Conceptual Model for Virtual Learning Environments Enhanced by Artificial Intelligence (2025)

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***Abstract*— Virtual Learning Environments (VLEs) have played an increasingly relevant role in contemporary education, particularly when integrated with emerging technologies. This study proposes a conceptual model for the implementation of Artificial Intelligence (AI) techniques in VLEs to enhance personalization, engagement, and the overall effectiveness of the teaching and learning process. The model is intended as a practical tool for educators and researchers operating in diverse educational contexts. The study adopts a qualitative and exploratory methodology based on the Design Science Research (DSR) framework, leveraging services from Amazon Web Services (AWS). The findings suggest that the proposed model can serve as a reference to support innovation in digital education practices by promoting deeper interaction between students, instructors, and intelligent systems within **virtual learning environments.**

***Index Terms*— Artificial Intelligence, Digital Education, Personalized Learning, Virtual Learning Environments**

I. Introduction

Contemporary education is undergoing significant transformations driven by the evolution of digital technologies and the increasing demand for flexible and innovative teaching methods. Within this context, Virtual Learning Environments (VLEs) have emerged as strategic tools to support education in a global and connected society. These environments help to overcome geographical and temporal barriers, offering dynamic and interactive access to educational content. The COVID-19 pandemic accelerated this trend, positioning VLEs as essential instruments to address educational challenges while reinforcing the urgency to enhance these platforms in response to growing demands for quality in teaching and learning practices [1].

In this scenario, the integration of Artificial Intelligence (AI) techniques into VLEs represents an innovative approach that can improve the educational experience by enabling more responsive and adaptive environments. AI can support the generation of automated feedback, personalized content, and immersive learning experiences. Technologies such as artificial neural networks, intelligent agents, and machine and deep learning algorithms have the potential to move beyond simple automation and foster truly personalized and adaptive learning processes.

Despite these advances, VLEs still face critical challenges, such as the limited capacity to monitor student progress in real time and provide adaptive feedback to support effective learning strategies. In diverse educational contexts, where students exhibit different learning styles and levels of knowledge, personalized instruction becomes a significant factor. Furthermore, low interactivity and a lack of engagement-oriented features remain common barriers. Studies indicate that the use of narratives and storytelling in gamified environments can improve engagement by encouraging continuity in the learning process. In this context, AI may help mitigate these limitations by implementing monitoring agents and information analysis systems that dynamically adjust the educational experience. Recent studies, such as the one conducted by [2], demonstrate that although higher education students increasingly accept AI tools, they still encounter challenges related to perceived usefulness and technological adaptation.

Nevertheless, implementation barriers and the absence of integrative models continue to constrain the effective use of these technologies [3]. This study proposes a conceptual model for the implementation of Artificial Intelligence (AI) techniques in VLEs to enhance personalization, engagement, and the overall effectiveness of the teaching and learning process. Although previous studies have explored specific aspects of AI integration in VLEs, such as personalized instruction [4], technology acceptance [2], and feedback automation[5], these approaches remain limited to isolated solutions. The lack of comprehensive conceptual models highlights a research gap that this study seeks to address.

The proposed model aims to serve as a practical and replicable reference for researchers, experts, and educators interested in the implementation of AI in virtual learning environments. Recent research has demonstrated that

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techniques such as data mining, automated planning algorithms, and neural networks can enhance both academic performance and learning experiences by translating theoretical knowledge into adaptable strategies for a wide range of educational contexts [6]. [5] emphasize the potential of AI to improve peer assessment processes by offering automated and adaptive feedback, reinforcing the role of AI in advancing digital pedagogical practices.

The second phase of this study adopted the Design Science Research (DSR) methodology, which focuses on the development of artifacts such as models, methods, and frameworks to address practical problems identified in the research process. In this phase, a conceptual model was designed to represent, in an abstract and structured manner, the elements and processes involved in the integration of AI into VLEs. The model reflects the outcomes of the exploratory research and is grounded in theoretical and methodological principles established in the academic literature, following the guidelines proposed by [7], [8] and [9].

This article is organized into six sections. In addition to this introduction, Section 2 presents the materials and methods, describing the AI techniques and their application in virtual learning environments. Section 3 explores how these techniques can be implemented in practice. Section 4 introduces the conceptual model, including the implementation guidelines. Section 5 presents the results and discussion, analyzing the implications and potential adaptations of the model. Finally, Section 6 provides the conclusions, highlighting the main contributions of the study.

II. MATERIALS AND METHODS

This study adopts a hybrid methodological approach, combining exploratory research with Design Science Research (DSR) to investigate the implementation of Artificial Intelligence in Virtual Learning Environments and to propose a structured conceptual model. The methodological choice is justified by the need to connect the current state of the art with the identification of challenges and opportunities in these environments. Based on this analysis, the study aims to contribute to the construction of a viable and theoretically grounded model. The practical development of the conceptual model involved the use of Artificial Intelligence services provided by Amazon Web Services, incorporating features for personalization, performance analysis, and adaptive feedback.

The theoretical and technical foundations that support this study, including the characterization of Virtual Learning Environments, their functionalities, the historical trajectory of Artificial Intelligence, and the main AI techniques and their applications in educational contexts, have been relocated to the supplementary material attached to this article. This decision was made to preserve the coherence and clarity of the main text, focusing on the methodological approach and the model construction process.

The study was conducted in two phases. The first phase was exploratory in nature, an appropriate strategy when there is a need to gain a better understanding of the investigated problem, allowing for more accurate definition of the research object and formulation of hypotheses or conceptual guidelines for the subsequent stages[10]. In this phase, a literature review was carried out focusing on the application of Artificial Intelligence in Virtual Learning Environments. The review aimed to understand current approaches, techniques, and challenges related to personalized instruction, performance monitoring, and AI-mediated learning support. Based on the findings, the study identified relevant gaps and opportunities, particularly the absence of a structured model that systematically integrates AI in VLEs. This exploratory analysis supports the need for the proposed conceptual model and provides a foundation for its development, ensuring alignment with observed practices and limitations in related studies.

