverman Learning Style Model) that scales the student

[1] Moodle is one of the most widely used virtual learning environments (VLEs) (Behar, 2013) (Gomes and Pimentel, 2021), as it offers a range of possibilities in terms of displaying content (such as hypertexts, links, documents, etc.), and a varied number of different types of assessments (forums, uploading files, quizzes, etc.). Its expansion is due to a number of reasons, including being open source, scalable and flexible in terms of configuration. It also complies with interoperability standards (Sharable Content Object Reference Model - SCORM) which makes it easier to transfer content between different platforms (Yan et al., 2010).

[2] https://docs.moodle.org/22/en/Conditional_activities_settings

[3] https://moodle.org/plugins/availability_quizquestion

[4] https://www.rasch.org/rmt/rmt22g.htm

between visual or verbal, active or reflective, sequential or global. This model allows us to evaluate the student's relationship with the learning objects and determine the best way for this student to process the information.

Li and Abdul Rahman (2018), Azzi and Radouane (2020), and Sheeba and Krishnan (2018) propose the use of probabilistic models based on student interaction with the system, which, after training, recommend customizations of activities more adapted to students.

The relevance of this Systematic Literature Review (SLR) lies in considering the multidimensionality of the human condition. It states that learning is much more complex to understand and evaluate and cannot be captured simply by checking a Boolean metric. Given this, we raise the following research question: Which educational performance indicators are most used in the literature to direct teaching and learning in a personalized and adaptive way in virtual learning environments?

Systematic reviews that relate virtual learning environments and adaptive learning are more concerned with describing the tools used to adapt learning (Fontaine et al., 2017; Zawacki - Richter et al., 2019; Martin et al., 2020 ; Li et al., 2021; Shemshack and Spector, 2020), than to uncover the set of learning indicators necessary for adaptive learning to occur. However, the bibliography has discussed a series of educational performance indicators that should also be considered (Camillo & Raymundo, 2019; Miquelante et al., 2017; Moraes, 2014). In order to encourage a discussion about the topic addressed, which is relevant to both technological and pedagogical processes in the context of online teaching and learning, this SLR aims to elucidate the research question described previously.

This SLR differs from previous ones in that it seeks to present and discuss educational performance metrics that have not yet been addressed in earlier reviews. Furthermore, this review aims to integrate multidimensional perspectives, considering the complexity of the human condition and the need for a more personalized and adaptive approach to online teaching. In this way, we hope to contribute to a significant advance in the understanding and application of educational metrics on virtual platforms, promoting more effective and student-centered teaching.

2. Methodology

SLR is a mechanism for identifying, evaluating, and interpreting all available research relevant to a phenomenon of interest. An essential part is the protocol, which is the basis for planning and conducting the review. Therefore, we adopted the principles of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) as a systematic review protocol (Page et al., 2021).

The PRISMA protocol starts by searching for articles using search strings in databases and other data sources. In the case of this systematic literature review, we chose to search for articles only in scientific databases. After the search returns, the articles are filtered based on duplication, inclusion and exclusion criteria, and quality analysis. Finally, the remaining articles are those that will be part of the discussion corpus that will support the answers to the research questions investigated.

This systematic literature review has some limitations, which are listed below: (1) The search was carried out only on articles written in English, as it is a lingua franca in terms of scientific research. (2) Only articles maintained by the three digital libraries most commonly cited in other RSLs were searched: ACM Digital Library1, IEEE Xplore2 e Scopus3. (3) We do not adopt Snowballing (Wohlin, 2014), a technique that allows the inclusion of references from accepted articles in the research corpus that meet the inclusion and exclusion criteria. (4) As operational support, we use the online tool Parsifal4. Below, we describe the eligibility criteria, sources of information, search strategy, study registries, and data synthesis recommended in the methods portion of the PRISMA checklist. Using the PICO (Population, Intervention, Comparison, Outcomes) strategy, we specified the characteristics of the studies to be included in our review: (a) Population: virtual learning environment. (b) Intervention: adaptive learning. (c) Results: indicator, metric, criterion, index. We created the inclusion and exclusion criteria to define the quality of the articles that would be extracted from the databases. The chosen inclusion criteria were: (1) Articles written in English. (2) Articles published from 2016 to 2023. (3) Articles that are primary studies. (4) Studies relating VLEs and adaptive learning. The exclusion criteria chosen were: (1) Articles that are not related to research. (2) Articles that are review or meta-review. (3) Article that is an older version of another article already considered in this SLR.

