Evaluating the Adherence of Synthetic Digital Educational Content to Kolb's Learning Theory

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Abstract: The use of generative AI can be a powerful ally in combating dropout rates in online courses. This study explores the application of artificial intelligence (AI) to personalize educational content, aligning texts with the learning styles identified by David Kolb (Converging, Diverging, Assimilating, and Accommodating). This research proposes a generative AI algorithm capable of creating texts tailored to these styles, specifically designed for distance education (DE), in which personalization is essential due to the diversity of learning profiles and the lack of face-to-face interaction. Besides the initial development of the generator programs, this study reports on the proposal of a methodology used to validate the quality of the generated texts and their adequacy to Kolb's learning styles. The methodology was applied by six experts. The results show a high alignment of the texts with the Converging, Diverging, and Accommodating styles (100% on the Content Validity Index), with room for improvement in the Assimilating style (83%). The research highlights the technical feasibility of the proposed approach, both from the perspective of generative AI and the methodology for certifying the quality of synthetically generated material.

1 INTRODUCTION

Distance Education (DE) in Brazil faces the persistent challenge of high dropout rates, with figures ranging from 21% to 50% in fully online courses, according to surveys by ABED (BR, 2018). This reality has a negative impact on educational institutions, leading to financial losses, underutilized infrastructure, and idle faculty and staff, while also limiting the expected social and educational returns.

A promising approach to address this issue is the personalization of educational content, adapting it to the diverse learning preferences of students. For this, we can make use of the principles of Kolb's Theory, which are widely applied in corporate training, personal development, and, above all, in education (Kolb and Kolb, 2009).

According to Kolb (2014), there are four learning modes: (i) Concrete Experience (CE), characterized by a preference for learning through direct, sensory experiences, as well as intuitive, hands-on approaches; (ii) Reflective Observation (RO), marked by analyzing and reflecting on experiences before acting, with a focus on examining different perspectives; (iii) Abstract Conceptualization (AC), oriented towards logical and theoretical analysis, prioritizing concepts and analytical reasoning; and (iv) Active Experimentation (AE), characterized by the immediate application of what has been learned, with a preference for testing ideas and learning by "doing" and observing the results. Kolb also states that when two of these modes interact, the learning styles are formed. These are four as well: (i) the Assimilating style results from the interaction between RO and AC, characterized by a preference for analyzing ideas in

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a structured and logical manner; (ii) the Converging style is formed by AC and AE, combining theoretical analysis with practical application and problem-solving; (iii) the Diverging style combines CE and RO, emphasizing the exploration of multiple perspectives and valuing sensory experience; and (iv) the Accommodating style integrates CE and AE, favoring a practical and experimental approach to learning through action, as shown in the graph in Figure 1.

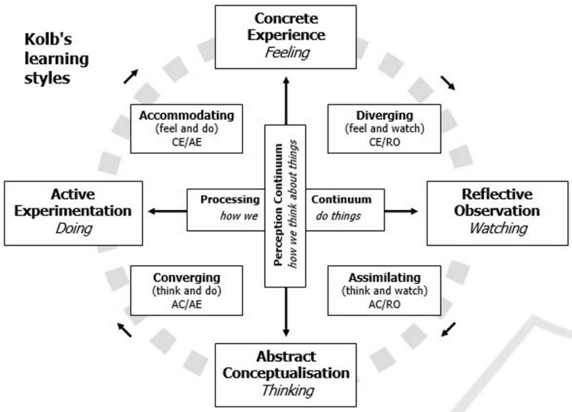

Figure 1: Learning styles and modes according to Kolb's theory.

Taking these differences into account in the development of educational materials can increase student engagement and retention, especially in distance education (DE), where the lack of face-to-face interaction demands more personalized and effective learning strategies. Based on this perspective, this study proposes the use of generative artificial intelligence to create personalized texts, adjusted to Kolb's learning styles. To assess the feasibility of this approach, a methodology was developed based on a checklist that verifies the alignment of the texts with the proposed styles, using objective criteria to ensure the reliability of the analysis.

Initial results suggest that it is feasible to artificially generate texts aligned with Kolb's styles and that the assessment methodology contributes to enhancing the quality of the final product.

