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Transforming Learning with Generative AI: From Student Perceptions to the Design of an Educational Solution

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Abstract: Education is another field which generative artificial intelligence has made its way into, intervening in students' learning processes. This article explores students' perspectives on the use of generative AI tools, specifically ChatGPT-3.5 (free version) and ChatGPT-4 (with a subscription). The results of the survey revealed a correlation between the use of ChatGPT and the perception of grade improvement by students. In addition, this article proposes an architecture for an adaptive learning system based on generative artificial intelligence (AI). To develop the architectural proposal, we incorporated the results of the student survey along with insights gained from analyzing the architectures of other learning platforms. The proposed architecture is based on a study of adaptive learning platforms with classically virtual assistants. The main question from which the current research started was how artificial intelligence can be integrated into a learning system to improve student outcomes based on their experience with generative AI. This has been sectioned into two more specific questions: 1. How do students perceive the use of generative artificial intelligence tools, such as ChatGPT, in enhancing their learning journey? 2. Is it possible to integrate generative AI into a learning system used in education? Consequently, this article concludes with a proposed architecture for a learning platform incorporating generative artificial intelligence technologies. This article aims to present a way to understand how generative AI technologies support education and contribute to improving academic performance.

Keywords: adaptive learning; artificial intelligence; educational system architecture; generative AI; personalized learning

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1. Introduction

Artificial intelligence (AI) offers promising avenues to revolutionize education, notably through adaptive learning systems. These systems tailor the content to the individual understanding and pace of each learner, freeing teachers from repetitive tasks and allowing them to focus on fostering communication and higher-order thinking skills [1]. As AI takes on subject-specific tasks in education, teachers can focus on fostering creativity and critical thinking. With tools such as ChatGPT capable of learning, processing information, coding, and debugging, educators can redesign assignments to prioritize these skills over rote problem solving [1]. This empowers students to actively participate in their learning and develop skills that transcend current AI capabilities.

Personalized education, achieved by adapting to different learning styles and interests, can significantly improve the achievement of learning objectives and prepare students for future careers [2].

However, the implementation of adaptive learning systems presents challenges. These include data collection, processing, and centralized management concerns. Moreover, AI models struggle to understand nuanced user intent, a capability that remains largely human [3]. Ideally, future adaptive systems should better understand the cognitive processes that underlie learning to fully personalize the educational experience. This means that new learning solutions come with technologies and methods to cover these requirements.

This article aims to present a way to cover these requirements. Accordingly, this research proposes investigating students' views on the application of ChatGPT in learning and, at the same time, examines the potential for integrating generative AI into learning systems, with the aim of identifying benefits for students. To achieve this, we address two specific questions:

1. How do students perceive the use of generative artificial intelligence tools, such as ChatGPT, to enhance their learning journey?
2. Is it possible to integrate generative AI into a learning system used in education?

The answer to the first question in this article is obtained by analyzing data from a questionnaire sent to students. The results of this questionnaire helped to answer the first question and, at the same time, contributed to proposing an architecture for the learning system. This architectural design proposal represents the way in which question two of this article was addressed.

The architectural proposal is also based on an analysis of four existing learning platforms, none of which currently uses generative AI to improve responses to learner questions. Only one platform incorporates large language models (LLMs) for personalization. On the contrary, our architecture emphasizes the role of generative AI in supporting student learning.

This paper contributes to a novel architecture of adaptive learning systems that uses generative AI. Through this architecture, our aim is to demonstrate how generative technologies can overcome current limitations in addressing learning needs. We also provide examples of potential learning solutions based on this architecture, illustrating how AI-based generative platforms can create more engaging and motivating learning experiences. Additionally, we explore how components of the proposed architecture can be integrated into other systems to provide continuous access to learning resources.

The proposed architecture aligns with Seymour Papert's constructionist theory, which emphasizes that new knowledge builds upon existing knowledge and that learners should actively construct their understanding through practical application. The teacher's role in this model is to guide, not simply to instruct. Our architecture encourages the participation of learners and promotes learning through construction and discovery [4].

Generative AI, which is central to our system, is a subset of AI that creates new content by learning from and reinterpreting existing data. It differentiates itself from predictive or analytical AI through its creative capabilities, generating text, visuals, code, and audiovisual content. In education, generative AI has the potential to transform the landscape by enabling personalized, immersive, and innovative learning experiences.

A key advantage of generative AI in education is its ability to deepen student understanding. Tools that incorporate these models can generate age-appropriate explanations, facilitate self-assessment through question generation, and nurture analytical and critical thinking by challenging learners to filter and integrate AI-generated ideas on their own [5].

The growing adoption of AI in sectors such as information and communication technology are driving the demand for AI specialists and encouraging the integration of AI into universities [6]. Technological advances, coupled with public and private investment, are fueling the growth of AI in the education market, which is projected to expand at a CAGR of 36.0% between 2022 and 2030 [7].

This article explores the transformative potential of generative AI in education. Specifically, this article presents a structured and data-driven analysis of students' perspectives regarding the use of generative artificial intelligence technologies in learning. Additionally, it includes a review of existing learning platforms, highlighting their main features, with a particular focus on those based on generative AI. Our objective is to contribute to the development of more effective, engaging, and personalized learning experiences, proposing an architecture for a novel learning system in the light of constructionist learning theory, based on students' perceptions in using large language models (LLMs) technology in their learning, and incorporating generative AI affordances not found in existing solutions.

This paper is structured as follows: Section 2 provides a review of the literature review; Section 3 presents the methods and materials (methodology) used to analyze student perceptions and evaluate and compare existing learning platforms; Section 4 describes the results obtained from the questionnaire responses and describes the proposed architecture for the learning system along with its components; Section 5 comprises the discussion; and Section 6 includes the conclusions, limitations of the study, and directions for future research.

2. Literature Review

2.1. Adaptive Learning Theories

Although technologies and ways to make learning adaptive and personalized are new, they are based on theories of adaptive and personalized learning. An example of such a theory is Vygotsky's zone of proximal development (ZPD), according to which learning is truly effective and useful when the learner is challenged beyond his current ability. This theory refers to both what a person can do without help and what they can do with the help and support of another more skilled person [8].

When it comes to artificial intelligence tools used in learning and education and the application of Vyagotsky's theory, it is found that artificial intelligence can personalize self-assessment, provide support in education, solidify social interactions, and make participants in the learning process more motivated and involved. All of this leads to better academic results [9].

The article [10] presents how generative artificial intelligence can contribute to expanding the proximal zone of development by serving as a support point in procedural activities and thus creating room for participation in advanced cognitive processes.

Self-regulated learning refers to the way in which the learner has control over their own learning processes. As Zimmerman highlights in [11], self-regulated learning occurs in achieving learning objectives by appealing to cognitive, metacognitive, and motivational processes. In the paper [12], three essential phases of self-regulated learning are described: the forethought phase, when learning objectives are established, the performance phase, when planned strategies are implemented, and the self-reflection phase, when self-evaluation plays a role after completing the task.

As demonstrated by the data in [13], generative artificial intelligence has a positive impact on self-regulated learning strategies. More precisely, generative artificial intelligence intervenes in all three specific phases of self-regulated learning monitoring in supporting planning and helping progress.

Experiments with a self-regulated learning model that incorporates generative artificial intelligence functionality have shown an increase in metacognitive engagement and clarity of goal setting. Other learning benefits, such as better time management and understanding of errors, have also been identified with this model [14].

2.2. Generative AI in Education

ChatGPT has emerged as a valuable tool for both teachers and students in engineering education, offering applications such as finding solutions to technical problems for research purposes [15]. Although large language models (LLMs), such as ChatGPT, may project confidence in their responses, these answers are not always accurate. LLMs can produce "hallucinations", confidently providing incorrect information. Therefore, users must critically evaluate the information, consider ethical implications and potential biases, and verify the accuracy of AI-generated content [15].

Instructors can use generative AI to create illustrative examples that improve student comprehension, while also reducing the time spent developing customized materials for specific topics or difficulty level. Generative AI can further personalize learning by tailoring explanations to individual student knowledge levels, starting with basic concepts and progressing to more complex ones, incorporating demonstrations and appropriate language [16].

The paper [17] identifies numerous benefits and future trends. These include fostering student creativity and engagement through unique design and music creation, personalizing learning experiences by adapting difficulty and pace, providing real-time adaptive learning and assessment, automatic classification, generating educational materials (textbooks, worksheets, quizzes, and interactive models), and creating virtual instructors or speech agents for tailored feedback. In [18], some researchers predict that the future of generative AI in education will involve an "appropriate curriculum, interactive simulations, custom feedback, and integration with Augmented Reality (AR) and Virtual Reality (VR) for experiential learning", leading to more immersive educational experiences.

The authors of [18] discussed how students can use generative AI to access knowledge from multiple disciplines, facilitating interdisciplinary learning. With the help of the Internet and cloud technology, generative AI could promote cross-school collaboration through course platforms and virtual laboratories. In our interconnected world, cross-cultural education and communication are vital and AI-based technologies may enhance students' cultural literacy and global awareness.

A previous study [19] reported that students perceive generative AI favorably both for teaching and self-study purposes, including writing and brainstorming support, research and analysis support, and administrative tasks. There are concerns about accuracy, transparency, ethical issues, and maintaining human values, but these concerns are not exclusive to the use of generative AI in education.

Google has integrated generative AI into its enterprise search offerings, allowing users to create personalized search tools that retrieve data from their own structured and unstructured datasets, as well as personal websites. This discovery tool could be adapted for educational settings at the course or tutorial level, allowing the precise retrieval of indexed data, follow-up questions, and content translation within a secure cloud environment [20].