The inclusion criteria were established to ensure that the selected articles are aligned with the objectives and scope of the research, are written in English to facilitate understanding and global access, published in the last five years to ensure the timeliness of the information, being primary studies for providing original and relevant information, and relating VLEs and adaptive learning to meet the specific focus of the research. On the other hand, exclusion criteria were established to remove articles that do not directly contribute to the research, such as those that are not primary studies and articles that are older versions of articles already considered, thus ensuring the relevance and effectiveness of the SRL.

We perform an automatic search in information sources using a search string that combines keywords and synonyms related to two main domains: virtual learning environments, adaptive learning and their indicators, which translates into the following form:

> ("virtual learning environment" OR "VLE" or "distance education" OR "virtual education" OR "e-learning") AND ("adaptive learning" OR "adaptive teaching" OR "adaptive system" OR "adaptive educational learning") AND (metric OR criterion OR index OR indicator)

Once we have all the research export files, we include them in the digital data management tool Parsifal. This tool offers import options and supports the following steps: automatic checking for duplicate studies and manually labeling each article as accepted or rejected.

The combination of exported files created a database with all candidate documents. First, we delete duplicates automatically using the Parsifal tool. We then reviewed the titles and excluded articles that included the word "review" to limit them to primary studies. Afterward, we manually examined the journal names because some Scopus results were unrelated to the educational context, and we excluded articles from health, veterinary, and other areas. Therefore, we read the title and summary of the other candidates following the defined inclusion and exclusion criteria to refine the results. We did not consider articles that met at least one exclusion criterion. On the other hand, an article to be included in the final list must meet all inclusion criteria.

After applying the inclusion and exclusion criteria, we read the articles and applied a quality assessment checklist to this remaining selection. The quality assessment form had five questions and answers with specific weights: yes (2.0), partially (1.0), not specified (0.0), and no (-0.5). The questions used can be seen below:

Q1. Does the article describe how student difficulties are measured?

Q2. Do any metrics guide adaptive learning?

Q3. Was the proposal implemented in the form of a digital artifact? (or is it just a proposal?)

Q4. Is adaptive learning implemented on a VLE?

Q5. Do the results provide qualitative or quantitative assessment data?

The maximum score was 10.0, calculated based on the number of questions and the answer with the greatest weight. Therefore, we accept 4.9 as the cutoff score. Consequently, after reading the content, articles with lower than the cutoff score were excluded.

After reading the studies in full, we extracted metadata and other information relevant to our research. These data include the country, year, metrics used to guide adaptive learning, the implementation of adaptive learning tools in VLEs, and which VLEs are used for this purpose.

3. Resultados

The protocol described in the previous section carried out this systematic literature review. Figure 3 illustrates the detailed process of the review phases. Initially, the automated selection returned 276 records when applying the search string to the previously mentioned databases.

Of these, 39 duplicate articles were removed. The analysis of titles and abstracts allowed the pre-selection of 67 studies that met the established inclusion and exclusion criteria. Finally, the quality checklist was applied to analyze the 67 eligible works, which resulted in 16 articles being selected.