The remainder of this paper is organized as follows. Section 2 discusses the different types of dropout in distance education, highlighting course and content quality as key factors and suggesting AI-driven adaptation to mitigate dropout rates. Section 3 presents a systematic literature review on the use of generative AI for personalizing educational content in distance learning, focusing on learning styles and assessing the feasibility of this approach. Section 4 examines the findings of the bibliographic research, revealing a lack of studies applying generative AI to Kolb's learning styles despite widespread discussions on AI-driven personalization. Section 5 details the proposed AI approach, outlining its three main stages: preprocessing, information retrieval, and content generation. Section 6 describes the research methodology used to validate AI-generated texts, including a structured checklist and the Content Validity Index (I-CVI). Section 7 presents the validation results, demonstrating strong expert agreement on the effectiveness of AI-generated texts for most learning styles, except for the Assimilating style, which requires further refinement. Finally, Section 9 provides conclusions, emphasizing the high alignment of AI-generated texts with Kolb's learning styles, the need for improvements in Assimilating content, and the potential for future testing in distance education environments.

2 METHODS FOR TACKLING THE PROBLEM

According to Silva and Rocha (2020, p. 04, apud Rocha and Santos, 2021, p. 5) , in distance education, the types of dropout can be classified as follows: dropout occurs when the student abandons the course; stopout refers to a temporary interruption of the course; attainer characterizes the student leaving the course before completion, but with the acquisition of knowledge or achievement of personal goals; and the non-starter represent cases in which students do not even begin the course.

According to Antunes Garanito et al. (2024, p. 11) , the "courses and content" category, which encompasses course structure and content such as the assessment of exercises, activities, and exams, the connection between theory and practice in the subjects, and the quality of the teaching materials, is identified as the main cause of dropout in distance higher education. The authors further emphasize that the quality of the content and its presentation are essential to maintain student interest and motivation, as well as help minimizing dropout. When there is no clear connection between theory and practice, or when the teaching materials are inadequate, lack incentive or are difficult to understand, students tend to lose interest and abandon the course.

According to Rocha and Santos (2021, p. 16) , some strategies are suggested to minimize dropout, such as revising the course's pedagogical and methodological proposal and using technology to support learning.

Thus, it is clear that both approaches can be enhanced with the support of artificial intelligence in distance education. The use of AI allows for the rapid adaptation of pedagogical content to meet the specific needs of each student based on their individual learning styles, promoting a more personalized and efficient educational experience.

3 USE OF AI IN PERSONALIZING EDUCATIONAL EXPERIENCES

A systematic bibliographic review was conducted on July 31, 2024, with the aim of identifying studies that use generative artificial intelligence for adapting educational content, focusing on the learning styles defined by Kolb (diverging, converging, assimilating, and accommodating) in the context of distance education. To ensure the organization and relevance of the studies identified in this research, the PICOC protocol was applied, which structures the research into five main elements: Population, Intervention, Comparison, Results, and Context.

The population included distance education students and professionals in the field; the intervention analyzed was the use of generative AI in the production of educational content adapted to learning styles; and the comparison was made with content produced by education professionals. The main outcome investigated was the effectiveness and feasibility of this approach in personalizing content, aiming to increase student engagement and motivation. Finally, the context focused on distance education.

A quality assessment verification was used to ensure the careful selection of articles related to the topic. This list considered the relevance and consistency of the content addressed in the identified studies, through the following questions:

1. Does the article address the use of generative artificial intelligence in the production of educational content in the context of distance education?
2. Is the research objective clearly defined?
3. Do the authors describe the limitations of the study?
4. Does the article discuss the relevance of learning styles in the presented context?

These criteria aim to ensure that only studies aligned with the research objectives were included in the analysis, guaranteeing the quality and relevance of the data collected.

The searches were conducted in the following databases: Scopus, Google Scholar, IEEE Xplore, and ACM Digital Library, using a search string developed with keywords related to content production, learning styles, and generative AI. The string used was ("Learning Styles") AND ("Content Production" OR "Content Creation" OR "Content Generation" OR "Content Manufacturing") AND ("Generative AI" OR "Generative Artificial Intelligence" OR "IA").