According to the study in [21], 50% of teachers preferred ChatGPT for teaching programming, but with a satisfaction rating of 3 out of 5. ChatGPT was found to provide incorrect solutions to even relatively simple problems, such as basic counting algorithms. Despite these limitations, ChatGPT's value in explaining programming concepts and other areas should be acknowledged. Research indicates that generative AI is being used in various fields. In advertising and marketing, 37% of professionals reported using generative AI in their work. Teaching is another prominent field where such tools are employed.

This suggests that AI integration and the use of such technologies are increasingly being embraced by educators [22].

2.3. Addressing Current Educational Constraints with Generative AI

In the complex educational landscape, achieving optimal results often depends on addressing the diverse needs of learners. Traditional teaching methods, while generally effective, often struggle to recognize and accommodate the diverse profiles present within a classroom. This oversight can hinder the educational experience of many students, leaving them feeling isolated or unsupported [23].

Generative artificial intelligence (AI) offers a promising solution to this challenge. By enabling truly personalized learning experiences, generative AI has the potential to revolutionize education. Personalized learning involves tailoring educational pathways to the specific cognitive and academic needs of individual learners. Using generative AI, educators can create customized content, such as concise summaries, engaging quizzes, real-time feedback, and in-depth explanatory modules. This personalized content ensures that students learn at their own pace and in a way that suits their learning style, while also benefiting from immediate and contextually relevant support [24,25].

A review of the research by [26] highlights the increasing importance of personalized learning in primary, secondary, and tertiary education. The authors emphasize the need for a structured, theory-driven approach to designing and evaluating personalized learning experiences. The advantages of personalized learning extend beyond academic achievement. It can also increase motivation, improve engagement, improve overall learning outcomes, and foster a lifelong love of learning.

Based on comprehensive educational theories, the approach proposed by [26] illuminates the complex relationships between learner attributes, instructional design elements, and resulting learning outcomes. Their methodological framework includes the following:

- A rigorous identification phase that focuses on the essential attributes of the learner for personalized instruction;
- An analytical selection phase aimed at determining instructional elements that can enhance these identified attributes;
- Clear delineation of the expected learning outcomes resulting from personalization;
- An empirical testing phase employing rigorous research methods to assess the tangible impacts of personalized learning initiatives.

The integration of generative AI into education holds the promise of overcoming the limitations of traditional teaching methods. By fostering a more inclusive, adaptive, and tailored learning environment, generative AI aims to optimize educational outcomes for each learner, ultimately enriching the overall learning experience [26].

2.4. Generative AI as a Catalyst for Innovation

Generative AI has rapidly emerged as a powerful tool for fostering creativity, with immense potential to revolutionize education by enhancing the innovative capabilities of both educators and learners. It serves as a wellspring of inspiration, a platform for experimentation, and a valuable source of feedback. The unique ability of generative AI to transcend traditional boundaries opens new avenues for innovation. Educators and students should use artificial intelligence to create cutting-edge designs, captivating artwork, original music, or compelling narratives. This is not just a theoretical possibility, but a reality grounded in current technological advancements [27].

To illustrate this concept, consider these real-world examples of generative AI applications:

- GPT-4 by OpenAI: As demonstrated by [28], a major breakthrough in natural language processing, especially when it comes to translation capacity. The authors of article [29] demonstrate the potential and ability of ChatGPT to support medical educators and students. GPT-4 can generate text on a wide range of topics, helping educators and students understand and express complex ideas [30];

- StyleGAN: Pushing the boundaries of visual creativity. StyleGAN [31] has surprised the world with its ability to generate highly realistic portraits of people who do not exist. As stated by [32,33] this technology can be used in digital art and design courses to expose students to the possibility of digital imagery;
- Jukebox by OpenAI: An example of auditory innovation, Jukebox leverages generative models to compose music in various genres and styles. For example, ref. [34] use Jukebox to carry out a cross-cultural study of the arts. Music educators and students can use Jukebox to explore new melodies and deepen their understanding of musical nuances [35];
- OpenAI Codex: Demonstrating the convergence of language and programming. According to [36], OpenAI Codex can translate natural language prompts into functional code. It is shown by [37] that this tool can be invaluable when it comes to semantic analysis, and when it is about getting code from natural language, this tool is even better than ChatGPT 3.

In essence, generative AI not only expands the toolkit available to educators, but also cultivates a culture of continuous exploration and refinement. This mindset, focused on pushing boundaries and seeking new solutions, is at the core of innovation in all disciplines. Platforms such as Hugging Face further empower users to create, train, and deploy AI models. They offer both datasets and pre-trained models for various applications, including text-based video generation, image generation, text generation, and audio generation [38].

An example is Mistral 7B, a text generation model that can also generate code, thanks to its 7 billion parameters. It outperforms earlier models in areas such as mathematics and reasoning [39,40].

Another model, TinyBERT, is designed for natural language understanding tasks such as question answering. In particular, TinyBERT achieves 96.8% of the performance of the larger BERT BASE model, making it possible to integrate such powerful models into edge devices [40].

2.5. Recognizing the Limitations of Generative AI in Education

Although generative AI offers transformative potential for education by creating dynamic, learner-specific content, it also presents complexities and challenges that educators and institutions must address.

(a) Ensuring the Credibility of AI-Generated Content

A key factor in the adoption of any educational technology is the precision of its output. Generative AI, while capable of producing diverse content, is not foolproof. Ensuring the reliability and validity of AI-generated content is crucial. For example, if a generative model proposes a solution to a maths problem, how can we verify its correctness and appropriateness for the educational context? [41]. Or, as in the case of research [42] where training data are generated to recognize mathematical formulas that have been handwritten. Another example would be the study [43] in which a model can solve university-level maths problems, explaining solutions with the ability to generate new questions.

(b) Navigating ethical minefields: ownership, authorship, and accountability

Generating content through AI raises significant ethical questions. Who owns AI-generated content, AI developers, users, or AI itself? The concept of authorship, which is essential for academic integrity, becomes blurred when content is produced by algorithms. Furthermore, determining the accountability for misinformation or biases present in AI-generated content requires clear guidelines [44,45]. Therefore, as underlined in article [46], to ethically use these technologies, it is important that the principles are concretized in a set of concrete practices for each organization.

(c) Charting the Path Forward: Collaborative Frameworks and Ethical Guidelines

The relatively new presence of generative AI in education requires a comprehensive and collaborative approach to developing guidelines for its responsible use. Engaging a wide range of stakeholders, including educators, students, policymakers, and technology experts, can lead to the creation of a robust ethical framework. This framework should include the following:

- Clear definitions of roles and responsibilities for all parties involved;
- Strategies to ensure the quality, relevance, and originality of AI-generated content;
- Protections for intellectual property rights and academic integrity [47].

(d) Learning from the Vanguard: Best Practices in AI-Driven Education

As generative AI gains traction in education, we are witnessing examples of its successful integration into platforms and curricula. Analyzing these early implementations can offer valuable information. Whether it is an online course that uses artificial intelligence for personalized study plans or a platform that generates study materials through generative models, understanding their strategies and ethical considerations can guide wider adoption [48–50].

While the advent of generative AI in education presents exciting possibilities, a thoughtful, ethically grounded approach is essential to navigate the multifaceted challenges it presents.

2.6. The Way Forward

In the midst of a rapidly evolving educational landscape, this article explores the interplay between current learning systems and the transformative potential of generative AI. By examining existing systems, we lay the foundation for a more informed perspective on the future of AI in education [50].

(a) Unpacking the present: Generative AI in today's learning ecosystems

Before envisioning the future, it is crucial to understand the present. Modern learning systems, which increasingly rely on technology for instruction and engagement, have begun to harness the power of generative AI. For example, platforms that use GPT-3.5 or GPT-4 have customized reading materials to student proficiency levels, ensuring that learning remains challenging but achievable [50,51]. Article [52] presents the case of medical students who want to integrate AI technologies in medical practice. These examples highlight the nascent but growing integration of generative AI into current educational tools.

(b) The Pedagogical Revolution: Generative AI's Promise

Education has always been a field of evolution, but generative AI is poised to usher in a true renaissance. Imagine a system where content is co-created in real time, adapting to the learner's evolving needs, interests, and feedback. Such adaptive learning, powered by AI, could provide each student with a truly personalized educational experience tailored to their pace and style [50,51,53]. However, as the author of [54] concludes, the responsibility for the scientific process is also the human factor.

(c) Charting the path: A blueprint for AI-Driven Learning Systems of Tomorrow

Building on the insights gained from current applications, this document proposes a vision for the future. This includes an architectural framework for learning systems that seamlessly integrate generative AI. Such systems could foster creativity, encourage critical thinking, and crucially, promote educational equity by offering resources tailored to individual needs, and as outlined in [55] can introduce a new way of access to quality education. As the authors demonstrate in [56], social robots can help in the learning process because they apply methods that improve their critical thinking. Such technologies help reduce problems in school performance [57].

As education is at a crossroads, generative AI emerges not only as a tool, but also as a guiding light, leading us toward a future rich with unprecedented opportunities to acquire and share knowledge [57].

In [58], the World Economic Forum identified eight key characteristics of quality learning in the context of Education 4.0. These include personalized and self-paced learning, as well as lifelong and student-centered learning, emphasizing the importance of personalization achievable through adaptive learning systems.

The literature on educational technology underscores the importance of adopting student-centered approaches to provide personalized learning, tailoring instruction to each student's level. This approach is expected to increase student motivation by adapting the curriculum to their individual needs and learning styles [59].