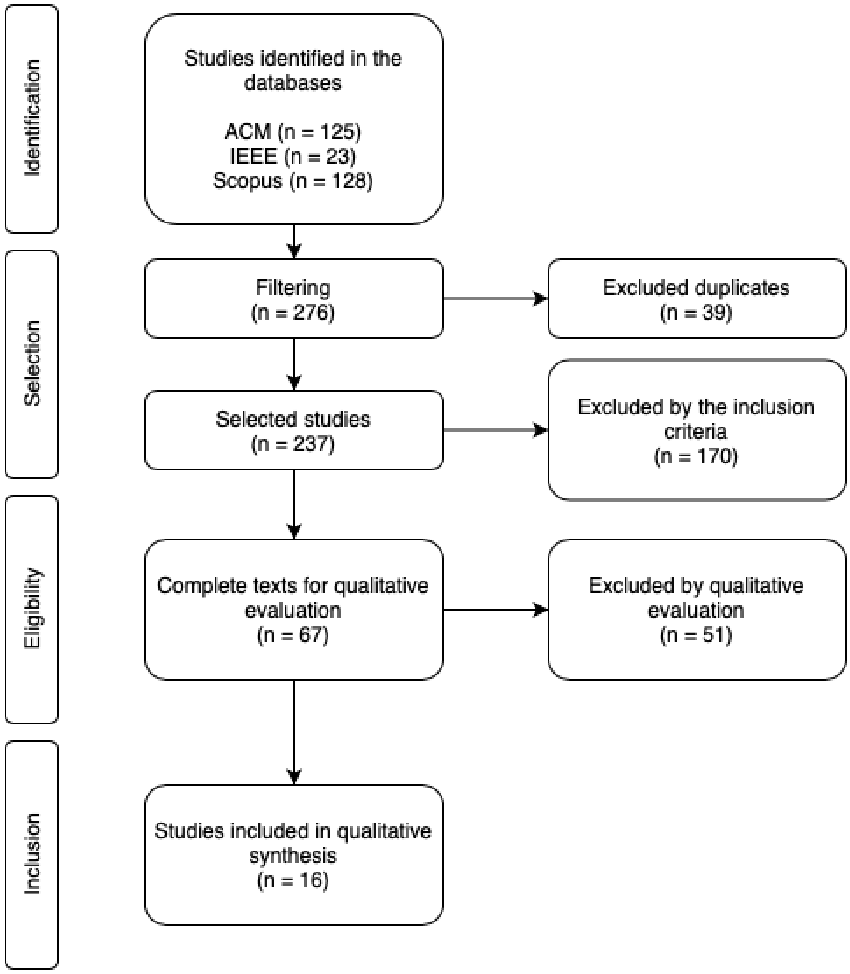

Figure 3. PRISMA-based systematic review protocol.
Source: Research data extracted by the authors.

Figure 4 shows the percentage of articles retrieved by the search string in the three databases used in this study. It can be seen that the majority of articles found on the topic were returned by Scopus, possibly because many articles indexed in other databases are also present in Scopus.

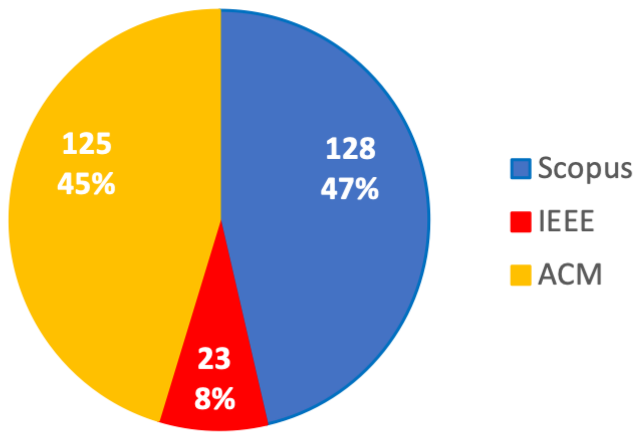

Figure 4. Amount of articles returned on each base.
Source: Research data extracted by the authors.

Figure 5 presents a stratification of the search results, organized based on the year of publication of the articles returned. A significant increase in the number of articles published on this topic is observed in 2023, indicating continued interest and research on the part of the scientific community in proposing and developing solutions in this area.