The search results included 1 article in Scopus, 140 articles in Google Scholar, 90 articles in IEEE Xplore, and 58 articles in ACM Digital Library. To select the most relevant studies, inclusion criteria were applied, such as publications from 2020 onwards, articles available in English, Portuguese, or Spanish, and studies addressing content creation with generative AI for distance education or the adaptation of content to individual learning styles. Duplicated studies, out of scope, or published before 2020 were excluded.

Three or more articles were selected for a preliminary analysis, in order to map the relevance of the content. Additionally, the first 10 titles were read to check if they addressed the keywords of the research. If so, the entire article was read.

This preliminary approach proved to be interesting for several reasons:

- Focus and Efficiency: Selecting three or more articles for preliminary analysis allows for focusing efforts on the most relevant materials initially, optimizing the available time.
- Relevance of Content: Analyzing the first 10 titles to identify keywords related to the research theme helps ensure that the reading of the study aligns with the established objectives. This initial screening allows for quickly filtering out materials that do not significantly contribute to understanding the theme.
- Effectiveness in Data Collection: The initial reading of the titles, followed by the selection and analysis of the most promising articles, enables a targeted data collection process, avoiding distractions with irrelevant information.

The quality of the selected studies was evaluated based on a checklist that considered content relevance, clarity of objectives, description of the limitations of the study, and discussion of learning styles. Each criterion was scored, and only studies with a minimum score of 3.0, out of a total of 4.0, were included in the analysis. The results obtained serve as a basis for discussing the applicability of generative AI in personalizing educational content, contributing to innovation in the field of distance education and to improving the learning experience for students.

4 RESULTS OF THE BIBLIOGRAPHIC RESEARCH

Despite the application of a systematic search protocol in the Scopus, Google Scholar, IEEE Xplore, and ACM Digital Library databases, no study was found that specifically addressed the use of generative artificial intelligence (generative AI) for creating educational content in distance education adapted to Kolb's learning styles (diverging, converging, assimilating, and accommodating).

The articles identified in the bibliographic review broadly explored the impact of generative AI in education, highlighting expectations and challenges. Among the topics discussed were personalized learning, the automation of pedagogical tasks, the creation of immersive content, and the use of algorithms to adapt teaching materials to the individual needs of students. For example, the paper *Challenges and Opportunities: Integrating Generative AI into Education for Future Learning* discusses ethical challenges and opportunities associated with the use of generative AI, such as personalized learning, but does not address Kolb's learning styles.

Similarly, the article *Educational Innovation: Challenges and Opportunities with Generative AI Integration* explores the benefits of AI, such as automation and personalization, but does not focus on adaptation to Kolb's styles. The study *Generative AI in Education: Technical Foundations, Applications, and Challenges* analyzes the technical applications of generative *AI in education but does not consider Kolb's learning styles. The paper Generative AI in Education: Challenges and Opportunities for Future Learning* emphasizes personalization and adaptive feedback without exploring the application to Kolb's styles.

The article *Using Generative AI and ChatGPT for Improving the Production of Distance Learning Materials* addresses the use of AI in the production of materials but does not include adaptation to Kolb's learning styles. Finally, the study *IA Generativa na Educação: Moldando o Futuro da Aprendizagem* explores personalized learning pathways but does not specifically apply Kolb's styles.

The studies collectively summarize that personalized learning can facilitate student engagement and motivation. In this way, learning becomes more meaningful when learning activities align with students' interests and goals. Additionally, discussions highlight how AI can provide targeted support to students facing challenges and propose additional challenges for those demonstrating advanced performance. However, the reviewed works did not address the application of generative AI in producing content tailored to Kolb's learning styles, which propose an approach based on the four learning styles previously mentioned: diverging, converging, assimilating, and accommodating.

Furthermore, the reviewed studies emphasized significant challenges, such as ethical concerns, algorithmic bias, data privacy, and the need for clear guidelines for implementing AI in education. Nevertheless, the transformative potential of generative AI is widely recognized in various studies, particularly in developing personalized learning environments and providing adaptive pathways that meet each student's individual needs. Therefore, although the existing literature explores relevant aspects of generative AI integration in education, it does not specifically address its application to Kolb's learning styles.