As highlighted in [60], the need for and benefits of personalized learning are well recognized, acknowledging its role as a tool for teachers, students, and professional learning communities in driving continuous improvement. Three levels of personalization are proposed: individualization (adapting pace), differentiation (customizing learning approaches), and personalization (customizing learning goals, methods, and pace). Personalization, the highest level, tailors learning to individual student needs, encompassing the other two levels [61].

The integration of AI into education has yielded numerous student-centered benefits, as described in [62]. AI systems facilitate the understanding of student challenges and offer solutions. Additionally, intelligent systems can identify gaps in the learning and teaching process, contributing to inclusive education that satisfies all student needs.

The article [63] on AI's role in creating digital classrooms and beyond emphasizes the advantages of AI systems in simplifying content presentation. These learning systems provide resources that span various subjects, empowering students to learn independently.

3. Materials and Methods

To answer each of the two questions in this article, different approaches were used. This section is divided into two parts: the approach used to answer Question 1 and the approach used to answer Question 2.

3.1. Methodology for Analyzing Survey Responses to Address Question 1

A quantitative method was employed to explore students' opinions on the use and integration of a generative AI-based tool, explicitly the ChatGPT tool [64].

The data analyzed were collected from responses to the questionnaire titled 'Students' Perception of ChatGPT', initiated by the Faculty of Public Administration of the University of Ljubljana, Slovenia, Europe, in collaboration with more than 200 international partners. The data were retrieved from the Mendeley Data website and are available at the following address: https://data.mendeley.com/datasets/ymg9nsn6kn/ (accessed on 30 December 2024).

Among the main reasons for choosing this dataset is the amount of responses from real ChatGPT users that can be used as a solid and reasoned foundation for a rigorous analysis of opinions about this technology. Another reason is the diversity of backgrounds from which respondents to this questionnaire come. In this way, the perspectives on this tool are diverse and useful for integration into a large-scale applicable architecture [65–67].

The purpose of this questionnaire is to determine how ChatGPT influences the learning journey, experiences, and results of students enrolled in a faculty program. The results obtained served as a foundation for proposing an architecture, as they helped us understand how generative artificial intelligence tools can support global education and contribute to improving academic performance.

The questionnaire consists of 42 questions divided into 11 sections, and participants were required to be students enrolled in a study program at a faculty, regardless of their location, and to be over 18 years old. The 11 sections of the questionnaire are organized as follows:

Section 1: Includes sociodemographic information such as citizenship, gender, age, country of study, university name, program type and year of study, field of study, learning method used at the time of completing the questionnaire, as well as the level of confidence in finding a job upon graduation.

Section 2: Comprises questions that focus on the use of ChatGPT in the learning process. Specifically, it includes questions about the version of ChatGPT being used, the frequency of use, the user experience with ChatGPT, and how often ChatGPT is involved in tasks such as learning, project completion, and assignments.

Section 3: Participants were asked a question about ChatGPT's capabilities in various learning scenarios.

Section 4: Consists of questions that address the topic of ethics and the legal implications of the regulations governing ChatGPT usage.

Sections 5 and 6: Focus on satisfaction and outcomes achieved after the integration of ChatGPT by students.

Sections 7 and 8: The questionnaires contain questions related to skill development and the impact of ChatGPT on the labor market on the acquisition of new competencies.

Section 9: Includes questions about emotions associated with using ChatGPT.

Section 10: Involves questions about the level of difficulty of studies and factors that influence academic performance.

Section 11: Contains open-ended questions regarding general opinions about ChatGPT.

The dataset, available on the Mendeley Data website, initially contained 23,218 recorded entries. However, for the purpose of this article, only the responses of students who were studying at a European university at the time of completing the questionnaire were considered. Thus, the analysis was conducted exclusively on students who, regardless of their citizenship or country of origin, were enrolled in a European university. Only responses from students in Europe were selected to ensure the contextual and cultural coherence of the analysis presented. Solutions in the European education area present common functionalities in terms of adoption and integration. Responses provided by participants in the same educational process and part of the same environment allow for more relevant analyses to propose a solution adapted to the context and reducing variability [68].

In order to obtain the data necessary for the analysis for this article, the following steps were implemented:

1. The Excel file with the 23,218 questionnaire responses was retrieved and the column containing responses to the question "Q4, In which country are you studying during this semester?" was identified. This question helped us to include only the responses of participants from European countries;
2. A custom filter was applied to the column with Q4 so that only the answers containing a European country remained. As a result of this filtering, responses from students not studying in Europe were removed, leaving 10,145 responses.
3. Data cleaning operations have begun on the file with the 10,145 responses. Furthermore, incomplete responses, those missing answers to some questions, were also

removed. Specifically, participants who did not fully answer all questionnaire items were removed, resulting in 4345 records;
4. An analysis was performed on the 4345 records. In the Excel document, multiple copies of the same sheet with 4345 responses were made in order to be able to do a different analysis. In each data sheet, indicators were calculated, such as average student responses needed to address research Question 1 and beyond;
5. On the basis of these calculations, graphs were created to better represent the data. The necessary data were selected and graphs were generated. In addition, the results obtained served as a starting point for proposing the architecture of the learning system. The results are detailed in the "Results" section.

3.2. Methodology for Comparative Analysis of Platforms to Address Question 2

To answer question number 2 of this article, it should be mentioned that the questionnaire results also contributed, but an analysis of other existing platforms was also conducted. This section presents the methodology applied to select and analyze the architecture of other existing platforms.

To see how generative AI can be part of an educational system and propose an architecture for it, a comprehensive analysis of existing learning platforms was performed. The focus was placed on their components and how they interact. Therefore, the PRISMA methodology was used to obtain the results essential for answering Question 2 [69–71]. The steps involved are schematized in Figure 1.

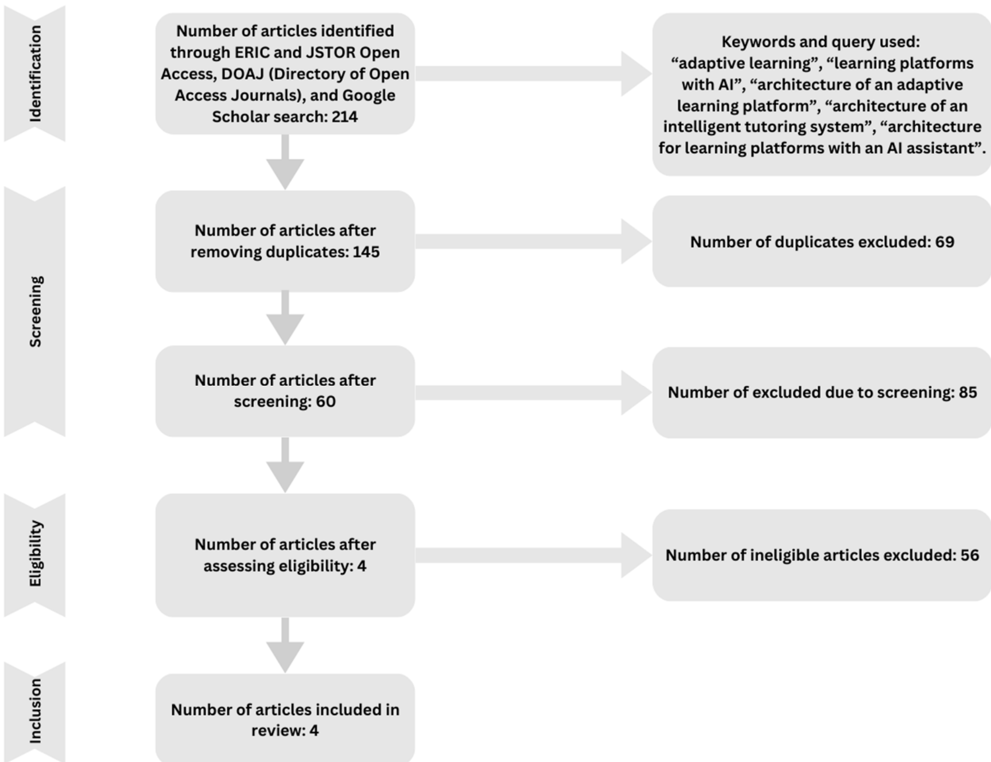

Figure 1. Approach for selecting relevant architectures for comparison analysis.

Relevant articles containing architectures of learning platforms currently in use were identified and obtained. After the architectures of adaptive learning platforms were identified, a comparative analysis was performed.

By meticulously documenting our methodology and providing detailed descriptions of the comparison criteria, we aim to ensure the reproducibility and validity of our research. Our findings lay the groundwork for the development of a novel adaptive learning system architecture that harnesses the power of generative AI to improve the educational experience.

3.2.1. The Systematic Approach That Our Analysis Followed Is as Follows:

1. Database Search using Keywords and Queries: In the search for articles on architectures of adaptive learning platforms that also incorporate artificial intelligence, search engines and electronic databases in the field of education, which provide information on educational technology, adaptive learning platforms, and others, were used. These include the following: ERIC and JSTOR Open Access, DOAJ (Directory of Open Access Journals), and Google Scholar. To search databases and search engines, multiple keywords were used. To ensure relevant results, queries were also constructed using these keywords. Consequently, searches were conducted using the following terms: “adaptive learning”, “learning platforms with AI”, “architecture of an adaptive learning platform”, “architecture of an intelligent tutoring system”, and “architecture for learning platforms with an AI assistant”;
2. Articles screening and eliminating duplicates: This stage involves removing duplicate articles and passing them through a screening process. As a result of this screening, only the articles that were relevant to the investigation remained. The filtering process was based on the following elements: (a) the article must refer to an adaptive learning platform used in the field of education; (b) the article must have been published between 2011 and 2023; and (c) the article must be written in English, and the full text must be publicly available;
3. Determining the eligibility of the articles: The articles that remained at this stage were subjected to a review process conducted by each author. During the review process, the authors considered the following: (a) whether the article presented and provided access to the architecture of a learning platform with artificial intelligence; (b) whether the main use cases of the platform were presented; and (c) whether the articles described the components of the architecture, the technology used, their purpose and roles, and how they interact. Importantly, criterion (a), specifically the availability of the platform’s architectural schema, was particularly crucial in this review process;
4. Including the articles in review: As a result of the steps mentioned above, 4 articles were included, each referring to an AI-based learning platform architecture. In addition, a comparative analysis of their architectures was performed.

