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Exploring the Feasibility and Limits of Generative AI–Based Adaptive Instruction in K–12 Mathematics

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Advisor: Prof. Flavia Santoro

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Resumo

Este relatório apresenta os resultados de um projeto de pesquisa e desenvolvimento conduzido ao longo de um ano, cujo objetivo foi investigar a viabilidade e os limites do uso de inteligência artificial generativa em sistemas de ensino adaptativo para a Educação Básica, com foco em Matemática no 8º ano. O trabalho foi estruturado em quatro módulos acadêmicos, abrangendo uma revisão sistemática da literatura, o desenvolvimento de um artefato tecnológico funcional, a validação empírica em contexto real de sala de aula e a consolidação científica dos resultados por meio da submissão de artigos acadêmicos. A revisão sistemática identificou lacunas relevantes na literatura, especialmente no que se refere à explicabilidade dos modelos, ao alinhamento curricular e à escassez de validações em ambientes escolares reais. Com base nesses achados, foi desenvolvido um sistema adaptativo que integra representação automatizada de conhecimento, acompanhamento do progresso do aluno e geração de explicações personalizadas por meio de modelos de linguagem. O sistema foi implementado como uma aplicação web e avaliado em um estudo quase-experimental com estudantes do 8º ano. Os resultados indicam que o uso do sistema é viável em contexto educacional real e pode contribuir para ganhos de aprendizagem, retenção de curto prazo e trajetórias de estudo diferenciadas, ainda que com variação no engajamento dos alunos, resultando como principais contribuições um artefato funcional, dois artigos acadêmicos e evidências empíricas sobre o uso pedagogicamente fundamentado de IA generativa na Educação Básica.

Palavras-Chave: Educação adaptativa; Educação básica; Inteligência artificial; Grafos de conhecimento.

Abstract

This report presents the results of a year-long research and development project aimed at investigating the feasibility and limitations of generative artificial intelligence in adaptive learning systems for K–12 education, with a focus on 8th-grade mathematics. The project was structured across four academic modules, encompassing a systematic literature review, the development of a functional technological artifact, empirical validation in a real classroom context, and the scientific consolidation of results through the submission of academic papers. The literature review identified relevant gaps related to model explainability, curriculum alignment, and the scarcity of validations conducted in authentic school environments. Based on these findings, an adaptive learning system was developed integrating automated knowledge representation, student progress tracking, and the generation of personalized explanations through large language models. The system was implemented as a web-based application and evaluated through a quasi-experimental study with 8th-grade students. The results indicate that the system is feasible for real educational use and can support learning gains, short-term retention, and differentiated learning trajectories, albeit with variability in student engagement, yielding as main outcomes a functional artifact, two academic papers, and empirical evidence supporting pedagogically grounded uses of generative AI in K–12 education.

Key words: Adaptive education; K-12; Artificial intelligence; Knowledge graphs.

List of Abbreviations and Acronyms

K–12	Kindergarten through 12th Grade Education
GenAI	Generative Artificial Intelligence
AI	Artificial Intelligence
LLM	Large Language Model
SLR	Systematic Literature Review
KTS	Knowledge Tracing System
BNCC	Base Nacional Comum Curricular

Summary

1 Introduction

This report presents the results of a year-long undergraduate Final Course Project developed throughout 2025, structured across four academic modules. The project investigates the feasibility, limitations, and educational implications of generative AI–based adaptive instruction in K–12 mathematics, combining theoretical analysis, system design, empirical validation, and scientific consolidation into a single coherent research trajectory. Rather than documenting a single experiment or artifact, this report aims to provide a comprehensive account of the research process and outcomes achieved over the entire academic year.

Personalization has emerged as a central objective in contemporary education, particularly in response to persistent challenges such as heterogeneous classrooms, uneven learning outcomes, and student disengagement. Advances in artificial intelligence have enabled adaptive learning systems capable of modeling student knowledge, predicting performance, and recommending personalized learning paths. While such systems have been extensively studied and deployed in higher education, their application in K–12 contexts remains comparatively limited and insufficiently validated in real classroom environments (KABUDI; PAPPAS; OLSEN, 2021; BERNACKI; GREENE; LOBCZOWSKI, 2021).