5 ARTIFICIAL INTELLIGENCE APPROACH

The generative AI approach proposed in this article focuses on the personalization of educational texts using advanced Natural Language Processing (NLP) and Machine Learning (ML) techniques. This approach is structured into three main stages, as illustrated in Figure 1: (i) Text Preprocessing, (ii) Information Retrieval, and (iii) Content Generation.

In the first stage, Text Preprocessing, the approach takes an educational base text as input, which undergoes a series of extraction and text-cleaning procedures. During this process, noise is removed, terms are normalized, and the vocabulary is standardized. The goal of this phase is to ensure the quality of the input data and to facilitate the identification of textual elements that will be adapted to Kolb's learning styles. The use of machine learning techniques at this stage ensures that the content is properly structured and ready for subsequent stages.

The second stage, Information Retrieval, is inspired by the Retrieval-Augmented Generation (RAG) strategy, which combines information retrieval with context enhancement to ensure that the generated content is contextualized and coherent (Lewis et al., 2020). This stage consists of four main activities. First, text splitting is performed, where the text is divided into smaller parts, e.g., paragraphs.

Then, what we call chunk generation occurs, and those parts are organized into even smaller units called chunks. The third activity is embedding generation, where each chunk is transformed into a high-level numerical vector that captures its semantic meaning. Finally, in Vector Database (VD) persistence, the generated embeddings are stored in a vector database, enabling efficient future searches.

The third and final stage, Generation Content, is responsible for producing texts personalized to Kolb's four learning styles (LS). This stage is composed of three main activities. In the first, Get embeddings from VD, the embeddings are retrieved from the vector database. The second activity, Prompt adjustment for LS, involves the application of prompt engineering techniques that use specific characteristics of each learning style, such as their key properties, appropriate tone, and personalized text examples. These adjusted prompts are then used in the third and final activity, Large Language Model (LLM) text generation.

This activity employs the LLM, an artificial intelligence model trained on large volumes of textual data, capable of interpreting and generating content in a highly contextualized and personalized manner to meet the application's specific needs (Johnsen, 2024).

The chosen model for this activity was the Large Language Model Meta AI (LLaMA) 3 70B, developed by Meta, an open-source model comprising 70 billion parameters and trained on 15 trillion tokens (Meta, 2024).

Its main advantage lies in its ability to perform prompt-based customization, allowing the structure and content of the text to be tailored to the specific demands of each context. This is essential for generating more cohesive, precise, and goal-aligned texts (Fernández-López et al., 2024). The LLaMA 3 generates personalized texts, which can then be validated by experts to ensure continuous quality assessment of the produced content.

This generative AI approach, when applied in distance education (DE) environments, enhances AI's ability to efficiently personalize teaching, catering to distinct learning profiles. The combination of these three stages results in a robust and replicable method, highlighting AI's potential to transform traditional pedagogical practices into personalized and inclusive approaches.

6 RESEARCH METHODOLOGY

The creation of evaluative instruments, such as questionnaires, requires methodological rigor and a solid theoretical foundation to ensure their efficacy and validity. According to Bardin (2012) , content analysis is a systematic technique that demands careful structuring for reliable data collection and interpretation. In a complementary way, DeVellis (2021) emphasizes the importance of grounding both the item construction and the stages of validation and analysis in well-established theoretical models.

In this study, Kolb's (1984) learning styles theory was used as the foundation to develop a checklist for evaluating the suitability of texts generated by artificial intelligence (AI) to different learning profiles: Assimilating, Converging, Diverging, and Accommodating.

6.1 Methodology Stages

1. **Development of the Checklist.** A checklist with 20 objective questions was developed, evenly distributed among Kolb's learning modes (5 questions per mode: CE, RO, AC, and AE). Each question was designed to capture specific elements of each mode and was accompanied by justifications, providing greater depth to the analysis.
2. **Structuring by Learning Styles.** Based on the combination of modes, the learning styles were organized with 10 questions per style:
   - **Assimilating:** 5 questions for RO + 5 for AC.
   - **Converging:** 5 questions for AC + 5 for AE.
   - **Diverging:** 5 questions for CE + 5 for RO.
   - **Accommodating:** 5 questions for CE + 5 for AE.
3. **Checklist Scoring.** For each question, a binary scoring system was assigned:
   - 1 point for affirmative answers (”Yes”), indicating that the text met the criterion;
   - 0 points for negative answers (”No”), indicating that the text did not meet the criterion.