A qualitative method was applied to analyze the platforms identified in the articles [72]. Furthermore, the 4 articles that were selected followed a process of extracting data from them. The purpose of these data is to aid in the comparative analysis that we need to conduct. Therefore, not all the data from the articles were extracted, but only the necessary data were extracted. We meticulously reviewed the materials collected for each platform, highlighting sections relevant to the established criteria. We documented the role and functionality of each architectural component, paying particular attention to how they interact to form a cohesive system. We also noted any commonalities or unique features across platforms. To ensure a complete understanding, we focused on parts of the articles that explicitly described the system components, their functions, and their interrelationships.

We organized our findings into a comparative table, summarizing the key characteristics of each platform based on established criteria. This allowed us to identify strengths, weaknesses, and potential areas for improvement.

On the basis of our evaluation, we synthesized our findings and proposed a new architecture that incorporates generative AI to address the limitations observed in existing platforms. This architecture aims to enhance personalization, expand the range of responses to learner queries, and ultimately improve learning outcomes.

3.2.2. Criteria for Comparative Analysis

On the basis of a review of the relevant literature, we established a set of criteria to guide our comparative analysis of the four platforms. These criteria focus on key aspects such as adaptability and personalization mechanisms, artificial intelligence techniques, domain specificity, and the target audience.

We employed four specific criteria to evaluate adaptive learning platforms:

- Adaptivity and personalization mechanisms: We assessed how each platform personalized the learning experience, distinguishing between content-oriented approaches (e.g., delivering lessons and recommendations on the basis of progress) and interaction-oriented approaches (e.g., continuous communication with a virtual assistant). This distinction is supported by [73], which suggests that learning outcomes can be influenced by the type of personalization mechanism employed;
- Artificial intelligence mechanism: We examined the specific AI techniques used by each platform, such as large language models, long- and short-term memory networks, gated recurrent units (GRUs), or bidirectional gated recurrent units (BiGRUs). According to [74], these techniques play crucial roles in enabling adaptive learning and personalizing the learning path. We also explore how these techniques are applied in practice, including the use of long- and short-term memory to recognize learning styles taking the example based on deep learning from [75] and GRUs/BiGRUs to understand implicit information as presented in [76];
- Focus domain: we determined whether the platforms catered to a specific subject area or offered content across multiple domains, as this can impact the breadth and depth of the learning experience [77];
- Target audience: We identified the intended age range for each platform, considering whether they focused on specific groups (e.g., young children) or offered content suitable for a wider range of learners [77]. This information is crucial to understanding the potential applicability of platforms in different educational contexts. As the authors demonstrated in [78], age is a significant factor because adult users benefit from the flexibility of these systems, but at the same time younger users need more guidance and help. As demonstrated by the results from [79], the adoption of learning platforms is different depending on the age group.

4. Results

4.1. Analysis of the Architectures of Identified Platforms

This section presents the architectures of the systems analyzed, specifically those with publicly available architectures. Existing educational platforms based on artificial intelligence offer significant advantages in adapting to the needs of students and teachers. However, there is room for improvement in how virtual assistants or intelligent tutoring systems interact with students, particularly in deep understanding user intent and providing assistance for topics not explicitly covered in the curriculum. In particular, there is a lack of components built using large language models (LLMs) to answer user questions. Our proposed architecture addresses these limitations by incorporating a generative AI component.

The Squirrel AI architecture is designed around a student-centric AI-based adaptive learning platform. This solution aims to make learning both efficient and engaging [80].

Students using the platform interact with an AI-powered virtual teacher that guides their learning while also receiving support from a human instructor [81].

At its core, the platform features an AI engine comprising AI algorithms, content, data, and pedagogical techniques. Squirrel AI emphasizes its large adaptive model, which combines adaptive methods with large models trained on 10 billion data points of student learning patterns. This model seeks to better understand how learners learn and how content relates to their learning capacity, enabling a more personalized learning experience [82,83].

The Squirrel AI architecture is organized into three main categories:

Learning Management System Core: As presented in [80], this module includes real-time event collectors that track student progress and generate learning maps that illustrate their mastery of theoretical concepts.

Learning Content: This includes a learning map, goals, and a content map.

API Services: These services provide real-time recommendations based on learning content and student interactions.

Figure 2 provides a visual representation of the Squirrel AI architecture, which is based on [80].

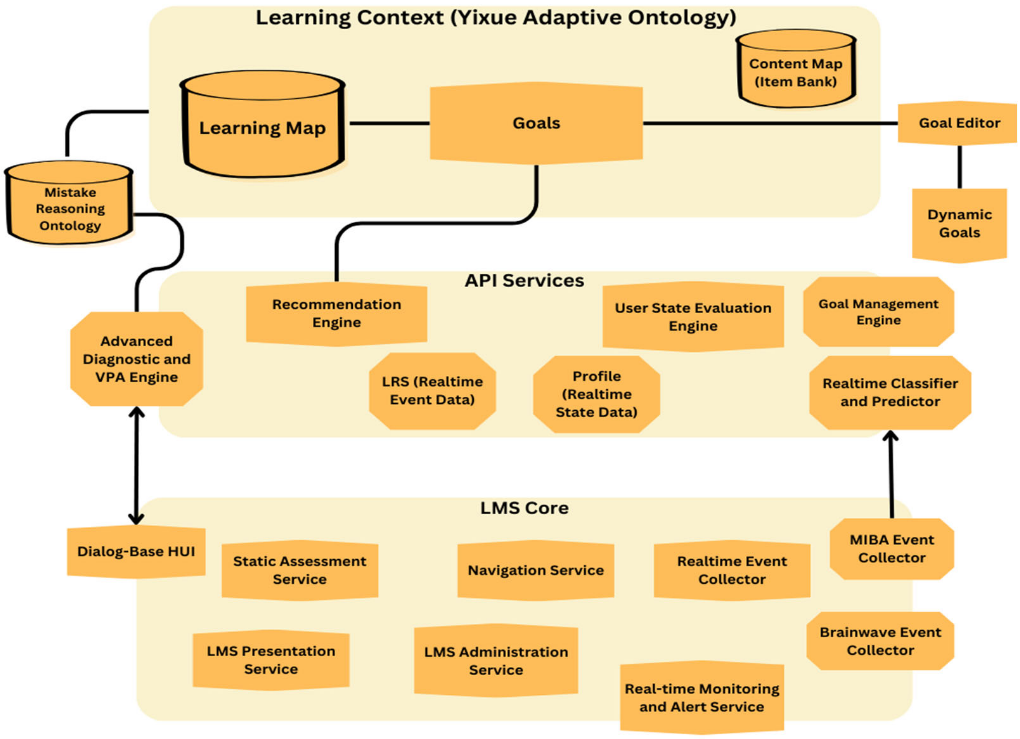

Figure 2. Squirrel AI architecture (based on [80]).

The Squirrel AI solution covers various STEM subjects (science, technology, engineering, and math) and language learning content. It serves students from kindergarten through grade 12 [84].

Knewton is another adaptive learning platform that we analyzed. It provides customized learning content tailored to the individual needs and level of the learner. This personalization is achieved through continuous data analysis and processing, which assesses the learner's current knowledge state and guides future performance improvements [85].

Figure 3 illustrates the complete architecture of the Knewton solution, which also integrates Amazon services. This figure is adapted from the original architecture presented in [85].

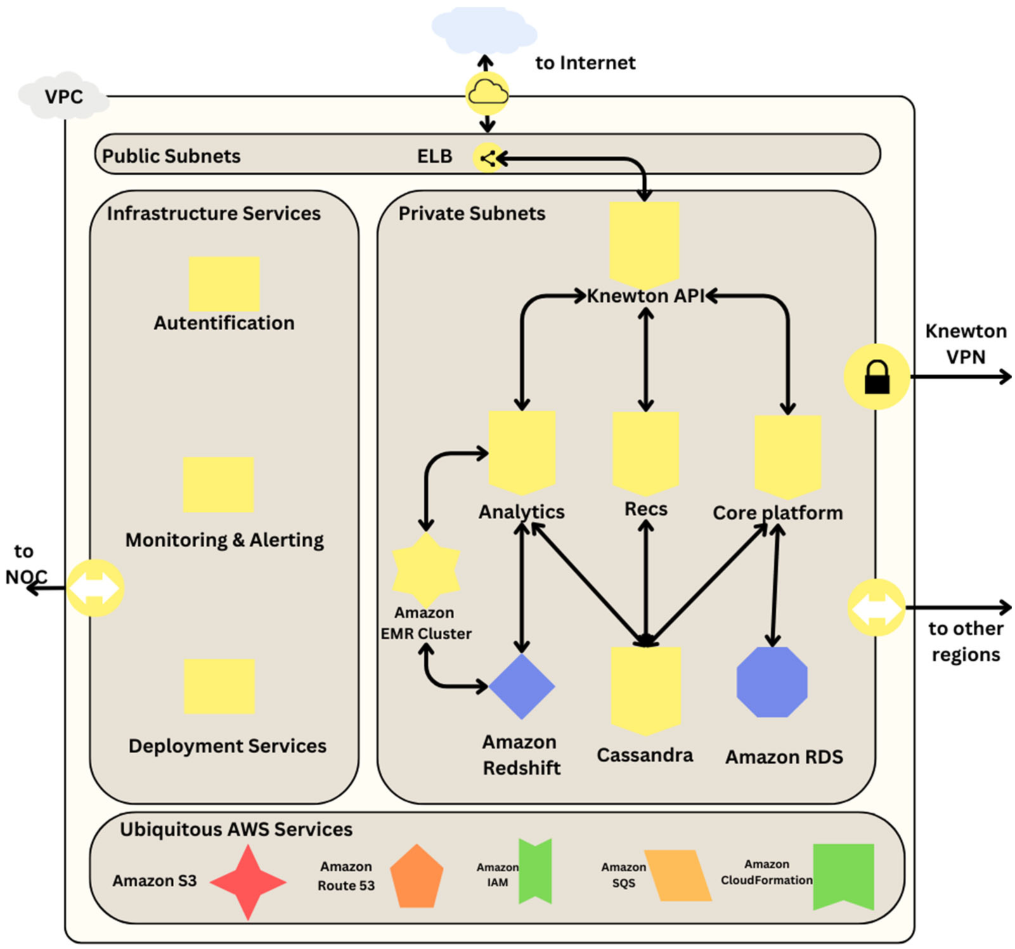

Figure 3. Knewton architecture (based on [85]).