The transfer of adaptive technologies from higher education to basic education is not straightforward. K–12 learners differ substantially in autonomy, cognitive development, and dependence on pedagogical mediation. Moreover, schools operate under rigid curricular standards—such as Brazil's Base Nacional Comum Curricular (BRASIL, 2018)—as well as constraints related to time, infrastructure, and teacher workload. Existing research indicates that many adaptive systems prioritize predictive accuracy and algorithmic performance over pedagogical interpretability, curricular alignment, and usability for teachers, limiting their adoption in authentic educational settings (BERNACKI; GREENE; LOBCZOWSKI, 2021).

In parallel, the lack of instructional personalization in basic education has been associated with low student motivation and high dropout rates, affecting millions of learners in Brazil and globally (FERREIRA; RIBEIRO; TAFNER, 2022). Recent studies suggest that adaptive and AI-supported approaches may contribute to more inclusive and engaging learning experiences; however, they also warn against uncritical adoption, particularly with the emergence of generative AI systems whose outputs may lack transparency, consistency, or pedagogical grounding (YUSUF et al., 2024).

Within this context, the central problem guiding this project is to understand whether and how generative AI and automated knowledge modeling can support personalized learning in K–12 mathematics while preserving pedagogical coherence, curricular alignment, and the central role of the teacher. Rather than assuming the effectiveness of adaptive technologies, this work adopts a critical and exploratory stance, seeking to identify both their potential contributions and their structural limitations when applied in real classroom contexts.

To address this problem, the project was developed incrementally over four modules, each corresponding to a distinct phase of the research. The first module consisted of a systematic literature review aimed at mapping the state of the art in AI-driven adaptive learning for K–12 education, identifying dominant modeling approaches, evaluation practices, and unresolved challenges. The second module focused on translating these theoretical insights into the design and development of an adaptive learning system prototype, emphasizing automated knowledge representation, explainability, and curricular alignment. The third module involved the empirical validation of the proposed system in a real classroom with 8th-grade students, enabling the analysis of learning outcomes, content retention, and student perception under authentic conditions. Finally, the fourth module consolidated the results of the year's work into an academic article, situating the findings within the broader research landscape and articulating their implications for future research and practice.

The general objective of this project is to assess, across an entire academic year, the feasibility and educational value of generative AI–based adaptive instruction in K–12 mathematics. Specifically, the project aims to: (i) synthesize and critically analyze existing research on adaptive learning and AI in basic education; (ii) design a system informed by both theoretical evidence and pedagogical constraints; (iii) empirically evaluate its application in a real classroom environment; and (iv) reflect on the broader implications of generative personalization for teaching and learning in K–12 contexts.

This report is organized to reflect the longitudinal and integrative nature of the project. Section 2 presents the theoretical background and related work derived from the systematic literature review. Section 3 describes the methodology adopted across the four modules, detailing the research design, system development, and empirical validation procedures. Section 4 presents the results obtained during the experimental phase. Section 5 discusses these results in light of existing literature and outlines the main contributions and limitations of the study. Finally, Section 6 concludes the report, summarizing the findings and suggesting directions for future research on adaptive and generative AI in K–12 education.

2 Theoretical Background and Related Work

The theoretical foundation of this project was established at its outset through a systematic literature review conducted during the first module of the year. This review aimed to synthesize recent research on AI-driven, self-paced adaptive learning systems for K–12 education and to identify prevailing modeling approaches, evaluation practices, and open challenges in the field. The review followed a structured and transparent protocol, analyzing studies published from 2020 onwards that combined algorithmic personalization with empirical validation in core K–12 subjects, particularly mathematics. The results of this review provided the conceptual and methodological grounding for all subsequent stages of the project, including system design, validation, and scientific dissemination

From an initial pool of over one thousand articles, 31 studies met the inclusion criteria and were analyzed in depth. Rather than treating adaptive learning as a monolithic concept, the review decomposed systems along four key dimensions: student modeling, domain knowledge representation, personalization mechanisms, and evaluation strategies. This analytical structure serves as the organizing framework for the theoretical background presented in this section.