   The maximum score for each style was 10 points, and the minimum was 0 points.
4. **Results Interpretation.** Scores were analyzed on an adapted Likert scale:
   - 9–10 points: ”Strongly Agree”
   - 7–8 points: ”Somewhat Agree”
   - 5–6 points: ”Neutral”
   - 3–4 points: ”Somewhat Disagree”
   - 0–2 points: ”Strongly Disagree”
5. **Content Validity Index (I-CVI) Calculation.** The I-IVC was calculated to consolidate the validity of the texts in each style, using the formula:

$$I\text{-}CVI = \frac{\text{Number of valid responses}}{\text{Total number of experts}} \quad (1)$$

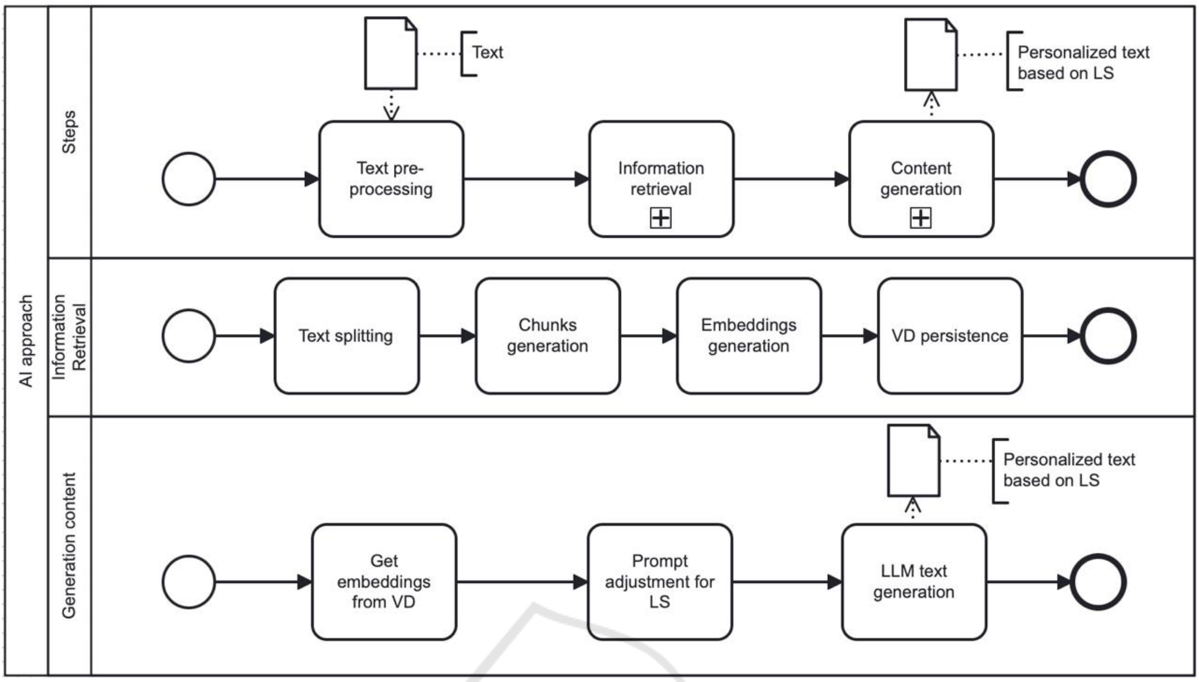

Figure 2: AI approach to generating content adapted to Kolb's learning styles.

7 RESULTS

7.1 Validation by Experts

A group of six experts in education was invited to evaluate four texts, each adapted to one of Kolb's learning styles. These experts, with professional experience ranging from 5 to 37 years, represented diverse backgrounds and areas of expertise, including distance education (DE) and educational technology.

The texts were evaluated based on their alignment with the learning styles, and the results were organized as follows:

- **Converging Text:** 100% total agreement.
- **Diverging Text:** 100% total agreement.
- **Accommodating Text:** 100% total agreement.
- **Assimilating Text:** 83% agreement (50% total, 33% partial).