A significant aspect of the Knewton platform is its emphasis on managing vast amounts of data related to student activity both inside and outside of the classroom. These data are analyzed in real time to update recommendations for users, facilitated by the system's built-in services [85].

Knewton employs artificial intelligence (AI) algorithms as a core element of its platform to personalize content [86]. These algorithms recommend personalized lessons and, on the basis of the learner's performance, identify areas for improvement within the content [87]. Knewton covers subjects such as mathematics, English, science, and history for students from kindergarten to grade 12 [88].

The architecture of the Knewton platform is based on modules with cloud services from Amazon Web Services (AWS) that are used to personalize live learning. The platform features components for collecting user data, analyzing their behavior in the platform, and rendering personalized content. The main elements of the architecture have the following functionalities: Amazon Elastic Map Reduce to collect and analyze user learning events in real time, Amazon Simple Storage Service (S3) that handles data storage, and Amazon CloudFormation, whose purpose is to manage instances of other Amazon services for scalability. Adaptive content is displayed using an API interface that communicates with the Amazon RDS and Cassandra databases [85].

DreamBox is an intelligent adaptive learning system that exemplifies the adaptation of real-time content. Its core principle is that the learning content dynamically adjusts to the learner's responses and actions. Teachers can benefit from this system by accessing comprehensive records of student activity for analysis and insights.

Figure 4 provides a visual representation of the DreamBox architecture, which is based on the official information found in [89,90].

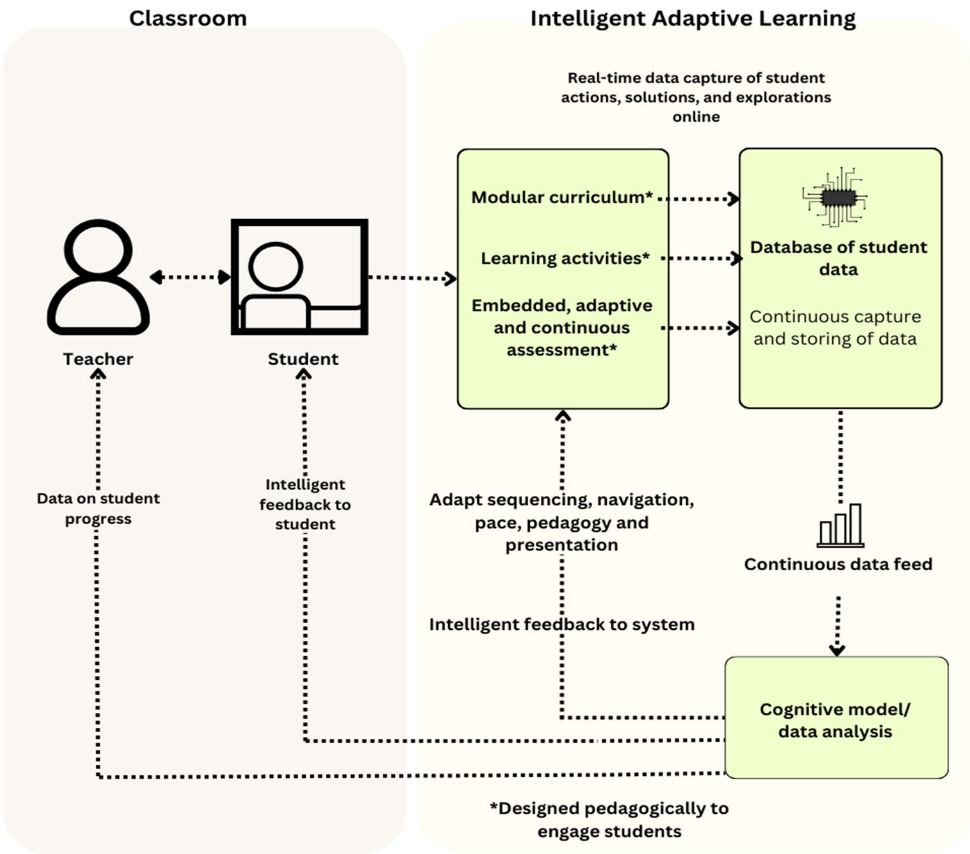

Figure 4. DreamBox architecture (based on [89]).

The foundation of an intelligent adaptive learning system consists of several key elements:

- Modularized curriculum: this allows flexible content delivery that can be easily adapted to individual learners' needs;
- Continuous data collection: the system constantly gathers data on the student's progress and performance;
- Cognitive model: this model serves as the brain of the system, interpreting student data to personalize the learning experience [91].

The cognitive model plays a crucial role in achieving personalization and content adaptation [89]. Processes information about the learner and his activity, creating a real-time snapshot of his current understanding. This enables the system to determine the next steps in the learning process, set an appropriate pace, and tailor the curriculum and activities accordingly. A continuous data collection and processing loop is essential for the effectiveness of a cognitive model [92].

DreamBox focuses on mathematics and reading for pre-K-12 students, providing a targeted and adaptive learning experience in these core subjects.

The architecture proposed by [93] relies on multiple interacting agents to facilitate personalized learning tailored to each student's needs. These agents consider various factors, including learning style, knowledge level, and visual or auditory impairments, to create personalized learning paths and suggest appropriate content.

Figure 5 illustrates the architecture of the multi-agent system, which is based on the original design presented in [93].

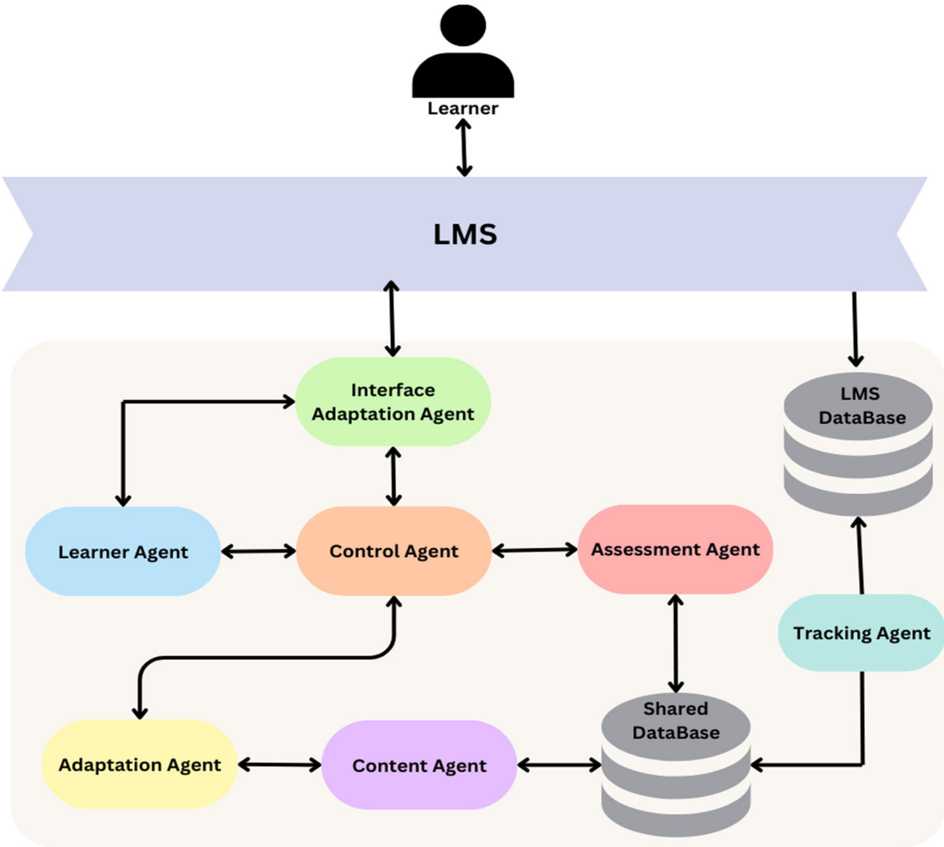

Figure 5. Multi-agent system architecture (based on [93]).

The key components of this architecture include the following:

- Learner agent: this component stores information about each learner, such as their name, age, learning progress, style, and any disabilities;
- Content agent: This component houses the learning content, organized hierarchically from the course level to individual learning objects. The content is personalized according to the needs of each learner;
- Adaptation agent: This component is responsible for creating a personalized learning experience. It continuously interacts with the learner and content models, using the Q-learning algorithm to select appropriate learning objects on the basis of the learner's characteristics and needs [93].