2.1 Adaptive Learning in K–12 Education

Adaptive learning systems aim to personalize instruction by dynamically adjusting content, sequence, or feedback based on a learner’s evolving knowledge state. While early conceptual foundations can be traced back to teaching machines and mastery learning theories [SKINNER, 1958], contemporary adaptive systems increasingly rely on artificial intelligence to automate these processes at scale.

Despite demonstrated benefits in higher education, the adoption of adaptive learning in K–12 contexts remains limited and uneven. Research indicates that younger learners differ substantially from adult learners in terms of autonomy, metacognitive skills, and dependence on teacher mediation [KABUDI; PAPPAS; OLSEN, 2021]. Moreover, K–12 education operates under stricter curricular constraints and accountability frameworks, such as national curricula and standardized assessments, which complicate the deployment of flexible, data-driven systems.

The literature reviewed highlights a persistent tension between technical sophistication and pedagogical alignment. Many systems demonstrate strong predictive performance but fail to integrate meaningfully with classroom practices or curricular structures [BERNACKI; GREENE; LOBCZOWSKI, 2021]. These challenges underscore the need for adaptive systems that are not only accurate, but also interpretable, curriculum-aware, and compatible with the realities of basic education.

2.2 Student Modeling Approaches

Student modeling constitutes the core of adaptive learning systems, as it determines how learner knowledge, behavior, and progression are inferred. The reviewed literature reveals three dominant paradigms: knowledge tracing, cognitive diagnosis models, and latent embedding or matrix factorization approaches.

Knowledge tracing models estimate a student’s mastery over time, updating latent knowledge states as learners interact with instructional content. Classical probabilistic approaches, such as Bayesian Knowledge Tracing, offer transparency through interpretable parameters but may struggle with sparse or complex data [TAKAMI et al., 2024]. In contrast, recent deep learning–based models, particularly Transformer architectures, achieve higher predictive accuracy by modeling long-term dependencies and temporal patterns [LEE et al., 2022; LU et al., 2024]. However, these gains often come at the cost of reduced explainability, raising concerns in K–12 contexts where trust and pedagogical clarity are essential.

Cognitive diagnosis models focus on fine-grained skill mastery, enabling the identification of specific misconceptions or missing prerequisites. While highly interpretable, many CDMs rely on manually constructed Q-matrices, imposing significant expert effort and limiting scalability across curricula and subjects [JIANG; WANG, 2020].

Latent embedding and matrix factorization approaches offer a more scalable alternative by learning representations directly from interaction data, without explicit concept annotations. These models support flexible personalization but often lack explicit links to curricular knowledge structures, making pedagogical interpretation difficult [SUN et al., 2023].

2.3 Domain Knowledge Representation

Effective personalization requires not only modeling learners, but also representing the structure of domain knowledge. The literature distinguishes between expert-defined and data-driven representations, as well as between graph-based and non-graph-based approaches.

Expert-defined representations, such as curriculum-aligned concept graphs or Q-matrices, provide strong pedagogical grounding and interpretability [LI; WANG, 2023]. However, they are costly to maintain and adapt, particularly in large-scale or multilingual educational systems. Data-driven representations, including automatically inferred graphs or latent concept embeddings, improve scalability and adaptability but often obscure the semantic meaning of concepts and their instructional relevance [LEE et al., 2022].

The review highlights a growing interest in hybrid approaches that seek to balance these trade-offs by combining curriculum alignment with automated structure extraction. Nevertheless, fully automated, curriculum-aware knowledge modeling remains an open research challenge, particularly in K–12 education.

2.4 Evaluation Practices and Research Gaps

A critical finding of the literature review concerns evaluation practices. While most systems report gains in predictive accuracy using benchmark datasets, relatively few studies conduct robust real-world evaluations. Only a small subset of reviewed works employed randomized controlled trials or longitudinal classroom deployments [LEITE et al., 2022]. As a result, evidence regarding long-term learning impact, scalability, and classroom integration remains limited.