These results indicate a high level of alignment between the AI-generated texts and the learning styles, as assessed by the experts.

7.2 Methodological Conclusion

The applied methodology proved promising for evaluating the suitability of AI-generated personalized content to the learning styles proposed by Kolb. The application of the checklist, complemented by the I-CVI, revealed potential to validate and improve the personalization of educational materials, contributing to more inclusive and effective approaches in distance education.

7.3 Discussion

The results of the checklist application demonstrated the adequacy of the texts with Kolb's learning styles, according to the responses of the six experts. By using both the dichotomous scale and the Likert scale for interpretation, it was possible to measure and classify the texts' adequacy with each style. The findings for each evaluated text are discussed below:

- **Converging Text.** All of the experts gave this text scores between 9 and 10, reflecting a total agreement index (I-CVI = 100%). This unanimity suggests that the converging text clearly aligns with the modes "Abstract Conceptualization" (AC) and "Active Experimentation" (AE), which define this style. The structure and elements of the text seem to have fully met the criteria evaluated in the checklist, such as the practical application of concepts and emphasis on objective solutions.
- **Diverging Text.** Four experts gave this text scores between 9 and 10, while two rated it between 7 and 8, resulting in an I-CVI of 100%. Although all

experts agreed that the text aligns with the Diverging style, the degree of agreement varied between total and partial. This result suggests that the text effectively captured the core aspects of "Concrete Experience" (CE) and "Reflective Observation" (RO), but there may be room to improve elements that fully address the more specific preferences of some evaluators.

- **Accommodating Text.** The Accommodating text also achieved an I-CVI of 100%, with four experts assigning scores between 9 and 10, and two between 7 and 8. This indicates a widely perceived alignment with the characteristics of the style, such as learning through practice and action-oriented content. The combination of "Concrete Experience" (CE) and "Active Experimentation" (AE) appears well-represented in the content, although minor adjustments could further enhance the perception of total alignment.
- **Assimilating Text.** Unlike the other styles, the Assimilating text showed greater variability in evaluations. Two experts gave it scores between 9 and 10, while three scored it between 7 and 8, and one rated it between 5 and 6, resulting in an I-CVI of 83%.

  When analyzing the justifications presented by the specialists which led to this lower performance, it was found that five of the participants in the experiment considered that most of the characteristics of reflective observation were not present in the text. Upon a more detailed analysis, four specialists stated that in regards to reflective observation, the text did not promote elements that would invite the reader to reflect on and observe a past experience to aid in understanding the content or making decisions. This was the case in spite of the fact that the text presented the concept of variables to facilitate comprehension, as highlighted by one of the evaluators when justifying their response. When asked whether the text encourages the reader to reflect on the information before applying it, three out of the six specialists answered that it does not. One of them justified that, although the text encourages reflection, it does not make it clear that this process needs to be carried out before and after the practical application. Another specialist pointed out the absence of examples of situations that would encourage reflection before acting. Still on reflective observation in the assimilating text, one of the specialists argued that the text provides only the perspective of the concept in programming and, for this reason, does not present multiple perspectives or viewpoints on the concepts addressed. Finally, another specialist highlighted that they could not identify, in the assimilating text, elements that would invite the reader to reflect on their own experiences before reaching a conclusion. Moving on to the analysis of the characteristics of abstract conceptualization in the assimilating text, only one specialist considered that, throughout the text, there were no connections between ideas or theories that would promote a broader understanding of the content, justifying that the text only addressed the concept of variables in programming. Lastly, one specialist disagreed with the statement that the author discussed the logic behind the concepts to facilitate the understanding of the text, arguing that they could not identify passages explaining the "logic behind the concepts." Instead, they only observed the presence of practical examples and real-life situations where the concept is applied. More structured and theoretical elements, which are valued by this profile, may not have been sufficiently emphasized, highlighting the need for further refinement of the generated text for this learning style.
- **General Considerations.** The results analysis suggests a consistent validation of the adopted methodology. Texts aligned with the Converging, Diverging, and Accommodating styles achieved the maximum I-CVI, demonstrating that the question formulation and evaluation criteria were effective in capturing the characteristics of these styles. On the other hand, the more variable performance of the Assimilating text highlights the need for improvement both in the generated content and in the formulation of questions associated with the checklist.