The system is termed "multi-agent" because it consists of several agents that work together, each with specific roles, to provide learners with relevant content. Agents communicate and share information, contributing to the overall efficiency and effectiveness of the system.

4.2. Comparative Analysis of Adaptive Learning Platforms

Table 1 summarizes the comparative analysis of the four platforms (Squirrel AI, Knewton, DreamBox, and the multi-agent system) on the basis of the criteria outlined in Section 3.2.2. Notably, only the Squirrel AI incorporates a component built using large language models, namely, the large adaptive model, trained on billions of data points to personalize content on the basis of the learner's profile. Squirrel AI also includes an assistant to guide the student during learning. While the other platforms utilize AI algorithms for content adaptation, the specific technologies used are not explicitly mentioned.

Table 1. Comparative analysis of the adaptive learning platforms Squirrel AI, Knewton, DreamBox, and the multi-agent system.

Name of the Platform	Adaptivity and Personalization Mechanisms	Artificial Intelligence Mechanism	Focus Domains	Target Audience
Squirrel AI	AI-based teacher	AI algorithms, large adaptive model (based on large models)	K-12 Subjects	K-12 students
Knewton	Content-focused	AI algorithms	K-12 subjects (math, science, English, history).	K-12 students
DreamBox	Content-focused	Cognitive model	Mathematics and reading	PreK-12 students
Multi-agent system	Content-focused	Q-learning algorithm	Not specified	Not specified (students)

Commonalities across the evaluated platforms include the target audience of K-12 students and a limited focus on specific subject domains (math, science, English, and history for Knewton; mathematics and reading for DreamBox). The multi-agent system does not specify its target audience or focus domains.

Our analysis revealed that none of these architectures includes a generative AI component that allows users to interact with an interface for querying or content generation. One potential framework for addressing this is LangChain [94], which can be used to develop applications such as virtual learning assistants that provide answers and explanations. These assistants could be integrated into more complex applications, such as adaptive learning platforms, to enhance the learning experience.

4.3. Results of the Survey of Students

An analysis was performed based on participants' responses to questions related to the integration and use of ChatGPT in their learning activities, study efficiency, improvement in assignment quality, and grade improvement.

In general, what we have obtained aligns with findings from other research, which shows that generative artificial intelligence or tools based on this technology (such as ChatGPT) in the learning process of students lead to improvements in their results [95,96].

Figure 6 presents the average scores calculated based on the responses evaluated on a scale from 1, representing strong disagreement, to 5, representing strong agreement. An average score of 3.27 indicates a positive perception among students of grade improvement after the integration of ChatGPT.

Regarding the improvement in the quality of assignments using ChatGPT, this is supported by an average score of 3.47. At the same time, ChatGPT is perceived as a useful tool to improve study efficiency, with an average score of 3.55.

The highest average score, 3.58, reflects students' satisfaction with the level of assistance provided by ChatGPT. Moderate satisfaction with the quality of the data offered by ChatGPT is indicated by an average score of 3.33, while an average score of 3.14 supports perceptions of the accuracy of the information provided.

Similarly, when using ChatGPT as a replacement for a search engine like Google, students expressed greater satisfaction, with an average score of 3.34.

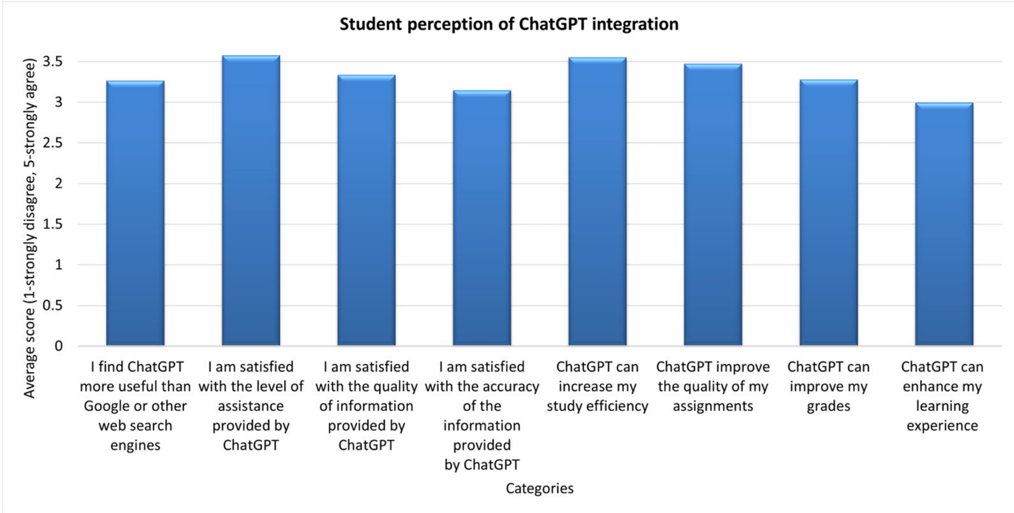

Figure 6. Students' perception of ChatGPT integration.

What we can see in Figure 6 seems to be a general picture regarding the integration of ChatGPT tools. If we look at the first four statements that students responded to, they refer to the usefulness they see in this tool and use cases. These results help us draw a conclusion regarding the degree of technological acceptance. The last four statements presented in Figure 6 pay attention to the perspectives that students have regarding the support provided in learning: improvement of study, quality of assignments, performance, and educational experience.

An evaluation was conducted to explore how technologies like ChatGPT can be integrated into education or the learning process. Accordingly, questions from sections where respondents expressed their opinions on ChatGPT's capabilities, learning outcomes achieved through ChatGPT and institutional policies regarding the use of ChatGPT were considered.

As we presented in the chart with number 7, the high average scores obtained for questions related to ChatGPT's ability to summarize extensive information (average score of 3.82) and respond in human-like language (average score of 3.70) suggest that students perceive it as a valuable tool for processing and summarizing complex information. At the same time, ChatGPT can also be utilized as a virtual learning assistant due to its ability to simulate human interactions. As shown in Figure 7, it can be observed that ChatGPT is considered more useful for online learning, with an average score of 3.51, compared to its use in traditional learning, where an average score of 3.14 was obtained. This highlights ChatGPT's adaptability to integration within learning platforms.

With an average score of 3.24, ChatGPT is considered capable of providing reliable information, while its ability to deliver personalized learning is supported by an average score of 3.20. This indicates that ChatGPT is perceived as capable of tailoring its content to meet individual students' learning needs. Additionally, ChatGPT is noted to contribute to increased motivation for studying, with an average score of 3.09.

Regarding awareness of ethical policies related to ChatGPT, an average score of 2.42 was obtained, reflecting the need for institutions to pay more attention to these aspects and improve awareness about the ethical and responsible use of this tool.

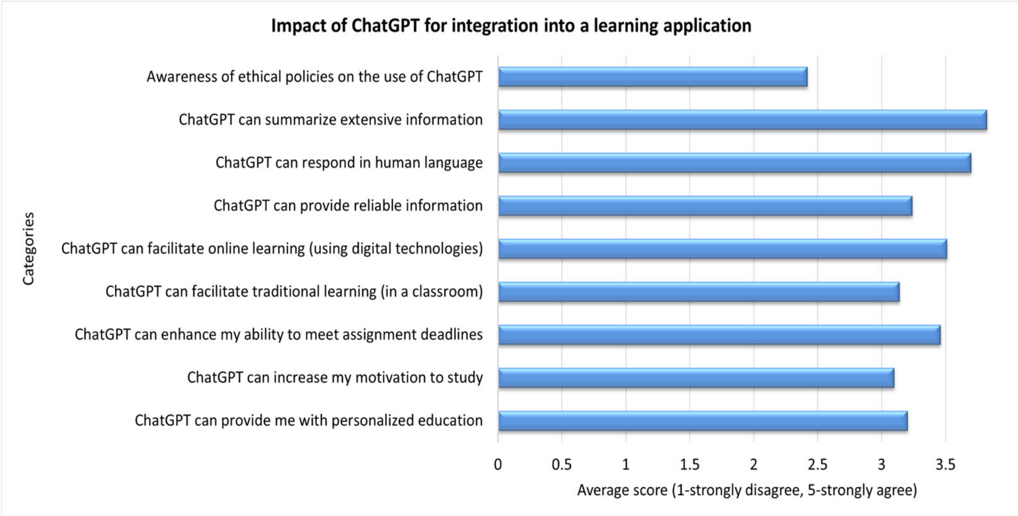

Figure 7. Impact of ChatGPT for integration into a learning application.

Regarding the awareness of ethical policies by students, a score of 2.8 was recorded, which may lead to the idea that there is a lack of both clarity and interest in the ethics of use. Items 2, 3, and 4 in the graphic represent functionalities found by students to be useful for supporting learning. At the same time, the last four items are directly related to the learning process because they contribute to increasing motivation, offer support regarding personalized learning, and respect for deadlines. These are supported by a score above 3.3, suggesting a positive opinion of ChatGPT.

Using survey responses regarding the use of the ChatGPT generative artificial intelligence tool and the question about perceptions of grade improvement, a correlation analysis was conducted between the two.

As shown in Figure 8, the data points are distributed in a way that indicates a positive relationship between the two variables (frequency of use of ChatGPT and perception of grade improvement). In other words, as the frequency of ChatGPT usage increases, so does the perception of improved academic performance by students.