The second phase followed the Design Science Research methodology, which emphasizes the creation of artifacts such as models, methods, and frameworks to support the resolution of practical problems identified through research. The approach adopted in this study is based on the principles proposed by [7], [8] and [11]. During this phase, a conceptual model was developed to represent, in a structured and abstract manner, the elements and processes related to the integration of Artificial Intelligence into Virtual Learning Environments. The model was designed based on theoretical and methodological principles aligned with the academic literature.

The construction of the model was conducted in three interconnected stages. First, the requirements for an AI integration model in VLEs were defined, establishing criteria based on the challenges and opportunities identified in the literature. The focus included personalized instruction, automation of pedagogical support, and performance analysis. Next, the conceptual modeling stage structured the components required for implementation and organized the theoretical and technical principles that support the model, ensuring its adaptability across different educational settings. Finally, structural reviews and conceptual validations were conducted to ensure that the proposed model aligns with methodological, theoretical, and technical guidelines and is suitable for future implementation. Figure 1 presents a schematic overview of the methodological process adopted for constructing the conceptual model proposed in this study.

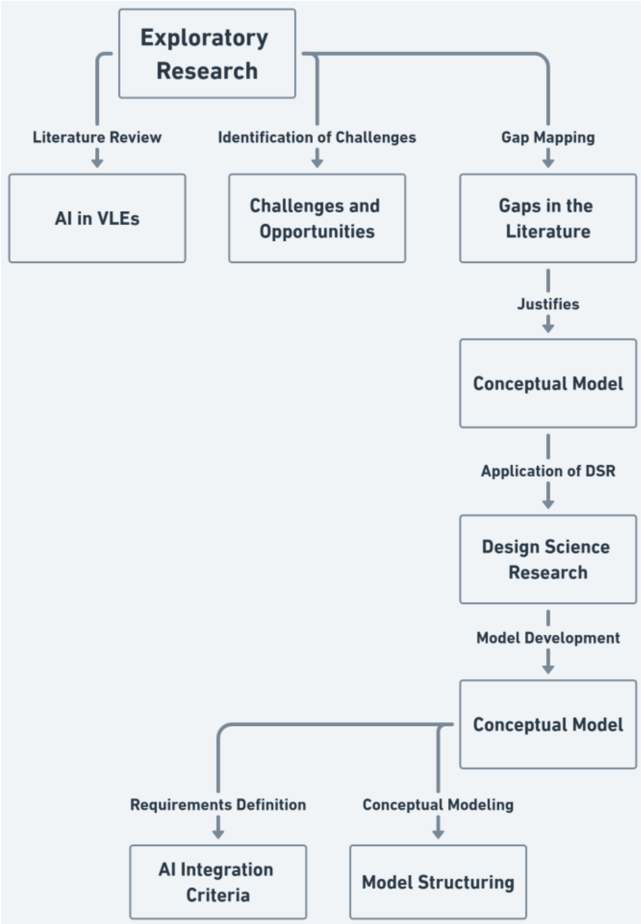

Fig. 1. Methodological Process

The visual representation reinforces the relationship between the exploratory stages and the application of the DSR framework in the development of the conceptual model, providing a clearer understanding of the methodological decisions and the interconnections between the different phases of the study. The detailed conceptual and technical foundations, including types and functionalities of VLEs, the evolution of Artificial Intelligence, and its main techniques, are presented in Appendix A as supplementary material to this article.

Based on this process, the next section introduces the conceptual model for the integration of Artificial Intelligence in Virtual Learning Environments. The model is structured around pedagogical and functional components designed to support personalization, student engagement, and performance analysis in educational contexts.

III. CONCEPTUAL MODEL OF ARTIFICIAL INTELLIGENCE IN VIRTUAL LEARNING ENVIRONMENTS

The application of Artificial Intelligence techniques in Virtual Learning Environments aims to promote innovation in teaching and learning by providing more dynamic, responsive, and personalized educational resources. The proposed conceptual model seeks to integrate technological solutions with pedagogical goals, enhancing engagement, supporting personalized learning processes, and contributing to performance assessment and continuous monitoring. By aligning AI-based functionalities with instructional practices, the model intends to enrich the educational experience, meeting the needs of different student profiles and supporting the development of competencies aligned with contemporary demands.

The model is structured into components that guide the design of adaptive VLEs and foster more effective interactions between instructors and students. These components cover the organization of content and learning activities, personalized delivery, and the analysis of educational outcomes. The structure is designed to reflect the typical learning path within VLEs and to contribute to the innovation of teaching and learning practices by connecting instructional strategies with student-centered learning dynamics. Table 1 presents a detailed description of each component.

TABLE I
MODEL COMPONENTS

Model Component	Description
Contextualization	AI is used to organize and deliver study materials in a structured manner, aligning with the instructional plan and adapting content to individual student needs.
Activities	A dynamic bank of activities is suggested by the model, with AI selecting exercises to reinforce areas where students demonstrate difficulty.
Assessment	An automated evaluation system generates adaptive assessments tailored to each student's level using AI-based techniques.
Discussion Forum	AI is used to enrich and facilitate online discussions, fostering meaningful interactions and collaborative knowledge construction.
Performance Analysis	AI improves the analysis of individual and collective student performance, generating graphical insights and detailed diagnostics.
Personalized Teaching and Learning Process	AI adjusts content and activities in real time based on student interactions and performance.
Future Analysis of Educational Outcomes	AI supports long-term assessment of educational results, evaluating the effectiveness of teaching strategies and student progress.

To illustrate the relationship between these components, Figure 2 presents a pedagogical and personalization flowchart that highlights how the model supports the learning process. The figure shows how content delivery, student interaction, and continuous adaptation form a connected and cyclical system.

