How the Educator 5.0 Will Not Be Replaced by AI: An Adaptive Microlearning Architecture Based on Augmented Intelligence

Emanuel Ferreira[1], Silvio E. Quincozes[1,2], Matheus M. Ciocca[1], Gabriel Silva[1], Paulo Souza[1], Gilleanes Guedes[1], Williamson Silva[2,3]

[1]PPGES / Campus Alegrete — Federal University of Pampa (UNIPAMPA), Brazil.

[2]PPGCO — Federal University of Uberlândia (UFU), Brazil

[3]Federal University of Cariri (UFCA), Brazil

{emanuelferreira, matheusciocca, gabrielbotelho}.aluno@unipampa.edu.br

{silvioquincozes, paulosilas, gilleanesguedes}@unipampa.edu.br

williamson.silva@ufca.edu.br

Abstract. *Education 5.0 proposes a human-centered model that integrates personalization, technology, and the active roles of both instructors and students. However, current educational tools still face limitations such as a lack of flexibility and monitoring capabilities. This work proposes an educational architecture that supports the Educator 5.0 in generating, customizing, and monitoring adaptive microlearning paths. The concept of augmented intelligence enhances the educator's role as a critical curator of AI-generated content, based on their teaching materials, and as a mediator of formative learning experiences. As a result, learners obtain customized, real-time adaptive content blocks, ensuring learner diversity is respected and enabling the generation of pedagogical alerts.*

1. Introduction

Education 5.0 drives the integration between technological advances and human development, promoting adaptive and student-centered learning environments [Agarwal et al., 2025]. In this context, the incorporation of technologies based on Artificial Intelligence (AI) boosts the profiles of Educator 5.0, who has access to augmented intelligence (AuI) by expanding their performance with the support of intelligent systems, and Learner 5.0, who leads their formative journey, assisted by technologies that promote their autonomy and respect their learning pace [Franqueira et al., 2024].

Despite advances, many systems still hinder the full adoption of innovative approaches due to the lack of integration between planning, personalization, and evaluation, as well as the overload caused by complex and disconnected tools [Bezerra et al., 2024]. Microlearning proposals often do not include pedagogical alerts [Zhu et al., 2025], customization by the instructor [Wang, 2025], or adaptivity to student progress [Kohnke et al., 2025]. Those that incorporate these functions generally do not adopt microlearning [Cuellar et al., 2025; Kwon, 2022; Mrabet et al., 2024]. Thus, a gap persists between the potential of emerging technologies and their practical application in learning [Silva and Janes, 2020]. Overcoming it requires fluid integration between the training stages,

DOI: 10.5753/sbie.2025.12439

respect for the diversity of Learners, and optimization of pedagogical decisions [Pestana and Santos, 2023; Silva and Janes, 2020].

This work proposes an educational architecture that supports Educator 5.0 in generating, customizing, and monitoring adaptive microlearning paths. Based on the concept of AuI, the Educator acts as a critical curator of AI-generated content from their own teaching materials and as a mediator of formative experiences. To achieve this, Large Language Models (LLMs) are utilized, which enable the creation and customization of personalized paths, in addition to generating dynamic content in real-time, tailored to different Learner profiles. Even with automation, the Educator maintains a central role by guiding content generation and carrying out individualized pedagogical interventions. The architecture was validated through a Proof of Concept (POC), presenting initial results. In this context, i) improvement points in the developed platform were identified and implemented based on Educators' feedback, and ii) the functionalities of adaptive microlearning were preliminarily validated, according to the performance of Learners in a Software Engineering course.

2. Theoretical Foundation

Education 5.0 proposes an integration between technology and humanization, promoting personalized, collaborative, and subject-centered learning experiences. In this model, two leading actors stand out [Damaševičius, 2025]: Educator 5.0, who acts as a strategic and critical mediator, and Learner 5.0, the protagonist of the training process itself, supported by educational technologies that are sensitive to their needs.