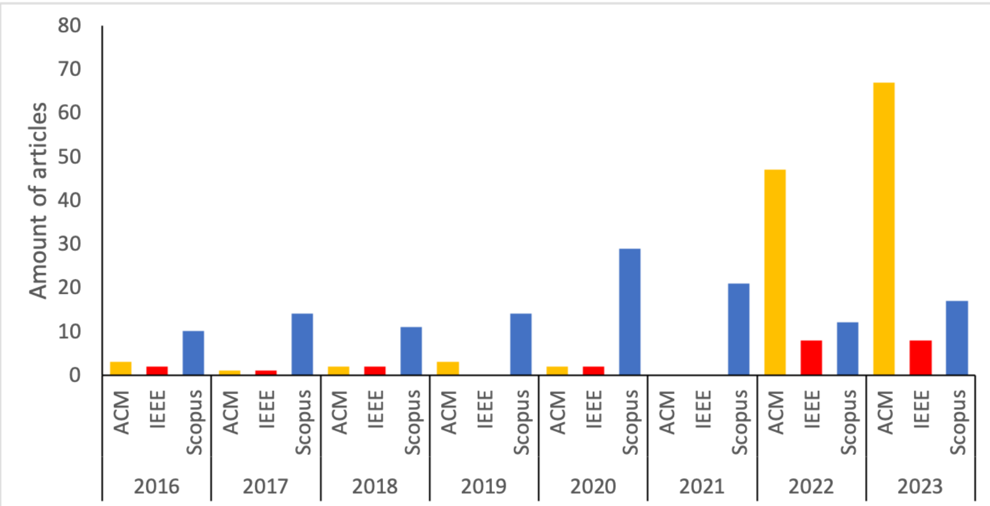

Figure 5. Recovered articles stratified by year.
Source: Research data extracted by the authors.

Figure 6 shows, by database, the number of articles selected in the first phase and, subsequently, in the second phase.

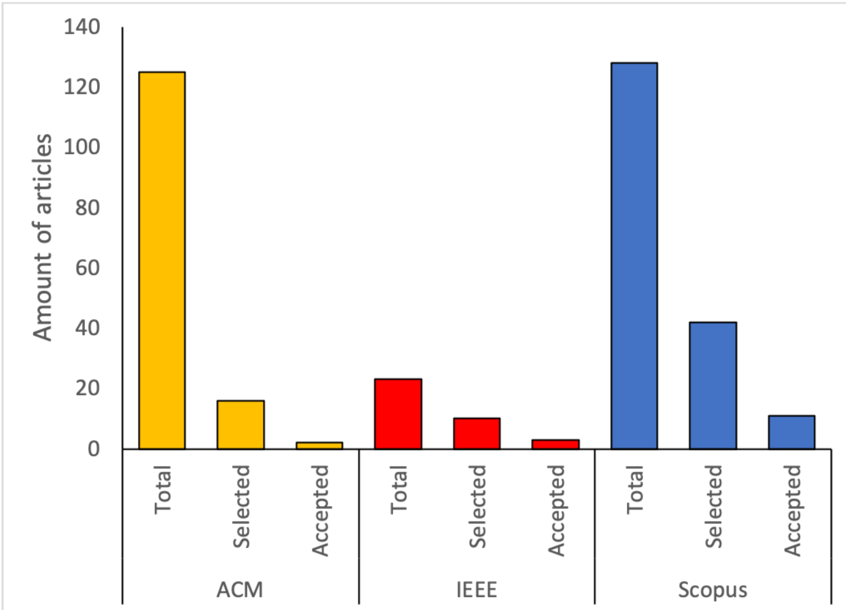

Figure 6. Selected articles and accepted by the criteria on the basis of databases.
Source: Research data extracted by the authors.