Across the reviewed studies, recurring gaps include the overreliance on manual labeling, limited interpretability of deep models, insufficient attention to motivation and engagement, and a lack of rigorous in-situ validation. These gaps directly informed the design choices and research questions pursued in the subsequent phases of this project.

3 Methodology

This project adopted a structured, longitudinal research methodology spanning an entire academic year and organized into four sequential modules. The methodological design combines principles from systematic literature review, design-oriented research, and empirical educational experimentation. Each module corresponds to a distinct phase of the research process, collectively forming a coherent roadmap from theoretical grounding to empirical validation and scientific consolidation. This modular structure ensures methodological rigor, traceability of decisions, and reproducibility of the study.

Across all modules, the research adhered to the following guiding principles: (i) transparency in methodological choices; (ii) alignment between theoretical evidence and design decisions; (iii) empirical validation in an authentic educational context; and (iv) documentation sufficient to allow replication by other researchers using the same parameters.

3.1 Module I – Systematic Literature Review

The first module focused on establishing the theoretical foundation of the project through a systematic literature review (SLR). The objective of this phase was to synthesize existing research on AI-driven, self-paced adaptive learning systems for K–12 education and to identify dominant approaches, evaluation practices, and unresolved challenges in the field.

The review followed a predefined protocol comprising: (i) formulation of research questions; (ii) definition of inclusion and exclusion criteria; (iii) database selection; (iv) systematic search and screening; and (v) structured data extraction and analysis. Searches were conducted in major academic databases, including Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. Only peer-reviewed journal articles and conference papers published from 2020 onward were considered.

Inclusion criteria required studies to: (i) focus on K–12 education; (ii) involve adaptive or personalized learning systems; (iii) employ AI-based student or content modeling; and (iv) report empirical evaluation or clearly defined methodological contributions. After title, abstract, and full-text screening, 31 studies were selected for in-depth analysis.

Data were extracted using a structured coding scheme covering student modeling approaches, domain knowledge representation, personalization mechanisms, evaluation methods, and reported limitations. The synthesis of this module directly informed the conceptual framework and design constraints adopted in subsequent modules.

3.2 Module II – System Design and Prototype Development

The second module translated the theoretical insights derived from the literature review into the design and implementation of an adaptive learning system prototype. This phase followed a design-oriented research approach, emphasizing iterative development guided by pedagogical and technical constraints identified in the SLR.

The system architecture was designed to support three core functionalities: (i) automated representation of domain knowledge aligned with formal curricula; (ii) modeling of student learning progress over time; and (iii) generation of adaptive explanations and recommendations using generative AI. Design decisions prioritized interpretability, modularity, and feasibility within real school contexts rather than algorithmic maximalism.

From a technological perspective, the prototype was implemented as a web-based application. The backend was developed using FastAPI, enabling modular APIs for student modeling, content management, and adaptive logic. The frontend was implemented using Next.js to support interactive visualizations and user interaction. Data handling and learning state tracking were performed using structured tabular representations, allowing transparent inspection and debugging.

Throughout this module, development iterations were documented, including architectural decisions, parameter choices, and identified limitations. Although no user-facing evaluation was conducted at this stage, internal testing was performed to verify system consistency and functional correctness.

3.3 Module III – Empirical Validation in a Classroom Context

The third module focused on the empirical validation of the proposed system in an authentic educational setting. The objective was to assess the feasibility and educational impact of the adaptive system when deployed in a real classroom, addressing a major gap identified in the literature.

The study was conducted with 8th-grade students enrolled in a mathematics course. The study followed a quasi-experimental design with pre-test and post-test assessments to measure learning gains and short-term retention.

Data collection instruments included: (i) standardized mathematics assessments aligned with curricular objectives; (ii) system interaction logs capturing student behavior and progression; and (iii) feedback interviews to capture student perceptions. All data were anonymized prior to analysis, and ethical considerations related to student participation and data handling were observed.