To fortify this ecosystem, the concept of AIu stands out, which does not aim to replace the teaching role, but to expand it through collaboration between humans and AI systems [Toivonen et al., 2019]. This integration enables the planning of formative paths, personalization of teaching, and monitoring of student progress, reinforcing the educator's role in pedagogical decisions. On the other hand, as direct support to the Learner, adaptive microlearning emerges as an effective strategy by organizing content into short, objective, and personalized blocks [Sirwan Mohammed et al., 2018]. This approach favors knowledge retention, that is, a knowledge management process [Agarwal and Islam, 2015] linked to the concept of maintaining and reusing knowledge [Levy, 2011], and adapts to different learning rhythms and profiles, promoting accessibility, continuity and engagement.

Knowing this, we also have the concept of Pedagogical Architecture, which, according to Carvalho et al. (2005), enables the development of pedagogical proposals aligned with digital technologies. This concept integrates several components, such as pedagogical approach, software, internet, and AI. In this scenario, Pedagogical Architecture organizes and articulates elements present in Education 5.0, allowing them to be coherently integrated into educational practices.

In this context, AI becomes a central ally. Natural Language Processing (NLP) allows students to interpret texts, generate feedback, and adapt content [Alhawiti, 2014], while LLMs expand this capacity with contextualized textual understanding and generation close to human discourse [Jyothy et al., 2024; Alfirević et al., 2024]. Generative AI enables the dynamic creation of personalized resources, aligning with the diversity of profiles and promoting more inclusive and flexible educational environments [Isotani et al., 2025].

3. Related Work

The related works are summarized in Table 1, where the adopted models are identified and the proposal is compared in light of the following criteria:

i) *Microlearning*: is there a microlearning structure with progressive segmentation (*e.g.,* division of content into short and incremental lessons)?
ii) *Pedagogical Alert*: does the proposal include any mechanism to signal errors, difficulties, or pedagogical intervention needs during learning?
iii) *Customizable (by Educator)*: does the proposal allow instructors to modify, configure, or customize aspects of the system or the content used?
iv) *Adaptive (real-time)*: is the automatic adaptation of the system based on the student's real-time performance foreseen (*e.g.,* adjustment of difficulty/content)?

Table 1. Mapping of the main related works.

Reference	AI Tool (Generative/LLM/NLP)	Microlearning (content blocks)	Alert Pedagogical	Customizable (by the instructor)	Adaptive (real time)
[Zhu et al., 2025]	GPT-4	✓	-	-	✓
[Kohnke et al., 2025]	Several	✓	-	Partial	-
[Kwon, 2022]	GPT-3	Partial	-	-	Partial
[Mrabet et al., 2024]	GPT-3.5	Patcial	-	-	✓
[Cuellar et al., 2025]	GPT-4	-	✓	-	Patcial
[Wang, 2025]	GPT-4	-	Partial	✓	✓
This work	Llama-3.3-70B-Versatile	✓	✓	✓	✓

The proposals by Zhu et al. (2025) and Kohnke et al. (2025) stand out for integrating microlearning structured into modular blocks based on LLMs. Zhu et al. (2025) employs the GPT-4 model to generate adaptive tutorials, verification questions, and contextualized support through a virtual assistant. The modular "bite-sized blocks" enable automatic adaptation according to the learner's progress. Kohnke et al. (2025) makes use of several LLM-based tools (ChatGPT, MagicSchool, Twee, Perplexity, Alayna) to design progressive microlearning blocks, each lasting between 1 and 6 minutes. However, both approaches lack pedagogical alert mechanisms. Moreover, Zhu et al. (2025) does not allow customization by the instructor, whereas Kohnke et al. (2025) does not adapt its content in real-time.

The approaches proposed by Kwon (2022) and Mrabet et al. (2024) include structures that approach microlearning by employing flows separated into stages. Kwon (2022) presents an approach to language learning, based on GPT-3, which adapts according to the context provided by the user. On the other hand, Mrabet et al. (2024) uses the GPT-3.5 model to adapt in response to the Learner's performance. Neither proposal includes features for the Educator, such as pedagogical alerts or customization options.