At this stage, it was noticed that some studies were not aligned with the objective of the investigation. Although 2022 and 2023 recorded the largest number of articles selected by the search string, none of these works discussed the metrics used to guide adaptive learning. Thus, among the studies evaluated, 16 obtained a satisfactory score in the quality assessment, as they presented and discussed the metrics of interest to this work. These works are discussed and summarized in depth to answer the research question of this Systematic Literature Review: Which educational performance indicators are most used in the literature to direct teaching and learning in a personalized and adaptive way in virtual learning environments?

Rezaei and Montazer (2016) present an adaptive learning system that employs a clustering methodology to evaluate its impact on the quality of teaching in an e-learning course. The authors are based on learning styles and divide the grouping system into four phases: identification of group structures, classification of students into corresponding groups, detection of expiration, and group modification. The implementation of this system demonstrated improvements in both student satisfaction and academic progress, demonstrating the system's effectiveness in improving students' educational results.

The research by Dolores et al. (2017) proposed a conceptual model with six adaptability indicators in a MOOC, and based on this, they developed and administered a questionnaire to participants. The indicators are accessible teaching materials and results in evaluated activities; access to content depends on the study pace; choosing between different levels of difficulty and evaluation methods; organization by area of interest; peer review organized according to the area of interest/training/level of experience. Dolores et al. (2017) concluded that participants emphasize two indicators: adaptation to the personal work rhythm and diversity in the levels of difficulty offered to achieve different objectives.

Su (2017) proposes a Hybrid Adaptive Learning Path Recommendation System designed to integrate individual learning styles employing fuzzy logic and suggest personalized educational itineraries. Each student's learning style is determined through a score based on their performance and success. The tool's effectiveness was evaluated in a study with an experimental group of 48 students, resulting in a significant increase in user satisfaction with the personalized service, reaching approval rates above 90%.

Hamada and Hassan (2017) developed the Enhanced Learning Style Index, which expands the Felder-Silverman model by incorporating a Fuzzy-type assessment system and adding a social-emotional dimension. This methodology was implemented in an adaptive learning system, testing it on a sample of 83 high school students. The authors concluded that the system can enable a more engaging learning experience.

Cai (2018) describes the implementation of the Intellipath platform, which was designed to enhance adaptive learning in online courses. The proposed system adjusts based on initial diagnoses and continuous evaluations (error or correct), providing an educational experience that evolves according to the student's progress. The implementation evaluation focused on criteria such as student engagement, progression, content mastery, and improvement in academic performance. The author concluded that courses that adopted the Intellipath model saw improvements in student performance and higher pass rates.

Chrysafiadi, Troussas, and Virvou (2018) investigated improving e-learning systems through a new structure for creating automated online adaptive tests, which was incorporated into two e-learning systems (one for intelligent tutoring for learning languages and one for learning programming languages). This approach uses multi-criteria decision analysis and the weighted sum model to assess the suitability of exercises for students, considering knowledge level, learning style, prior knowledge, exercise types, and learning objective, which are desirable according to Bloom's taxonomy. The proposed implementation was evaluated by computer science experts, instructors in the corresponding area, and students. The results highlighted by the authors highlighted the effectiveness of the proposed approach in reinforcing the adaptability and personalization of e-learning systems, leading to better educational results and student satisfaction.

Barbaguelatta et al. (2018) propose the development of a prototype for an educational platform that offers personalized learning experiences for eighth-grade students, using multimedia activities to develop geometry skills. Metrics employed to measure student learning include learning styles, difficulty factors, success rates in completing activities, and pre- and post-test comparisons. The results demonstrated improved learning outcomes when adaptive mechanisms were applied, regardless of whether they facilitated or challenged the learning process.

The article by Shubin et al. (2019) presents an implementation model for adaptive systems in VLE using the clustering technique through neural networks. These networks are used to classify students based on their performance in the proposed activities, using the percentage of correct answers and errors and, thus, adjusting subsequent activities according to each student's level of knowledge. To this end, the researchers adopted a combination of metrics, including numerical aspects - which evaluate study time and answers to questions -, verbal aspects - capable of identifying which subtopic the student is having difficulty with -, and graphs - which focus on precision of the answers to determine the user's level of knowledge.