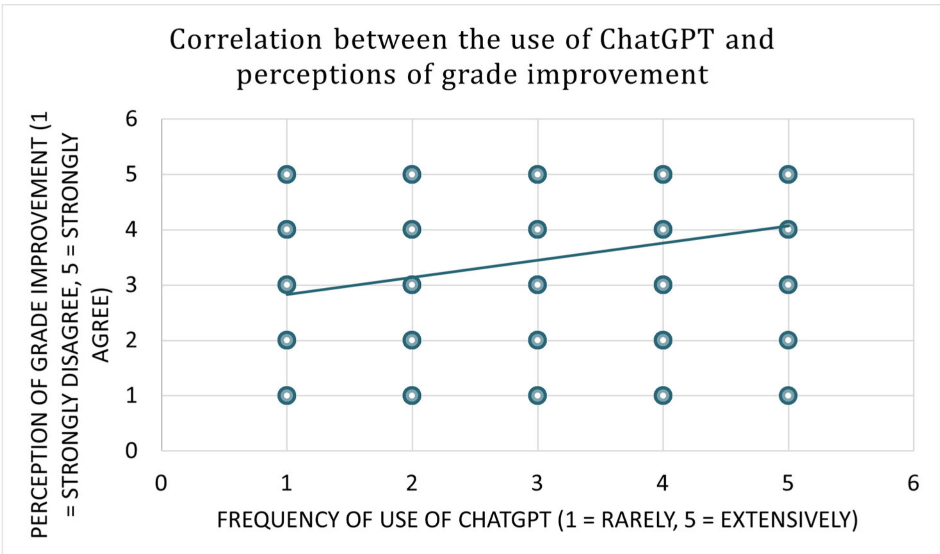

Figure 8. Correlation between the frequency of use of ChatGPT and perception of grade improvement.

Those who used the ChatGPT tool more frequently provided positive responses on its impact on their grades. The graph presented in Figure 8 gives an aggregated representation of the 4345 responses.

The line in the correlation has a positive slope, which translates into a positive correlation. Furthermore, we can assert that there is a relationship in which the use of an artificial intelligence tool such as ChatGPT is associated with a positive perception of improved learning outcomes.

The positive correlation resulting from the analysis also reflects the potential of a generative artificial intelligence application like ChatGPT to become an integral part of the educational process.

As concluded by other studies, such as [97], ChatGPT is an innovation in education because it transforms the way information is accessed and used. The authors of [98] identified that ChatGPT stimulates learning motivation and further leads to better results. On the topic of using ChatGPT in education, we obtained the following information:

- Based on the findings from [98], there is a direct link between the use of ChatGPT and the view that academic performance can be improved;
- The use of ChatGPT in learning is perceived by students as beneficial in bringing improvements to their results as revealed in [99];
- Through ChatGPT, an improvement in the quality of students' assignments is observed in the research in [100];
- As [101] evidenced, ChatGPT assists students in the learning process and helps them study more productively;
- The results from [102] suggest that the ChatGPT tool is preferred for conducting searches over a regular search engine and is also used for processing and summarizing text [103];
- Human interactions are emulated through the use of ChatGPT because it has the ability to respond in natural language [103];
- According to [104], an application like ChatGPT promotes online learning over traditional learning methods;
- As we discovered in [105], using a platform like ChatGPT, each student can benefit from personalized content.

4.4. The Proposed Architecture for the Learning System with Generative AI

In this section, based on the results obtained from the questionnaire and the conclusions from the comparative analysis of learning platforms, the proposed system architecture is detailed along with a description of its components and how they interact with each other. Additionally, the development of the proposed architecture was guided by Seymour Papert's constructionist theory, which was placed at the forefront to ensure a learner-centered and exploratory approach to education [4].

From the results of the questionnaire answered by the students (presented in detail in Section 4.1), concrete information was extracted on which the learning system architecture proposal can be based. Thus, the score for the item "ChatGPT can increase my study efficiency" of almost 3.5 and the score of 3.48 for "ChatGPT improve the quality of my assignment" represented a foundation for adding a module with a learning assistant (AI Assistant Module). The purpose of this module is to provide support and guidance in the learning process. The certainty that personalized learning can be provided by generative AI through the score of 3.45 for the item "ChatGPT can provide me personalized education" determined the introduction of a smart learning interface module that allows accessing customized content and interacting with the learning assistant.

The score of 3.14 recorded by the item "I am satisfied with the quality of the information provided by ChatGPT" led to the integration of a module that has a knowledge base from which the learning assistant can be fed with answers for users.

As highlighted in Section 3.2.2 our comparative analysis of existing platforms revealed a lack of generative AI components, particularly LLMs, to address scenarios where lesson content does not fully meet learners' needs. These systems lack knowledge bases to answer user questions and features to solve problems or improve engagement.

Our proposed architecture aims to bridge this gap by providing a knowledge base for each lesson, enabling the learning assistant to answer learners' questions. If the knowledge base lacks a suitable answer, an LLM can generate one, ensuring comprehensive support for learners.

The proposed architecture centers around an adaptive learning platform that uses artificial intelligence (AI) to deliver intelligent learning lessons with the help of a virtual assistant. A key feature is the incorporation of generative AI, as demonstrated by research, to expand the range of answers that the learning assistant can provide. This supports both students and teachers throughout the learning process, with the assistant adapting content to each learner's unique needs [106].

The core of the architecture is the learning assistant, on which several modules depend. These modules support smart lessons that students can access through the dedicated learning interface. Smart lessons are designed to incorporate open educational resources, allowing students to progress through the material at their own pace, as also demonstrated by [107]. The assistant can also suggest additional lessons to supplement the student's knowledge.

The smart learning interface delivers interactive educational content and grants access to AI-based assistants. It guides learners through the lessons, allowing them to navigate within a lesson, review content, and reread information from open resources. Importantly, the interface facilitates the interaction with the learning assistant. This approach is also highlighted by [108]. Students can pause the normal flow of the lesson to ask questions or seek clarification of challenging concepts. The assistant responds with explanations and directs the students to relevant resources.

The answers to the student questions are initially drawn from a predefined knowledge base associated with each lesson. However, if the knowledge base is insufficient, the proposed architecture integrates a generative AI component based on large language models. This component dynamically generates answers to questions not covered in the knowledge base, expanding the assistant's capabilities, and ensuring that learners receive comprehensive support. This method of integrating knowledge bases in learning platforms and associating them to an AI assistant is also endorsed by [109].

The integration of generative AI allows for a flexible knowledge base, as the assistant can provide different explanations for the same question, even when asked by different learners. This dynamic response mechanism improves personalization and adaptability in line with the findings from [110].

The following subsections describe each module of the proposed generative AI learning system architecture (Figure 9), outlining their roles and how students and teachers can utilize them. In the development of each module of the architecture, the features that students found useful during their use of ChatGPT in the learning process were also integrated.

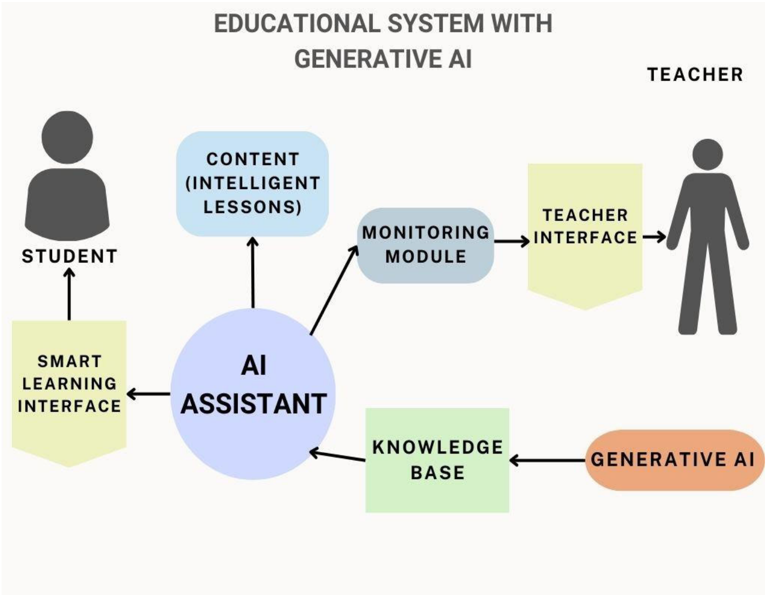

Figure 9. Educational system with generative artificial intelligence.

For a better understanding of how users interact with the solution, we have introduced a sequence diagram. Figure 10 illustrates a sequence diagram depicting the student's interaction with the learning assistant during a lesson.

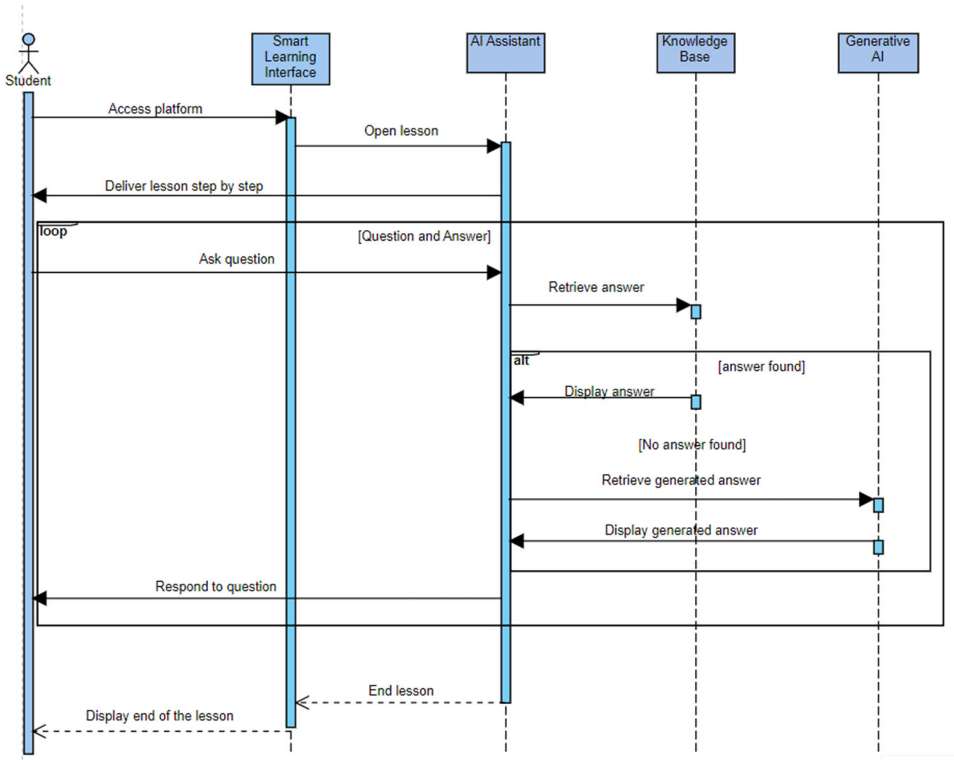

Figure 10. Sequence UML diagram for going through a lesson and asking questions.