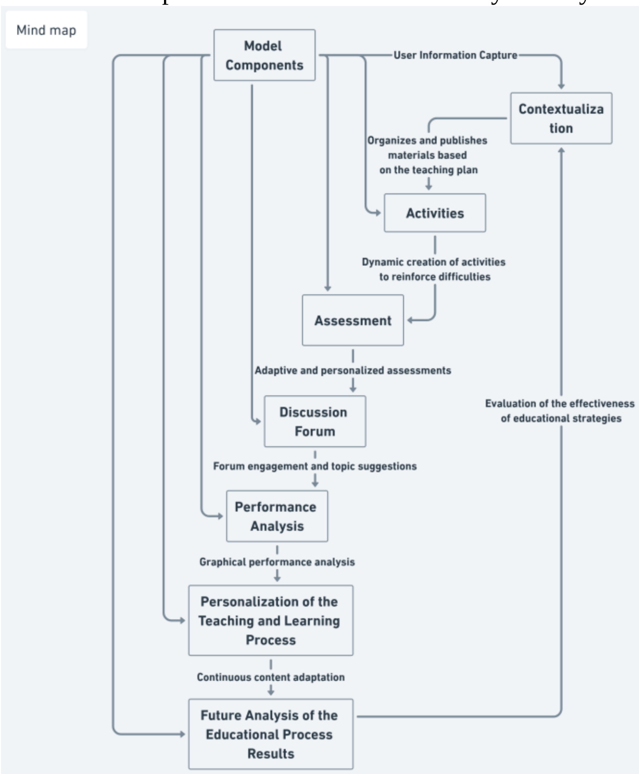

Fig. 2. Pedagogical and Personalization Flow in the VLE

The flowchart demonstrates how each stage of the model is interconnected to create a continuous cycle of learning and improvement. The process begins with contextualization, where AI assists in aligning study materials with the instructional plan. The model then enables the dynamic generation of activities that target student difficulties. Adaptive assessments form a central element, offering personalized feedback based on individual performance. Forums are enriched through AI-driven topic suggestions and interaction monitoring, promoting deeper collaborative learning.

The data generated throughout these stages are used to assess performance, providing insights that help educators refine their strategies. These diagnostics inform the personalization process, enabling the continuous adaptation of content based on student progress. Finally, the analysis of long-term educational outcomes completes the cycle, allowing for the ongoing evaluation and refinement of teaching strategies. This structure can be considered dynamic and adaptive, reinforcing the role of AI in delivering data-driven, student-centered, and responsive learning experiences.

A. Modeling Based on a Use Case

O understand the application of the model, it is important to contextualize the role of Virtual Learning Environments as support structures for a variety of educational initiatives, including full academic courses, standalone subjects, and professional training programs. In this study, a thirty-hour course module is used to illustrate the implementation path within a VLE, demonstrating how the essential components of the model can be applied in practice. The proposed structure emphasizes interactivity and supports multiple learning styles and paces.

According to [1], VLEs open pathways to new administrative, instructional, and pedagogical possibilities by enabling the design and organization of academic programs in multiple formats, including face-to-face, blended, and fully online learning. In this example, the course design illustrates how the model's components contribute to a coherent educational experience aligned with the demands of contemporary teaching and learning. Table 2 presents the main topics of the course structure.

TABLE II
COURSE STRUCTURE

Topic	Description
Course Planning	Define objectives, competencies, and a timeline to guide academic planning. Organize instructional resources in a way that promotes student autonomy and facilitates access.
Content and Methodology Development	Develop lessons focused on specific competencies, with adaptable content and practical activities that stimulate knowledge application. Each session should include learning goals, supporting materials, and interactive exercises with dynamic feedback.
Learning Monitoring and Assessment	Implement tools to track resource usage and analyze student engagement. Generate reports on both individual and group progress, with a focus on competency development.
Engagement and Motivational Strategies	Incorporate gamification elements, such as badges, to encourage active participation and promote healthy competition among learners.

The implementation of this course structure, commonly observed in teaching and learning processes, demonstrates how the components of the conceptual model can be integrated in a cohesive and practical manner. The environment is designed to support innovation, adaptability, and the development of skills that are aligned with current educational and technological needs.

B. Artificial Intelligence Techniques In The Cloud Applied To Virtual Learning Environments

The growing adoption of cloud-based Artificial Intelligence services has transformed the way organizations develop and integrate innovative solutions across multiple sectors, including education. As discussed by [12], [13], these services provide scalable and pre-configured tools to implement machine learning algorithms, natural language processing, computer vision, among other techniques. By removing the need for building and maintaining local infrastructure, cloud-based AI democratizes access to advanced technologies, allowing educational institutions of all sizes to explore their potential.

Companies such as Google, Microsoft, and Amazon Web Services have incorporated into their portfolios a variety of AI solutions, ranging from simplified integration APIs to fully customizable model development platforms. For example, Google Cloud Platform provides services such as Natural Language API for textual analysis and Vision AI for computer vision tasks, along with end-to-end machine learning tools through Vertex AI. Microsoft Azure offers Azure AI, which includes Azure Machine Learning and conversational AI tools like Azure Bot Service. Amazon Web Services provides a broad set of services for artificial intelligence, including Amazon Personalize for content recommendation, Amazon Comprehend for sentiment analysis, and Amazon Lex for intelligent chatbot creation ([14][15][16]).

All of these platforms support the integration of AI into Virtual Learning Environments, enabling personalized learning, greater student engagement, and performance analysis. The selection of the most appropriate service depends on each institution’s specific needs and the compatibility of the solution with its existing educational systems. Figure 3 illustrates examples of AI techniques available through cloud platforms, their educational applications, and expected outcomes.

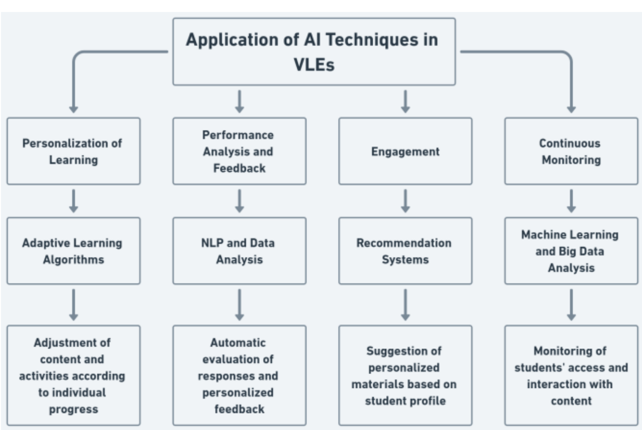

Fig. 3. Artificial Intelligence Techniques in Virtual Learning Environments

The steps shown in the diagram are organized to demonstrate how various AI techniques can be employed to enhance the learning experience in VLEs. Each step is detailed below, with a focus on the specific techniques and cloud services used to implement the proposed solutions. In this study, Amazon Web Services is used as a reference for exemplifying cloud-based AI services, although the approach is not limited to AWS and may be adapted to other platforms with equivalent functionality.