8 THREATS TO VALIDITY

- **Internal Validity: Expert Bias.** The evaluation of the adequacy of the texts was conducted by only six specialists, which may introduce interpretation bias and subjective judgment;
- **Influence of the Evaluation Methodology.** The use of a checklist may have guided specialists to assess the texts in a more homogeneous manner than they would have done naturally;
- **Generalization of the Learning Styles.** Kolb's categorization of the learning styles may not fully capture the complexity of the individual learning processes;
- **External Validity: Applicability to Different Student Profiles.** The study does not test the ef-

fectiveness of the texts on actual students, which may limit the generalizability of the results;

- **Focus on Distance Education**. The model may not be equally effective in in-person or hybrid learning contexts;
- **Dependence on the AI Model Used.** Since LLaMA 3 70B was used, other AI architectures may produce different results, impacting replicability;
- **Construct Validity: Definition of the Evaluation Criteria.** The checklist used to validate the texts may not fully capture their adequacy to the learning style;
- **Measurement of Personalization.** The study does not directly measure whether the texts effectively enhance the students' learning across different styles.

9 CONCLUSIONS

This study investigated the application of generative artificial intelligence (AI) in adapting educational content to different learning styles based on Kolb's theory. The research proposed an evaluation methodology using specific questionnaires to measure the alignment of AI-generated texts with the learning styles: Converging, Diverging, Accommodating, and Assimilating. The validation of this approach was conducted through an analysis by education experts, who assessed the suitability of the texts for each learning style using a checklist developed for this purpose.

Key findings of the study include the observation that the AI-generated texts demonstrated excellent alignment with the Converging, Diverging, and Accommodating learning styles, each achieving a Content Validity Index (I-CVI) of 100%. The Assimilating text, while well-evaluated, showed greater variability in participant responses, with an I-CVI of approximately 83%, suggesting the need for adjustments to enhance its consistency with this style's characteristics.

The proposed methodology also proved effective in evaluating the adaptation of AI-generated content to different learning profiles, enabling effective personalization of educational material.

The study further highlighted the importance of an ongoing process of validation and refinement of AI algorithms, ensuring that the generated content not only meets educational objectives but also aligns precisely with individual learning preferences. The use of a dichotomous scale (Yes/No) and the detailed structure of the checklist allowed for objective evaluation and minimized subjectivity in the validation process.

As a future relevant work, we can apply the methodology with distance education (DE) students. Evaluating the effectiveness of AI-generated texts in DE contexts will allow for analyzing the suitability of the content to learning styles in a real online teaching environment, considering limited interaction between teachers and students and the diversity of student profiles. This study could provide valuable insights into how to customize content to promote more efficient and inclusive learning in DE.

As a continuation of this research, an essential next step is the application of the methodology with students in Distance Education (DE). Evaluating the effectiveness of AI-generated texts in this context will allow for an examination of the suitability of the content to learning styles in a real online learning environment, taking into account the limited interaction between teachers and students and the diversity of student profiles. This study could provide valuable insights into how content personalization impacts engagement and learning in DE.

Furthermore, future investigations should explore comparisons between the text-generating algorithm and advanced artificial intelligence models, such as GPT-4 and BERT. This analysis will help identify which models are more effective in personalizing educational content, considering aspects such as adaptability and precision in generating texts aligned with different learning styles. A deeper study on the interaction of these models with students' individual preferences may reveal more effective strategies for the personalization of educational materials.

Another promising direction for future research is expanding the theoretical scope by comparing the adopted methodology with other learning approaches, such as the VARK model (Visual, Auditory, Reading/Writing, and Kinesthetic) and Gardner's Theory of Multiple Intelligences. Conducting an empirical study to assess the impact of personalized content on students' perceptions and performance will contribute to obtaining concrete data on the effectiveness of personalization. This approach will not only strengthen the external validity of the results but also enhance the understanding of how different learning styles and intelligences influence student experience and engagement in DE environments.

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