Dounas et al. (2019) aim to improve understanding of how adaptive systems work during the learning process and improve their design. The researchers conducted an empirical study that analyzed log files from 21 students, recorded over a three-month course offered in a VLE. Data collection included student behavior and interactions with the system, assessment results, and resources made available to students. Based on this study, they recommended four evaluation criteria: compatibility of the instructional material with the student's learning style, balance between free and guided navigation, promoting communication between students, and option for the student to disable adaptive mode.

Zaoud and Belhadaoui (2020) highlight the lack of personalization in e-learning platforms and propose the Learner Behavior Analytics model, which uses User Behavior Analytics and Artificial Intelligence to constantly adjust educational content to the student's level and learning style. Additionally, they introduce a new metric system, Score and Behavior Analytics, to evaluate student progress through scores - based on error and correct answers - and behavioral patterns - response time, clicks, and quality of answers. However, it is worth highlighting that Zaoud and Belhadaoui (2020) do not specify in their article the relevance of the metrics used, nor do they detail them extensively.

The research by Tnazefti-Kerkeni, Belaid, and Talon (2020) discusses implementing a personalized learning architecture with the following properties: a student model, learning strategies according to the student's profile, and personalized learning strategies. However, the work is in the development phase, initially focusing on finalizing the ontology applied to the student model, which uses intelligent agents to track students' activities (number of times they had to perform the exercise until they got it right). ; time on the platform; time to solve each activity) within a Learning Management System. Based on this data, the idea is to generate intelligent panels capable of automating the detection of difficulties faced by students, offering alternatives or personalized solutions.

D'aniello et al. (2020) investigate the high dropout rates from online courses, attributing the primary cause to students' lack of motivation and engagement. The authors propose an approach that involves developing a system that uses Fuzzy Cognitive Maps to verify student motivation and engagement (activity on the forum, task completion, and general interaction with the platform). Based on these metrics, personalized feedback is generated and delivered to improve students' learning experience.

https://doi.org/10.17398/1695-288X.23.2.69

Krechetov and Romanenko (2020) describe the possibility of developing adaptive learning solutions using extensive data analysis and AI to meet personalized learning paths. The authors use a genetic algorithm to optimize learning paths based on the relationship between the level of knowledge at course completion and the time spent, aiming for maximum retention with minimum time investment. The results demonstrated significant improvements in evaluations of various educational activities.

Qu and Ogunkunle (2021) discuss the development of a simple machine learning algorithm, which considers three indices of learning attributes - prior knowledge, perceived self-efficacy, and peer collaboration - as variables in a three-dimensional space of educational effectiveness. For the authors, this approach facilitates grouping students based on their learning attributes, thus providing personalized learning experiences. The results were demonstrated by applying this algorithm, which showed the ability to create clusters of students with similar learning attributes. This clustering enabled the prediction of learning advice with varying degrees of accuracy across different clusters, showing the potential of this algorithm to improve the adaptive learning decision-making process based on comprehensive analyses of students' learning attributes.

Ghergulescu et al. (2021) propose a conceptual framework for an Adaptive Learning System enhanced by Artificial Intelligence. This framework extends the Mastery Model by incorporating subskill modeling to provide educators with deeper insights, raise students' awareness of their proficiency in different subskills, and provide more effective learning recommendations. Furthermore, the article presents BuildUp Algebra Tutor, an online platform dedicated to teaching Mathematics. To assess the effectiveness of student learning, metrics such as progress after receiving a tip and progress after making a mistake were adopted, demonstrating that accurately identifying subskills and offering structured support are effective strategies to help students answer the questions successfully. The system received positive student reviews, standing out from traditional methods regarding usefulness and ease of use. The authors also highlight the system's potential to empower teachers through intelligent dashboards that provide information about students' knowledge and progress. Additionally, survey feedback indicated a positive impact on student self-assessment metrics, including increased confidence.