The first step, personalized learning, aims to accommodate different needs and learning paces. Amazon Personalize, an adaptive learning service, offers a scalable solution to dynamically tailor content and activities based on each student's progress and behavior. Data such as interaction history, performance on assessments, and time spent on content can be collected directly from the VLE and prepared using AWS Glue, which transforms the data into a suitable format for analysis. Once prepared, Amazon Personalize can train a recommendation model using machine learning algorithms to detect patterns, such as areas of difficulty or preferred content formats. After training, the model is integrated into the VLE through the Amazon Personalize API, allowing the automatic generation of tailored recommendations such as videos, exercises, or supplementary materials. System effectiveness can be monitored with AWS CloudWatch, which tracks metrics such as content engagement rates and student progress. These insights support continuous model adjustments to maintain relevance and effectiveness [9], [17].

The second step involves performance analysis and feedback, which support continuous and personalized learning. Using Amazon Comprehend, a natural language processing service, it is possible to implement an automated system that evaluates written responses and provides targeted, real-time feedback. Student responses in forums, assignments, or assessments can be collected through VLE APIs. Amazon Comprehend analyzes the collected texts by identifying key topics and textual structure. The system may be configured to assess coherence, the use of relevant keywords, and the alignment of responses with instructional objectives.

Based on the analysis, specific and personalized feedback is generated, highlighting strengths, suggesting improvements, and linking students to additional resources. Feedback is delivered through the VLE in an interactive format. For example, after submitting a written answer, the student receives an automatic analysis of the content with revision suggestions. The feedback system’s effectiveness is monitored using AWS CloudWatch, allowing refinements based on student usage patterns and instructor input. This approach ensures alignment with educational goals and meaningful contributions to learning outcomes.

Student engagement in VLEs can also be strengthened through intelligent recommendation systems, such as those developed with Amazon Personalize. These systems link students to content and activities aligned with their interests and behavior patterns, increasing meaningful interaction with learning materials. In the third step, trained models are used to provide personalized content suggestions based on individual progress and preferences, such as a student’s interest in neural networks leading to recommendations for deeper exploration of machine learning topics.

The recommendations are integrated into the VLE interface, offering easy access to suggested materials and fostering sustained student interaction. System performance is tracked via AWS CloudWatch, which provides metrics such as click-through rates and time spent with recommended content. The recommendation model is periodically updated to maintain accuracy and relevance based on student behavior patterns.

Finally, continuous monitoring of student activity in VLEs provides insights into engagement and opportunities for improvement. Using services such as AWS CloudWatch and Amazon SageMaker, institutions can implement solutions that combine data collection, behavioral analysis, and educational interventions. In this final step, real-time data on interactions such as login frequency, time spent on tasks, and resource consumption are captured and stored in an organized format for future analysis.

AWS Glue prepares the collected data by converting it into a structure suitable for machine learning analysis. Amazon SageMaker then applies algorithms to detect behavioral patterns. Clustering techniques, for example, can group students based on engagement levels, while predictive models can identify risks such as potential dropout.

The results are presented in reports and interactive dashboards generated with Amazon QuickSight, providing indicators such as activity completion rates, content access percentages, and performance comparisons across groups. These insights allow educators to track progress and make informed, data-driven decisions. In addition to these analytics, VLEs enable automated interventions, such as sending personalized notifications or links to interactive materials. These actions support targeted strategies that increase engagement and improve individual student performance.

IV. RESULTS AND DISCUSSION

This section presents the outcomes of the conceptual model designed to integrate Artificial Intelligence techniques into Virtual Learning Environments, highlighting its structure, operational logic, and potential for application in various educational settings. The model was developed based on a systematic literature review and grounded in Design Science Research methodology, aiming to address persistent challenges related to personalized learning, student engagement, and continuous performance monitoring.

The results are organized into two complementary parts. First, the model is introduced as a whole through a flowchart that synthesizes its data-driven cycle, from the collection of student interaction data to the application of Artificial Intelligence techniques for analysis, recommendations and pedagogical adjustments. Next, each component of the model is examined individually, focusing on its specific functions and the contributions it offers to innovation in technology-mediated teaching practices.

To support this integrated view, Appendix B presents the conceptual model flowchart, highlighting the relationship between data capture, information processing, and personalization mechanisms that guide adaptive adjustments throughout the learning process.

The model is based on the premise that Artificial Intelligence can help meet the increasing demand for personalization and innovation in digital learning environments. Its design integrates four foundational pillars: personalization, performance analysis and feedback, student engagement, and continuous monitoring. The personalization component focuses on delivering tailored content and activities according to individual needs by leveraging adaptive algorithms and recommendation systems. The goal is not only to improve learning outcomes but also to offer innovative educational experiences aligned with student profiles. Recent studies have demonstrated that machine learning methods can be used to predict academic performance and adapt learning materials to student needs, fostering more personalized and responsive instruction [18].

The performance analysis and feedback component is designed to support students throughout their learning journey. Through the continuous collection and interpretation of data, the model helps identify areas of difficulty and deliver targeted feedback, thereby supporting learning progress. Research has shown that intelligent tutoring systems are capable of interpreting student behavior patterns and adjusting instruction accordingly, making the learning process more efficient [19], [20].

The engagement dimension of the model emphasizes the importance of creating motivating learning environments. Gamification elements and storytelling strategies were included to support the design of interactive and appealing experiences. These strategies aim to increase student motivation and promote sustained participation. The literature supports the effectiveness of gamified approaches in enhancing interactivity and student involvement through challenges and adaptive rewards [21].