Quantitative data were analyzed using descriptive statistics and comparative analysis between groups. While inferential statistical power was limited by sample size, the analysis focused on identifying trends, effect directions, and feasibility indicators rather than definitive causal claims.

3.4 Module IV – Scientific Consolidation and Paper Submission

The fourth and final module focused on the scientific consolidation and dissemination of the results obtained throughout the year-long project. The objective of this phase was to transform the theoretical foundations, system design decisions, and empirical findings into a coherent academic contribution suitable for submission to a peer-reviewed venue in the field of educational technology.

This module involved the systematic organization and synthesis of materials produced in the previous modules, including the systematic literature review, technical documentation of the adaptive learning system, and data collected during the classroom validation. These elements were integrated into a structured academic paper, following standard conventions for empirical research in computer-supported education, with clearly defined sections for theoretical background, methodology, results, discussion, and contributions.

Methodologically, this phase emphasized analytical reflection rather than new data collection. Quantitative results from the empirical study were reanalyzed and contextualized within the existing literature, enabling direct comparison with prior work on adaptive learning and generative AI in K–12 education. Design decisions and system limitations were explicitly discussed to ensure transparency and to support reproducibility and critical assessment by the research community.

The paper was written with the explicit goal of external evaluation and was submitted for publication to a peer-reviewed academic venue. As such, particular attention was given to methodological rigor, clarity of argumentation, ethical considerations, and the articulation of contributions. This submission marked the culmination of the research process, extending the impact of the project beyond the academic requirements of the course and positioning the work within the broader scientific discourse on adaptive and generative AI in education.

4 Results

The results presented in this section reflect the cumulative outcomes of the year-long project conducted across four academic modules. Rather than reporting isolated findings, this section synthesizes the theoretical, technical, empirical, and scientific results obtained throughout the research process. Collectively, these outcomes comprise one functional technological artifact and two academic papers, which together represent the principal deliverables of the project.

From a theoretical perspective, the project resulted in a systematic literature review on AI-driven adaptive learning systems for K–12 education. The review analyzed 31 peer-reviewed studies published since 2020 and synthesized prior work along four analytical dimensions: student modeling, domain knowledge representation, personalization mechanisms, and evaluation strategies. One of the key results of this review was the identification of a strong emphasis on predictive accuracy—particularly through deep learning–based knowledge tracing models—accompanied by comparatively limited attention to pedagogical interpretability, curriculum alignment, and classroom feasibility. Additionally, the review revealed a scarcity of empirical validations conducted in real K–12 classroom settings, with most studies relying on synthetic datasets or controlled experimental environments. These findings were consolidated into an academic paper, constituting the first scientific output of the project.

Building on the theoretical insights obtained from the literature review, the project produced a functional adaptive learning system artifact. The system was implemented as a web-based platform integrating automated domain knowledge representation, student learning state tracking, and generative AI–based explanation mechanisms. From a technical standpoint, the artifact demonstrated stable operation, modular architecture, and transparency of learning state representations. Functionally, the system was capable of tracking student interactions over time, generating personalized recommendations, and providing adaptive explanations aligned with curricular objectives. This artifact represents the primary technological result of the project and served as the basis for empirical evaluation.

The empirical results of the project were obtained through the deployment of the adaptive system in a real K–12 classroom context with 8th-grade mathematics students. A quasi-experimental design was employed, involving an experimental group using the adaptive system and a control group receiving traditional instruction. Descriptive analysis of pre-test and post-test assessments indicated learning gains in both groups, with the experimental group exhibiting higher average improvements and stronger short-term retention on concept-based items. Interaction data revealed differentiated usage patterns among students, reflecting varied learning trajectories supported by the adaptive mechanisms. Qualitative feedback further indicated that most students perceived the system's adaptive explanations as clear and supportive of independent learning.

The theoretical, technical, and empirical results obtained throughout the project were subsequently consolidated into a second academic paper. This paper integrated findings from the systematic literature review, system design, and classroom validation, situating the work within ongoing research on adaptive and generative AI in education. The paper was written following peer-reviewed publication standards and submitted for external evaluation, marking the culmination of the year-long research process.