Moreover, the approaches by Cuellar et al. (2025) and Wang (2025) do not incorporate microlearning. Cuellar et al. (2025) provides weekly pedagogical alerts, allowing adaptation based on recent data, but without instructor customization. Wang (2025) identifies at-risk students and suggests interventions. Content recommendations are dynamically adjusted according to student performance. Therefore, it can be observed that most related works emphasize adaptivity but fail to integrate all four established criteria simultaneously. This represents a significant differentiating feature of the proposed architecture.

Despite the diversity of solutions analyzed, it is observed that current tools still exhibit a significant lack of flexibility. Each proposal tends to emphasize only one aspect: Wang (2025) it has adaptivity, Kohnke et al. (2025) has a partial customization, or the issuance of pedagogical alerts Cuellar et al. (2025), but none manage to seamlessly integrate planning, customization, assessment, and instructor supervision within a single ecosystem. This fragmentation creates an additional burden for the Educator, who must manually coordinate different technologies, and compromises the pedagogical coherence of the learning paths.

The differentiating feature of the architecture proposed in this work lies precisely in overcoming this limitation through the simultaneous integration of four critical dimensions: (i) microlearning structured in short blocks, (ii) real-time pedagogical alerts, (iii) instructor customization based on their own instructional materials, and (iv) dynamic adaptivity according to learner performance. This combination ensures greater flexibility, preserves the educator's central role as a critical mediator, and enhances the effectiveness of Learner 5.0's learning journey.

4. Proposed Architecture: Overview and Integrated Processes

This section presents a pedagogical architecture that fosters an adaptive educational dynamic, where generative AI and data analysis resources personalize the learning flow without overburdening the instructor. The architecture shown in Figure 1 aims to simultaneously optimize the work of the Educator 5.0 in designing adaptive microlearning pathways and the experience of the Learner 5.0. This figure will be further explained throughout this section.