Continuous monitoring is incorporated as a mechanism to regularly assess interactions and performance. By applying data analysis and machine learning techniques, the model enables educators and systems to identify behavioral patterns and plan timely interventions. Recent studies have demonstrated that sentiment analysis can be used in virtual environments to evaluate student engagement and anticipate learning challenges, allowing for personalized adjustments to instructional strategies [22].

During the model development process, the study also addressed common challenges observed in existing VLEs, such as limited interactivity, difficulty in tracking student progress, and the lack of mechanisms for real-time content adjustment. The model seeks to address these issues by establishing a continuous cycle of analysis and adaptation. The data generated through student interaction serve as the foundation for intelligent, automated processes that adjust the learning path in real time. Recommendation systems and analytical tools allow for continuous refinement of the educational experience, while engagement elements help strengthen the connection between students and course content. These innovations contribute to the development of more responsive and inclusive digital learning environments.

By offering a replicable framework, the model can serve as a foundation for future research, ongoing studies, and practical implementations. However, it is necessary to consider the limitations and challenges identified during this study, as well as those highlighted in related research. Among the most pressing challenges is the integration of AI technologies into diverse educational contexts. Differences in institutional infrastructure and organizational culture may affect adoption, requiring not only access to appropriate tools but also the training of educators to use them strategically. Therefore, the model's implementation depends on the successful execution of the proposed stages and may require technical support and cultural change in pedagogical practices.

According to [3], the adoption of Artificial Intelligence in education must include strategies that ensure data security and transparency in decision-making processes. Ethical implications are essential to consider, especially when algorithms are embedded in educational systems. It is crucial to establish clear regulations to guarantee fairness and mitigate algorithmic bias that could compromise equity in access to knowledge. The use of AI should aim not only to enhance the user experience but also to protect data integrity and adhere to ethical standards.

Additionally, the continuous analysis of educational data raises ethical and legal concerns, such as data privacy and responsible use of student information. The implementation of strong data governance policies is necessary to ensure that AI is applied responsibly and aligned with pedagogical and institutional priorities.

In this context, the conceptual model proposed in this study is positioned as a strategic solution for educational innovation, offering a structured and responsible approach to the integration of emerging technologies. The model considers not only the technical feasibility of AI implementation but also its relevance across diverse educational settings. It provides institutions with the means to adopt data-informed, innovation-oriented practices that are grounded in ethical and pedagogical principles committed to educational quality.

V. Conclusion

The objective of this study was to propose a conceptual model for the implementation of Artificial Intelligence techniques in Virtual Learning Environments, with the goal of improving personalization, engagement, and the effectiveness of the teaching and learning process. The model is intended to serve as a practical tool for educators and researchers operating in various educational contexts.

Structured around four educational pillars, the model incorporates the use of Amazon Web Services tools and aims to offer a reference framework for developing solutions that foster technological innovation and new pedagogical practices, enhancing the interactions that occur within Virtual Learning Environments. In this regard, the study presents an integrated approach that encourages reflection and inspires new applications, aligned with the growing trends in the use of AI in education.

By proposing a conceptual model that integrates emerging technologies to support pedagogical strategies, this study opens possibilities for application in different educational levels and institutional contexts. The model is designed to be flexible and adaptable, making it suitable for implementation in academic institutions, corporate training programs, and hybrid learning environments. Its emphasis on artificial intelligence as a strategic resource contributes to the personalization and automation of educational processes. Furthermore, the expected impact of the model aligns with global trends in AI adoption within education. The tools and techniques discussed in this study may serve as a foundation for initiatives aiming to enhance student engagement, optimize academic performance, and transform educational data into actionable insights. This perspective may expand the ongoing debate on the potential of AI to foster more dynamic, data-driven educational approaches.

Although the proposed model presents considerable potential to support technological advancement in Virtual Learning Environments, some limitations must be acknowledged. The model has yet to be empirically validated, and future work is required to test its applicability in diverse educational settings and across different levels of instruction. Challenges related to integration with existing platforms must also be explored, particularly in terms of interoperability and alignment with pedagogical practices. Another limitation concerns the reliance on specific tools exemplified in the study, such as AWS solutions. While these tools were selected for illustrative purposes, the implementation of any cloud-based AI platform may face obstacles such as cost, technical infrastructure, and the need for user training. These factors may require complementary strategies to expand the reach and impact of the model, adapting its structure to the realities of different institutions.

The limitations identified in this conceptual model offer valuable opportunities for future research. Related studies may investigate the model's effectiveness in terms of student engagement, academic performance, and user acceptance in varied educational contexts. Furthermore, research focused on integration with other platforms and emerging technologies may help overcome operational barriers and broaden the model's applicability. Additional efforts may also explore strategies to reduce implementation costs and simplify access to AI tools for institutions with limited resources. Collaborative initiatives involving educators, developers, and researchers can contribute to the creation of more accessible and scalable solutions.

Finally, the model may be adapted for use beyond formal education, such as in corporate training and professional development programs. These applications would enable the exploration of new possibilities for personalization and automation in different knowledge domains. These pathways may not only expand the model's scope but also reinforce its relevance in a global landscape increasingly shaped by Artificial Intelligence in education and beyond.

Appendix A – Theoretical And Technical Foundations

A.1. Virtual Learning Environments

The increasing presence of Virtual Learning Environments

(VLEs) in the contemporary educational landscape reflects the progress of digital technologies and their potential to redefine pedagogical practices. According to [23], VLEs are defined as digital media that employ virtual spaces to deliver educational content and foster interaction among participants in the learning process. Their impact is no longer restricted to distance education but has expanded into face-to-face instruction, creating new opportunities for connected learning.

Originally designed for distance education, these environments have evolved to become integral components of in-person learning as well. As [24] notes, educational institutions are now required to integrate technologies previously limited to online education into their face-to-face modalities. This transformation is reinforced by trends identified by the [25], which calls for continuous innovation and research on the use of educational technologies. In this context, technological advancement plays a central role in modernizing and enhancing teaching and learning practices through the use of VLEs.