Shabbir et al. (2021) propose a model that emphasizes the real-time identification and management of students' motivational states through a dual-module structure. This approach allows timely interventions, such as feedback, to increase student engagement. The authors suggested the analysis of log files as a method to detect student motivation in real time, using indicators such as reading time, mouse movement, and answers to questions, which are classified as correct or wrong, at the end of each topic. According to the researchers, the application of this model demonstrated promising results, significantly increasing student engagement and reducing school dropout rates.

Therefore, analyzing works filtered by qualitative assessment presents different indicators to assess students' knowledge and learning and thus enable adaptive learning in VLE. Figure 7 shows that most research uses error and success as a metric to decide which route the student should follow. However, this is still quite simplistic when it comes to effective student learning.

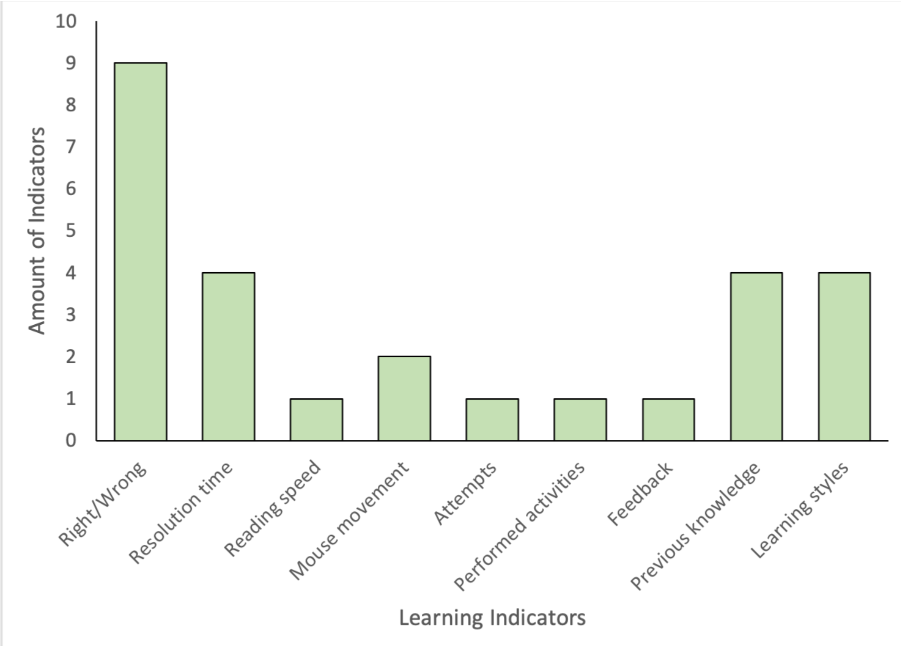

Figure 7. Learning indicators used..
Source: Research data extracted by the authors.

Table 1 expands Figure 7, briefly describing the authors of the 16 articles investigated and the indicators proposed by each one for adaptive learning to happen. It is noted that some of the articles employ more than one metric to guide this type of learning.

In this way, it is observed that the mentioned works can identify and dynamically adjust educational paths, adapting the content and learning activities in response to students' performance and preferences, such as learning styles, work pace, and levels of prior knowledge, among other factors. Some of the research covered implements adaptive processes guided by more than one metric, not limited only to the correctness of activity responses. This approach allows a more detailed look at the student's training process. The results of these methodologies point to an increase in student satisfaction and learning effectiveness.

Table 1. Learning indicators used in adaptive learning of the 16 filtered articles and their authorship. Source: Research data extracted by the authors.