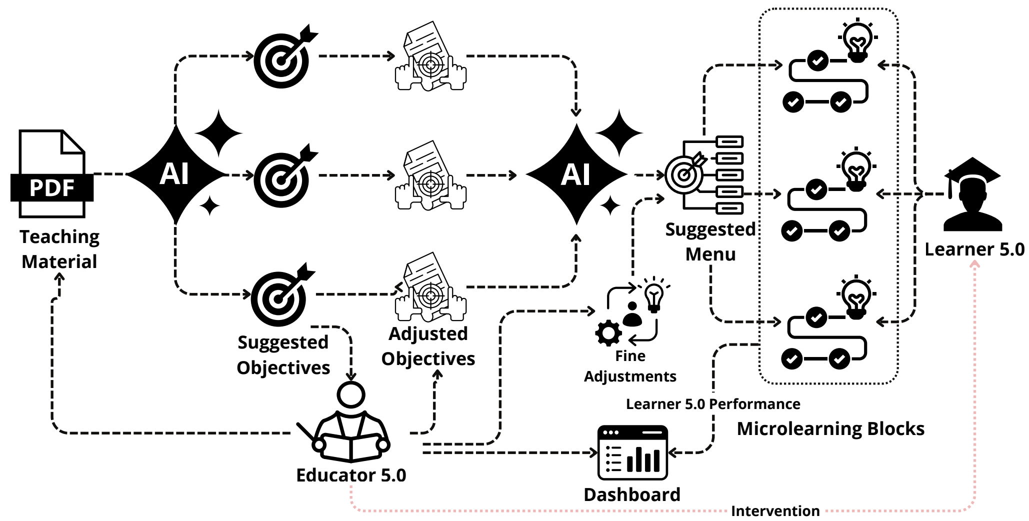

Figure 1. Proposal for pedagogical architecture

In this context, the Educator 5.0 is understood as a professional who operates mediated by technology, using intelligent tools to enhance their capacity for planning, customization, and monitoring of the educational process. Rather than assuming a purely transmissive role, this educator becomes a curator of formative experiences, a critical mediator of generated data, and an active agent in continuous pedagogical adaptation. Their work is not replaced by technology but augmented through the support of AuI mechanisms. The Learner 5.0, on the other hand, represents the student as the protagonist of their own learning journey, assisted by adaptive mechanisms that respect their pace, learning style, and cognitive needs. This profile demands not only interactive content but also environments that foster decision-making, self-assessment, and flexible learning path. In this context, technology becomes an ally in reducing inequalities, respecting neurodiversity, and ensuring greater engagement through tailored learning experiences.

4.1. Guided Generation of Syllabi and Specific Objectives

The process begins with the educator inserting teaching materials, such as handouts or PDF slides, into the system. The proposed architecture provides for the automated reading of these files using NLP algorithms, mapping key concepts, involved competencies, and implicit curricular structures. This mapping generates an initial proposal for specific learning objectives, aligned with the detected content and recognized educational taxonomies.

The proposed objectives are not definitive: the Educator can edit, reorganize, and adjust them based on their pedagogical intent and the context of application. This refinement stage promotes a fluid interaction between human and machine, in which the instructor contributes their experience and the AI learns pedagogical preference patterns. This feedback ensures greater alignment with each instructor's styles and methodologies.

Once the objectives are adjusted and validated, the platform automatically generates a structured syllabus covering the topics to be developed, indicating the logical progression between them. This syllabus can also be edited. After approval, a chronological list of content is generated, structuring the points to be addressed in sequence. This list guides the construction of microlearning blocks, providing a solid foundation for the next phase.

4.2. Structure and Functioning of Microlearning Blocks

Each item in the chronological list becomes a self-contained microlearning block, designed to be completed independently, respecting each learner's process. The block begins with a realistic and contextualized problem situation that sparks curiosity and highlights the practical application of the content. This resource not only motivates but also bridges the gap between knowledge and students' daily lives. Next, the system presents the learning objectives related to the problem-based scenario, highlighting the competencies to be developed. These objectives serve as guides for constructing the learning path of the module, ensuring alignment between diagnosis, content, and assessment. The student is then subjected to a diagnostic quiz that measures their prior knowledge on the topic, allowing for the personalization of the learning journey.

Based on the diagnostic results, the student is guided through an adaptive path. Those who demonstrate mastery advance directly, while others move through a paginated sequence of short, interactive content. This fragmentation prevents cognitive overload and is especially effective for groups with disorders such as Attention Deficit Hyperactivity

Disorder (ADHD) [Le Cunff et al., 2025], for example. Ultimately, an assessment quiz measures progress. If the minimum score is not achieved, a new block is automatically generated, with reconfigured materials to reinforce areas of difficulty. The process can be repeated iteratively, with a change of approach, until conceptual mastery is achieved. The entire process, including the number of times a block was repeated or advanced, is documented to generate data that supports the educator's decision-making.

4.3. Instructor Monitoring and Pedagogical Decision Making

The platform's dashboard provides the Educator with a detailed, real-time view of student progress. The data is organized in a student-content matrix, accompanied by a distribution map that highlights content areas with higher success rates, difficulties, or dropouts. This visual representation enables the detection of learning patterns, allowing for targeted or group interventions that promote precise and timely actions.

The system provides statistics, including average time per module, quiz success rates, the number of attempts required for success, automatic progress rate, and the recurrence of errors by content. Additionally, it is possible to assess the relative effectiveness of approaches used in previous cycles, guiding the planning of more effective reteachings. This data transforms the dashboard into a sophisticated, evidence-based tool for pedagogical analysis.