Technological evolution has enabled the incorporation of interactive tools into VLEs, including discussion forums, instant messaging, videoconferencing, podcasts, and video lectures. These tools contribute to more dynamic and accessible learning experiences. In addition, the use of emerging technologies such as 3D virtual environments and learning management systems powered by big data and artificial intelligence further expands instructional possibilities. However, the transition from traditional methods to virtual practices requires more than the adoption of tools; it demands a reconsideration of pedagogical structures and a cultural shift for all stakeholders involved.

The instructor's role evolves from being the central authority to becoming a mediator who promotes self-directed learning, collaboration, and critical inquiry. Meanwhile, learners are expected to take active ownership of their learning journeys in increasingly connected virtual spaces. This shift supports innovation in teaching and learning relationships and requires ongoing adaptation.

Given this context, exploring the diversity and characteristics of VLEs helps educators understand the tools, models, and applications available. Platforms range from open-source software such as Moodle to proprietary solutions like Blackboard and Canvas LMS. This exploration enables the adaptation of teaching strategies to meet student expectations and needs, while addressing pedagogical challenges posed by technological change. The transition from physical classrooms to digital environments requires instructional planning that takes into account the unique characteristics of online interaction and generational differences in student learning preferences. Understanding the types and features of VLEs reveals both the potential and challenges of implementing these technologies, highlighting the complexity of their integration into contemporary educational practice.

A.2. Types and Functionalities

Virtual Learning Environments can be classified into three main categories: open-source software, proprietary free or freemium platforms, and commercial proprietary platforms. Each category presents specific features that address different educational needs.

Open-source software, such as Moodle, is characterized by its flexibility and customizability, allowing educational institutions to adapt the platform to their specific requirements. A notable example is Sloodle, which integrates 3D virtual reality features to create a Multi-User Virtual Environment (MUVE), enhancing interactivity in online learning.

Freemium or free proprietary platforms, such as Edmodo and Google for Education, provide extensive features at no cost but limit customization options. Edmodo is recognized for promoting parental engagement in the learning process by allowing parents or guardians to actively follow student progress. Google for Education offers tools like Google Docs and Google Drive, facilitating the sharing of multimedia content and supporting academic task management.

Commercial proprietary platforms, such as Blackboard and Canvas LMS, require financial investment but offer personalized resources such as performance tracking dashboards and support for competency-based learning. Additionally, as highlighted by [26], virtual assistants have emerged as integrated components in many platforms. These assistants automate interactions and provide continuous support to both students and instructors, enhancing the educational experience through greater personalization and flexibility. As such, they have become strategic assets in the development of intelligent learning environments.

The diversity of models available illustrates how VLEs can incorporate a range of functionalities that enrich the educational experience. Discussion forums promote debate, live chats enable synchronous communication, and videoconferencing tools support real-time classes in all types of virtual environments. Furthermore, virtual assistants directly support learner autonomy by responding promptly to student needs. Assessment tools vary from automated quizzes to subjective assignments that generate detailed performance reports, enabling closer tracking of student progress.

A.3. History, Techniques, and Challenges of Artificial Intelligence

The evolution of Artificial Intelligence reflects a continuous effort to develop systems capable of replicating human cognition and reasoning across various levels of complexity. The earliest milestones in this field emerged in the 1950s, when Alan Turing proposed the Turing Test as a way to evaluate whether a machine could exhibit intelligent behavior equivalent to that of a human. This concept laid the foundation for subsequent research and was followed by the Dartmouth Conference in 1956, where John McCarthy formally coined the term "Artificial Intelligence," inaugurating a new era of focused and structured investigation.

In the decades that followed, research efforts concentrated primarily on rule-based systems and symbolic reasoning, such as ELIZA, a program that simulated simple dialogue. However, technological limitations in hardware and software led to periods of stagnation known as "AI winters," during which interest and funding significantly declined.

In the 1980s, a renewed phase of progress emerged with the introduction of artificial neural networks and machine learning techniques. These innovations enabled systems to learn from data and improve over time. This momentum increased significantly in the 2000s with the advent of deep learning, which uses multi-layered neural networks to process large volumes of data. Advances in this area have driven breakthroughs in image recognition, speech processing, and natural language understanding [27] Contemporary models such as OpenAI's GPT-3 represent the apex of this evolution, capable of performing complex tasks and generating human-like responses with remarkable sophistication.

Modern Artificial Intelligence techniques include a range of approaches that contribute to the development and deployment of intelligent systems. Machine learning has become a foundational component, relying on algorithms that can make predictions and decisions based on large datasets. These methods may be supervised, using labeled data to train models that predict specific outcomes, or unsupervised, which identify patterns in data without predefined labels. Reinforcement learning is another technique that trains agents to reach goals through trial-and-error interactions, guided by rewards.

Deep learning, a subfield of machine learning, expands these capabilities by employing deep neural networks capable of performing highly complex tasks such as visual interpretation and automatic translation. Convolutional Neural Networks (CNNs) are widely used for computer vision tasks, while Recurrent Neural Networks (RNNs) are more effective in processing sequences such as language and time series.

Natural Language Processing (NLP) has also become essential for enabling human-computer interaction, facilitating communication through chatbots, sentiment analysis systems, and automated language tools. However, the growing use of these applications has also introduced critical challenges related to the ethical and responsible use of AI. As noted by [28], although intelligent agents offer substantial benefits, ethical issues must be addressed, including data privacy, security, and algorithmic bias.

Algorithmic bias is particularly concerning, as systems trained on biased datasets may perpetuate social inequalities and unfairness. Another challenge involves the lack of transparency in AI models, especially in deep learning systems often described as “black boxes.” Their decision-making processes are difficult to interpret, which raises concerns in sensitive domains such as education, healthcare, and justice.

In Brazil, efforts to regulate Artificial Intelligence have advanced to promote ethical and responsible innovation. In 2023, the Federal Senate introduced Bill No. 2.338/2023, proposing guidelines to protect citizen rights and support responsible AI development. Drafted by a committee of legal experts and led by Senator Rodrigo Pacheco, the bill was based on international best practices. Its core principles emphasize human-centered design and the protection of human rights, and it outlines standards for public-sector AI use, including penalties for violations.