Indicators or metrics	**Authors**
Right/Wrong	Dolores et al. (2017) Su (2017) Cai (2018) Barbaguelatta et al. (2018) Dounas et al. (2019) Shubin et al. (2019) Zaoud e Belhadaoui (2020) Shabbir et al. (2021) Ghergulescu et al. (2021)
Resolution time	Zaoud e Belhadaoui (2020) Krechetov e Romanenko (2020) Tnazefti – Kerkeni et al. (2020)
Reading speed	Shabbir et al. (2021)
Mouse movement	Zaoud e Belhadaoui (2020) Shabbir et al. (2021)
Attempts	Tnazefti – Kerkeni, Belaid e Tailon (2020)
Performed activities	D'aniello et al. (2020)
Feedback	Ghergulescu et al. (2021)
Previous knowledge	Chrysafiadi et al. (2018) Qu e Ogunkunle (2021) Chrysafiadi et al. (2018) Dolores et al. (2017)
Learning styles	Rezaei e Montazer (2016) Hamada e Hassan (2017) Chrysafiadi et al. (2018) Barbaguelatta et al. (2018)

4. Discussion

Although it is a promising proposal, especially today, when remote teaching and distance learning are in evidence, the result of this Systematic Literature Review shows us that the digitalization of teaching is not being used within the context of adaptive learning, as it is still We checked the learning assessment in the same way as always, using, most of the time, only the correctness of the answers. This form of evaluation goes back to a past of Cartesian thinking.

Since the 19th century, the concept of assessment has prevailed along the lines of logical reasoning and memorization. The first attempt at what would become adaptive learning was developed in the 1950s with the work of Skinner (1970). The author created a teaching machine that focused on incremental skill building. The machine adapted, offering new questions to students based on previous correct answers. It also provided students with immediate feedback and allowed them to advance at their own pace.

Thus, the results reveal that adaptive learning is still influenced by a historical evaluation factor associated with a particular caution about the complexity of implementation. As for historical issues, 19th-century pragmatism influenced Skinner's first proposals for adaptive learning, which attempted, in a certain way, to mechanize (self)learning. The learning assessment was carried out based on the students' mistakes and successes, as the binary decision was mechanically more accessible to the development of the proposal.

What we recognize as adaptive learning technology originates in the development of artificial intelligence during the 1970s. Researchers began developing systems that could mimic the teacher's experience. Although the systems that resulted from this early work had some success, the computing power and artificial intelligence technologies of the time were not advanced enough for complex intelligence or widespread use.

However, the programming implementation of adaptive learning is still essentially binary, which means that “new” proposals still use a Boolean choice model that dates back to its first proposition. Therefore, error and success are still the predominant metrics due to the nature of programming languages, which are based on conditional deviations. In addition, other factors can be viewed, still trying to avoid complexity in developing solutions. The use of time (spent during and completing activities) as a complementary factor to verify learning refers to learning management in terms of discrete time, allowing the observation of the student's action in integer quantities.

In practical work and future investigations, one must consider the advancement of available processing power, rapid system development methodologies, and artificial intelligence that reach unprecedented levels of complexity and sophistication. This supports the implementation of more complex adaptive learning models. Such models must consider different aspects of students' knowledge and learning in correlation to consider the student a subject of their own educational path. This way, he will be evaluated for his complete training process and not just for his right or wrong answers in activities and assessments.

5. Conclussions

Adaptive learning is a teaching and learning method that considers difficulties and pace individually. It is based on the premise that the educational object can be adapted to the specific needs of the student. For this to occur, the algorithms present in the ICTs must be remodeled because as the user interacts with the platform, the system updates dynamically, providing the student with personalized guidance.

Considering that each person has their own way and time for learning and highlighting that they seek to adapt their own ICTs to assist in this process, this work sought to find in the existing literature, between the years 2016 and 2023, the indicators most commonly used to guide adaptive learning in virtual learning environments.

According to the work reviewed in this SRL, there is ample room for implementing learning adaptations in virtual environments. This is because the indicator widely used to guide adaptive learning consists of correct and incorrect answers. Learning cannot be reduced to such a reductionist metric that it does not give importance to social and emotional issues directly affecting the cognitive. This highlights the pressing need to seek and integrate a set of new metrics to promote a more comprehensive adaptation of learning, which can take into account more humanized issues.

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