With this information, the Educator can adapt their teaching plan, redistribute modules for specific student groups, or adopt methodological variations. Groups of students with similar profiles can receive personalized collective interventions. In this way, the dashboard not only informs but also supports data-driven pedagogical decisions, fostering a culture of responsive and inclusive teaching, as well as continuous improvement. This layer also feeds back into the adaptive engine, contributing to the ongoing enhancement of recommendations and content generation. By preserving instructor autonomy and enabling active curation of the learning process, this layer reinforces the Educator's role as a critical mediator in the educational dynamic.

5. Preliminary Result

To demonstrate the technical and practical feasibility of the proposed architecture, we performed a proof of concept (PoC) through a functional application. This educational platform combines generative AI techniques with adaptive microlearning strategies, enabling the creation, customization, and monitoring of learning paths centered on the Educator 5.0 (Figure 2) and the Learner 5.0 (Figure 3).

5.1. Proof of Concept Implementation

For the development of the system's user interfaces (frontend), a web application was implemented using the React.js library, with styling based on modular CSS. Reusable components were created to represent specific elements of the learning experience, such as learning path cards, content slides, and interactive quizzes. The Axios library was used for communication with the backend.

On the backend, the application logic was developed in Python using the FastAPI framework to expose RESTful services. The AI layer was implemented through a service integrated with LLMs, responsible for analyzing documents submitted by the instructor