In 2024, the Temporary Commission on Artificial Intelligence in Brazil (CTIA) published an updated report outlining rights, responsibilities, and oversight mechanisms for AI adoption. The report affirms the country's commitment to aligning with global standards in the development of intelligent systems. Additionally, the Brazilian government launched the Brazilian Artificial Intelligence Plan (PBIA), which includes an investment of R$ 23 billion to support sustainable and socially responsible innovation in AI [29].

These initiatives place Brazil on a trajectory of technological growth that seeks to balance economic development with citizen protection and ethical responsibility. As such, the country continues to position itself as a leader in creating a secure and equitable environment for AI-driven innovation.

A.4. Artificial Intelligence Techniques

The advancement of Artificial Intelligence techniques has brought significant transformations across various sectors, including education, business, and services. These advances enable greater personalization and adaptability to user needs. According to [27], AI is based on algorithms capable of processing large volumes of data to solve complex problems. It is widely applied in machine learning, deep learning, natural language processing, and computer vision, among other areas that interact and complement each other rather than operating in isolation. Figure A.1 presents a flowchart that illustrates key AI techniques, their interrelations, and how they combine to form intelligent systems.

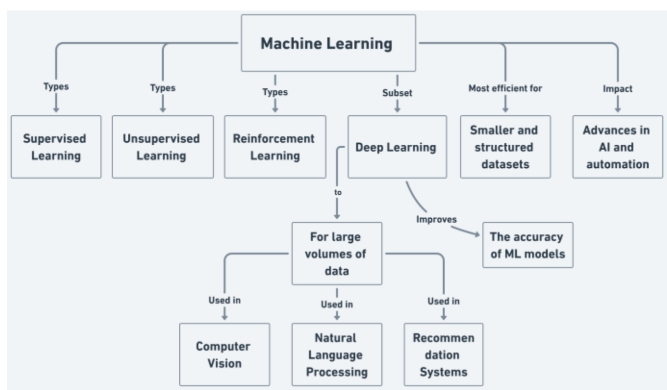

Fig. A.1. Artificial Intelligence Techniques

The organization and functioning of the techniques presented below follow the framework proposed by [22], which describes Artificial Intelligence as a structured field composed of various methods for processing, learning, and decision-making. The following sections detail these techniques, their characteristics, and applications.

A.4.1. Machine Learning

Machine learning is a subfield of AI that uses algorithms to identify patterns in data, enabling computational systems to make autonomous decisions. In supervised learning, models are trained using labeled data to make predictions. In unsupervised learning, the goal is to detect structures or groupings in raw datasets. Reinforcement learning involves agents interacting with an environment and learning to maximize rewards over time.

From a technical perspective, machine learning involves three main stages: data collection and preparation, model training, and evaluation. The first stage ensures that relevant information is organized and structured. During training, algorithms such as neural networks, decision trees, and regression methods are used to adjust model parameters. In the evaluation stage, the model's ability to generalize to new datasets is assessed to ensure its scalability and robustness.

A.4.2. Deep Learning

Deep learning is an extension of machine learning that employs deep neural networks to handle complex data representations. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are frequently cited for their ability to process images and sequential data, respectively. Techniques such as backpropagation are critical for adjusting weights and improving model accuracy.

The technical foundation of deep learning lies in the use of multiple layers of processing, which extract hierarchical representations of data. For example, in CNNs, early layers detect simple patterns such as edges, while deeper layers identify more complex structures. Backpropagation is used to calculate training errors and update connection weights accordingly, improving performance [27].

A.4.3. Natural Language Processing

Natural Language Processing (NLP) combines deep learning and semantic representations to allow machines to understand and generate human language. Models such as BERT and GPT are notable for their ability to capture complex linguistic context.

Technically, NLP starts with tokenization, the segmentation of text into smaller units, followed by vector representation through embeddings such as Word2Vec, GloVe, or transformer-based encodings. These vectors are processed by neural networks that analyze relationships between words, enabling solutions such as text classification, automatic question answering, and semantic analysis.

A.4.4. Computer Vision

Computer vision enables machines to interpret visual data, using CNNs for tasks such as object detection and image classification. The layered structure of convolutional networks allows them to extract features at different levels of abstraction, which is essential for the evolution of this field. Frameworks like TensorFlow support the implementation of these models.

From a technical standpoint, visual data is transformed into numerical matrices representing colors and intensities. These matrices are processed through convolutional layers that detect basic to complex patterns. Applications include facial recognition, visual analysis in educational assessments, and autonomous navigation systems.

A.4.5. Time Series Analysis

Time series analysis focuses on modeling data over time using methods such as RNNs and Long Short-Term Memory networks (LSTMs), which capture short- and long-term dependencies. This technique is widely used for forecasting, anomaly detection, and behavior prediction.

Technically, time series data is structured into sequences suitable for models like ARIMA or deep neural networks. LSTMs and GRUs use memory cells to store temporal information, allowing for accurate predictive modeling. Preprocessing steps such as normalization and gap handling are crucial to ensuring reliable results.

A.4.6. Time Series Analysis Pattern Recognition

Pattern recognition identifies recurring structures in large datasets. Algorithms such as k-means and deep neural networks automate the extraction and classification of features, with applications in both computer vision and NLP.

This process involves feature extraction, where raw data is transformed into informative representations. CNNs are typically used for visual patterns, while RNNs are better suited for sequential data. Algorithms like Support Vector Machines (SVMs) and k-means clustering are commonly applied in tasks requiring high-precision pattern classification.

A.4.7. Recommender System

Recommender systems apply machine learning to suggest personalized items to users. They are commonly used in e-commerce, streaming services, and educational platforms. These systems rely on collaborative filtering, content-based filtering, and increasingly, deep learning models.

Technically, they process user-item interaction data to build similarity matrices. Collaborative filtering identifies similarities between users or items, while content-based filtering analyzes item characteristics. Deep learning models and embeddings improve recommendation accuracy by modeling complex relationships between user preferences and item attributes.