In summary, the results of this project consist of: (i) a systematic literature review paper identifying key trends and gaps in K–12 adaptive learning research; (ii) a functional adaptive learning system artifact implementing curriculum-aware and explainable personalization; and (iii) an empirical research paper reporting classroom-based validation of the proposed approach. Together, these results provide both practical and scientific evidence regarding the feasibility and limitations of generative AI–based adaptive instruction in basic education.

5 Discussion and Key Contributions

The results obtained throughout the four modules provide a coherent perspective on the feasibility and limitations of generative AI–based adaptive instruction in K–12 education. Taken together, the findings suggest that the primary challenges of adaptivity in basic education are not purely algorithmic, but pedagogical and contextual. The systematic literature review revealed a field heavily oriented toward predictive accuracy, with limited attention to explainability, curriculum alignment, and validation in real classroom environments. The subsequent design, deployment, and evaluation of the adaptive system directly engaged with these gaps.

The development and classroom use of the artifact demonstrated that adaptive systems emphasizing transparency and curricular coherence can be successfully integrated into K–12 settings. Rather than relying on opaque predictive models, the system operationalized explainable learning representations and generative explanations, which proved to be understandable and useful for most students. The empirical results indicate that such an approach can support learning gains and short-term retention, while enabling differentiated learning trajectories. At the same time, heterogeneous usage patterns and varying levels of engagement highlight that personalization alone does not guarantee sustained interaction or uniform benefit, reinforcing the continued importance of teacher mediation.

From a research perspective, this project contributes evidence that generative AI can function as a complementary instructional support rather than a replacement for pedagogical practice. The results align with prior findings suggesting that adaptive technologies are most effective when embedded within structured curricular frameworks and used to augment, rather than automate, teaching decisions. The limited scale and duration of the empirical study constrain the generalizability of the findings, but the observed trends provide a grounded basis for further investigation.

Beyond its empirical outcomes, the project contributes to the field by documenting an end-to-end research process spanning theoretical synthesis, artifact development, classroom validation, and scientific dissemination. The production of one functional adaptive learning system and two academic papers demonstrates a reproducible pathway for conducting longitudinal research in educational technology. Collectively, these contributions advance a more pragmatic and transparent understanding of how generative and adaptive AI systems can be designed, evaluated, and positioned within K–12 education.

6 Conclusion

This report presented the outcomes of a year-long research project investigating the feasibility and limitations of generative AI–based adaptive instruction in K–12 mathematics. Structured across four academic modules, the project combined a systematic literature review, the development of a functional adaptive learning system, empirical classroom validation, and scientific dissemination. Rather than focusing on a single artifact or experiment, the work documented the complete research lifecycle, offering a comprehensive and transparent account of the process and its results.

The findings indicate that adaptive learning systems grounded in explainability, curricular alignment, and pedagogical feasibility can be successfully deployed in basic education contexts. The adaptive artifact developed in this project functioned reliably in a real classroom setting and supported learning gains, short-term retention, and differentiated learning trajectories. At the same time, the results highlight important limitations related to scale, duration, and student engagement, underscoring that adaptive technologies are most effective when used as complementary tools within established teaching practices.

From a broader perspective, this project contributes to ongoing discussions about the role of generative AI in education by demonstrating that its value lies not in full instructional automation, but in supporting personalization, feedback, and learner autonomy in a controlled and transparent manner. The production of two academic papers and a functional artifact extends the impact of the work beyond its institutional context and provides a foundation for future research.

Future work should explore longer-term deployments, larger and more diverse samples, and deeper integration with teacher workflows and assessment practices. Further investigation is also needed to examine how generative explanations can be adapted to different subjects, age groups, and learning needs while maintaining instructional quality and ethical responsibility. Overall, this project offers evidence that generative AI–based adaptive instruction holds promise for K–12 education when developed and evaluated with pedagogical rigor, empirical grounding, and critical reflection.

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