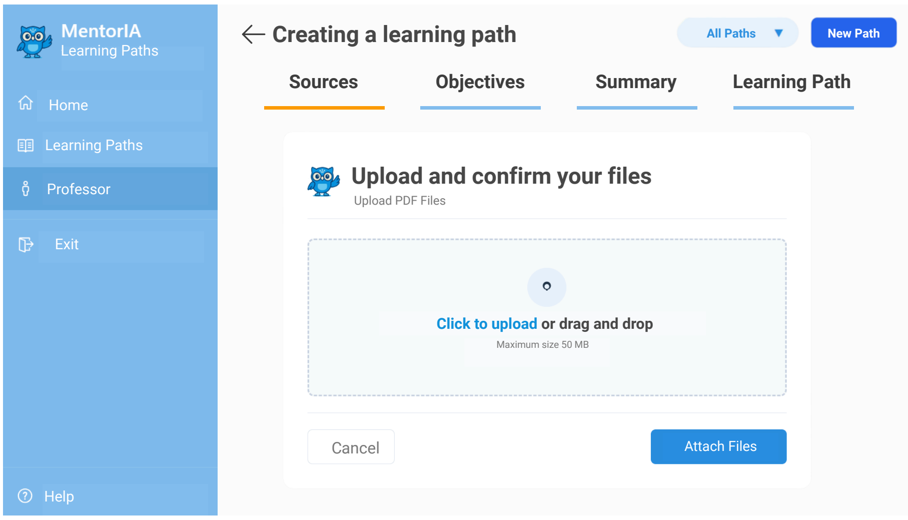

Figure 2. Teaching Materials Upload Screen

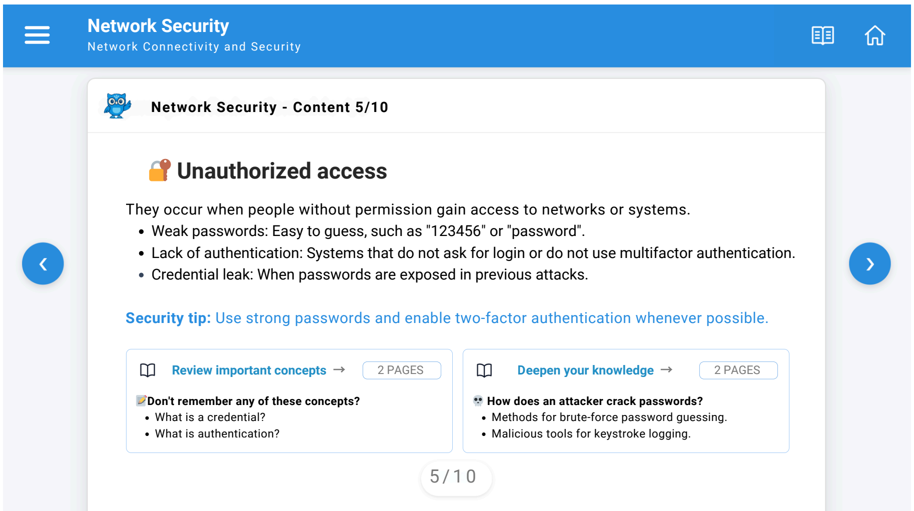

Figure 3. Learner 5.0 View When Accessing a Content Block

and automatically generating learning objectives, syllabi, and content sections. Responsibilities are segmented into this modular structure: authentication, course management, progress tracking, and interface with the language models. Each of these components was validated both individually and collectively, ensuring interoperability across the system.

5.2. Preliminary Validation and Improvements through Feedback

The whole architecture workflow was implemented and validated by the authors of this study. Three Learner 5.0 profiles were simulated by the student authors, each representing a distinct learning trajectory: high-achieving, struggling, and average-progress learners. These profiles were used to simulate corresponding performance on quizzes generated by the platform. In parallel, the instructor created simulated Educator 5.0 profiles, each specializing in a different subject area: Requirements Engineering, Cybersecurity, and Human-Computer Interaction. The Educators also employed different teaching strategies and types of materials (i.e., summaries, slides) that were submitted to the platform.

Through the developed PoC, the Educators 5.0 were able to access the platform's functionalities—from submitting teaching materials to creating and customizing learning paths—and interact with the system via an intuitive dashboard, adjusting the objectives and syllabus suggested by the AI. Based on the critical feedback generated from each Educator's experience, the prompts used and the user interfaces were refined to address identified improvement points. These included: i) blocks with insufficient text; ii) questions with inappropriate difficulty levels; iii) presentation of information with inadequate font size and layout. Through this iterative feedback process, the PoC was incrementally updated. The platform was met with a high degree of user satisfaction, confirming its acceptance and usability.

After obtaining a satisfactory level of acceptance from users simulating Educator 5.0, personalized learning paths were generated to serve as the foundation for evaluating the experience of Learner 5.0 profiles. The three simulated students were then guided adaptively through these paths, which included both diagnostic and evaluative quizzes.

The validation demonstrated that Learner 5.0, with high abilities and prior knowledge, was able to bypass foundational content and advance directly to more complex modules based on diagnostic results—thus avoiding unnecessary repetition and optimizing time and cognitive effort. In contrast, Learner 5.0, with a profile indicating learning difficulties, was allowed to revisit content blocks in a reconfigured format, accessing alternative representations aligned with the same learning objectives. Meanwhile, the student simulating a regular learning trajectory—characterized by low to intermediate diagnostic scores but above-average performance on final assessments—progressed linearly through the path, without revisiting earlier content or prematurely skipping ahead to more advanced topics.

6. Conclusion and Future Work

Education 5.0 proposes a human-centered model, focusing on personalization, student empowerment, and the valorization of the teaching role mediated by technology. However, many existing solutions still fail to integrate planning, personalization, and assessment, while also overloading educators with fragmented and poorly adaptive tools. Thus, the need was identified for an architecture that simultaneously addresses these gaps without compromising pedagogical autonomy.

This work addressed this gap through an educational architecture based on AuI, which enables the Educator 5.0 to generate, customize, and monitor adaptive microlearning paths. The proposal stands out by simultaneously integrating microlearning, pedagogical alerts, instructor customization, and real-time adaptation based on the cognitive profile observed through the Learner's interaction with the architecture. The proof of concept technically validated the architecture and demonstrated, through simulations with different instructor and student profiles, the platform's effectiveness in personalizing the learning journey. As future work, we plan to apply the MentorIA architecture in broader educational contexts, encompassing classes and instructors from various disciplines to enrich the evaluation by measuring its impact on learning and engagement metrics. Finally, we plan to expand the MentorIA features, including gamification features, emotion detection, and integration with public and open educational platforms such as Moodle.

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