A.4.8. Connecting AI Techniques in Virtual Learning

The integration of Artificial Intelligence techniques into Virtual Learning Environments requires a strategic combination of approaches that enhance the educational experience. According to [27], combining intelligent algorithms with computational infrastructure enables not only personalization but also the transformation of user-content interaction.

TABLE A.I
AI TECHNIQUES AND EDUCATIONAL APPLICATIONS IN VLES

Technique	Data Type	Main Algorithms/Models	**Applications in VLEs**
Machine Learning	Structured and unstructured	Neural networks, decision trees	Personalized content, performance analysis, learning gap identification
Deep Learning	High-volume, high-complexity	CNNs, RNNs, Transformers	Adaptive models for individualized support, behavioral pattern analysis
Natural Language Processing	Linguistic and textual	BERT, GPT, Word2Vec	Intelligent chatbots, feedback tools, language-based activity support
Computer Vision	Visual (images, videos)	CNNs	Facial recognition in assessments, video-based content analysis
Time Series Analysis	Sequential and temporal	RNNs, LSTMs, GRUs	Student progress monitoring, academic performance forecasting
Pattern Recognition	Multidimensional	K-means, SVMs, neural networks	Automated assessment enhancement, response classification
Recommender Systems	User preference data	Collaborative filtering, embeddings	Personalized learning material suggestions, adaptive learning strategies

These techniques not only personalize instruction but also transform how learners interact with content and educators. According to **Erro! Fonte de referência não encontrada.**, machine learning and deep learning can support the development of adaptive environments tailored to individual needs. NLP and computer vision provide more natural and immersive learning experiences, while time series analysis and pattern recognition support predictive and preventive strategies. Recommender systems ensure that each learner receives access to content aligned with their specific needs, reinforcing AI's role in fostering more effective and innovative digital learning environments.

APPENDIX B. CONCEPTUAL MODEL OF ARTIFICIAL INTELLIGENCE IN VLE

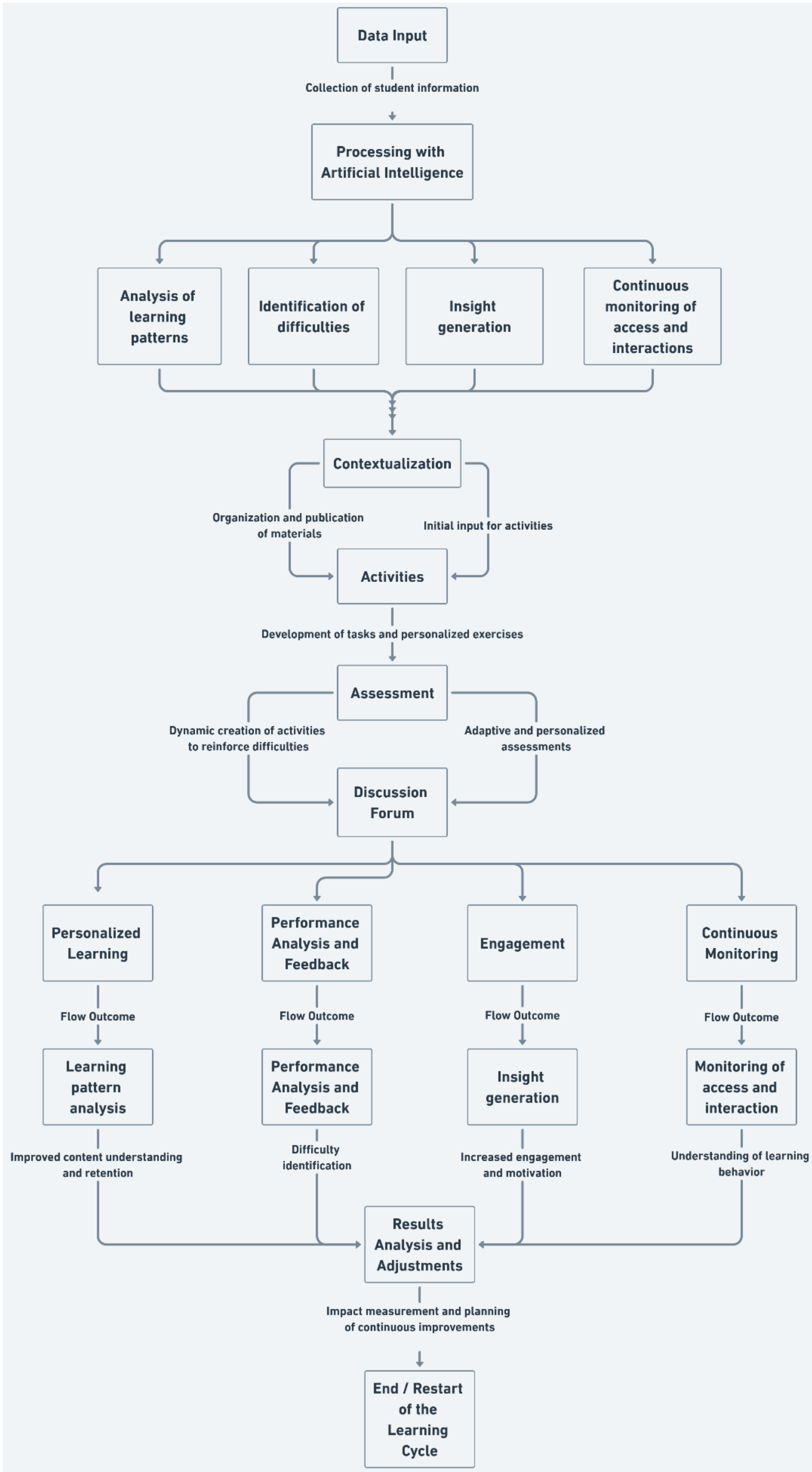

Fig. B.1. Conceptual Model of Artificial Intelligence in VLM

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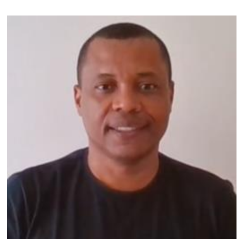

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