4.4.1. AI Assistant Module

The virtual learning assistant that can be built using AI algorithms and open-source technologies as the core component. It recognizes the intent of the learner and uses knowledge bases and generative AI to expand its query capabilities. The assistant is presented as a chatbot, facilitating natural language interaction. The effectiveness of this method is reinforced by [111].

This module is responsible for user interaction, providing educational content, and supporting learners throughout the learning process. It also calculates performance metrics for each student, tracking engagement and making personalized lesson recommendations [112]. By continuously monitoring student progress and providing tailored feedback, the AI assistant can enhance the overall learning experience as evidenced in [113].

4.4.2. Smart Learning Interface Module

The smart learning interface serves as the main access point for learners. It enables students to view available lessons, preview content, and start learning sessions. This type of interface, as demonstrated in the work of [114,115], is designed to enable communication with the learning assistant when a lesson is selected.

The lessons can be organized by subject area, age category, and class, allowing easy navigation and selection. The interface supports both text-based and text-to-speech interactions, catering to diverse learning preferences. This module not only provides access to educational content, but also facilitates seamless interaction with the virtual assistant. Messages are displayed in a conversational format, fostering a more engaging and personalized learning experience [116].

4.4.3. Content Module (Intelligent Lessons)

Content is organized hierarchically, with learning trajectories (collections of lessons) accessible from the smart learning interface. Within the interface, the lessons are divided into a logical sequence of steps (typically 10–12 steps per lesson). Each step introduces a new concept and incorporates open educational resources, such as videos, 3D animations, documents, or presentations, to cater to diverse learning styles. The organization of content in the form of learning sequences to improve performance, understanding, and knowledge transfer is also supported by [117].

The lessons are designed to be interactive and practical, with hands-on projects (e.g., in physics) that students can complete to demonstrate their understanding. The ability to revisit steps in any order allows for personalized learning pathways which further leads to the improvement of the learning process and better results, as demonstrated by [118].

4.4.4. Knowledge Base Module

The knowledge base module stores lesson-specific knowledge bases that the learning assistant uses to answer learner questions. Each base contains intentions or expressions to classify user input and link it to the corresponding answers. This enables the assistant to recognize and respond to various queries effectively, as also noted by [119].

The number of knowledge bases associated with a lesson depends on its complexity and scope. If a knowledge base lacks a relevant answer, the generative AI module can generate one, ensuring that learners receive comprehensive support [120].

4.4.5. Generative AI Module

This module, powered by an LLM, connects to the lesson's knowledge base and enhances the assistant's query capabilities. It generates answers for undefined intentions, providing learners with relevant information even when the knowledge base lacks a predefined response. This allows for a more dynamic and adaptable learning experience, addressing a wider range of learner questions, and fostering deeper understanding, which aligns with the observations of [21].

The way in which the learning assistant module and the knowledge base module combine is as follows: the student uses the communication interface with the learning assistant and asks a question such as "What are robotics?". The question is semantically preprocessed by the learning assistant module, which searches the knowledge base for validated content, intent, or expression corresponding to the question asked by the student. If the assistant finds the answer in the knowledge base, it will display it to the user, otherwise it will call on the generative AI module to give an answer. The source of the validated answer from the knowledge base can be done through the fusion decision module [121].

In order to address more precisely how the assistant decides whether the student's question is solved by the knowledge base module or by the generative AI module, a decision function can be used. This consists of combining semantic similarity scores and source trust. A user's question can be processed using semantic vectorization in time; the similarity with the information already in the database can be calculated by cosine similarity [122].

4.4.6. Teacher Interface and Monitoring Module

Teachers have a dedicated interface to access the platform, which allows them to review lessons with learning assistants, such as students. The primary functionality is the monitoring module, which enables teachers to track student progress in lessons.

Teachers can create learning activities by assigning lessons and monitoring student participation. The module displays the number of participants, their progress within the lesson, their completion status, and their engagement. These functionalities are from the monitoring module, where teachers can supervise student activities and review interactions between students and the learning assistant.

4.5. The Accuracy and Reliability of the Generated Content

In this section, we will also look at the possible risks that can arise in the context of using LLMs in education, as highlighted by [123], such as cultural bias, the lack of a real or factual basis, and hallucinations. Next, we present how our architecture responds to these challenges by integrating knowledge grounding and structured prompts.

From the point of view of the quality and correctness of the content generated by the generative AI module, it is necessary that the architecture we propose also includes techniques through which it can be controlled. Specifically, the solution will apply a strategy called knowledge grounding, helped by the content that the generative AI module will offer being based only on data from validated sources [124]. In addition to this technique, structured prompts will also be used, which will contribute through clear, verified, and education-specific formulations. In situations where the questions are difficult to understand, an element can be integrated to filter according to the level of confidence, and the answer that the user will receive will be labeled as having a certain degree of uncertainty. Therefore, among the elements that contribute to increasing accuracy, the use of external sources that have gone through a rapid validation process is provided [125].

The structured prompting component is inspired by the approach of [126], which is intended to improve the relevance of LLM-generated responses and their predictability. This framework, adapted for the proposed architecture that will be used in the learning, will organize the user prompts according to the intent they have. The query will be categorized before being sent to the LLM. To be more precise, the following prompt flags will be defined:

- Explanatory template: this is used for prompts that ask for explanations about a concept (e.g., "What is electrical resistance?");
- Comparative template: for prompts that ask for comparisons or differences (e.g., "What is the difference between a variable and a constant in programming?");
- Critical template: identifies those prompts for developing critical thinking (e.g., "Give me pros and cons for the use of artificial intelligence in medicine?");

- Exemplification template: used to generate concrete examples or situations (e.g., “Give me examples of using the furrier transform in real life?”);
- Summary and reformulation template: whose role will be to find prompts that require paraphrasing or summarizing (e.g., “Summarize Pythagoras’ theory by reformulating the terms for a 9-year-old student”).

4.6. Technologies for the Proposed Architecture

In order to support the functionalities of the proposed architecture, a series of technologies have been identified to be used for the implementation of the system. In order to be able to match the questions asked by the user using the smart learning interface module and implicitly to calculate semantic similarities, Sentence-BERT or similar will be used, with the help of which text transformations can be made into embedding vectors [127]. For the generative AI module, an open-source model such as LlaMA2 will be used [128].

The system is designed as a module-based web application, using the JavaScript programming language together with Node.js and Express.js. The frontend is built using React.js 19.1.0 [129–131]. The application modules will communicate with each other via RESTful APIs (currently version v1).

4.7. Academic Ethics

Given that artificial intelligence raises concerns about the respect of academic ethics principles, to cover these, the platform can include mechanisms to verify the authenticity of answers and prevent plagiarism. As recommended by specialized literature, the solution can include elements to detect user behavior regarding the tasks for which the assistant is interrogating (for example: writing essays) [132].

5. Discussion

The results we obtained from this study show that students perceive ChatGPT as a way to streamline the learning process (obtained with a score of approximately 3.2), improve the quality of the homework they do (with a score of 3.48), and help them to be motivated in terms of learning (with a score of 3.43). All these results are reinforced by other studies in the specialized literature that mark the fact that students put artificial intelligence in a favorable light when it comes to its use in the learning process [133].

At the same time, there are concrete examples of studies that demonstrate that positive feedback does not lead to improvements in learning outcomes, being an “illusion of utility” [134]. Having said that, this article aims to bring students’ opinions into balance and on the same line with functional techniques and technologies that ensure personalized learning [135].

Considering this study and specialized literature, several cases were identified in which a tool based on generative artificial intelligence such as ChatGPT can be used. Thus, we recall the following: generating simple explanations for advanced concepts, formulating quick summaries of other texts, and generating questions for self-assessment. These can occur in self-regulated learning and can reduce the burden on people who normally have this role [136]. Moreover, ChatGPT has the capacity to be used as a feedback tool for improvement by intervening in metacognition [137].

6. Conclusions

Through this article, relevant results are obtained regarding what students think about incorporating ChatGPT into learning activities to produce better learning outcomes. At the same time, the article proposes a design solution for creating a learning system with generative AI, demonstrating that it is possible to integrate such tools into an educational system. The results clearly highlight the fact that students perceive the use of ChatGPT as highly beneficial for their academic performance. In addition, it contributes positively to the quality of assignments, learning efficiency, and increased motivation. Its primary functions attributed to the learning process include serving as a virtual assistant capable of responding similarly to a human interlocutor, providing personalized information in a concise format. At the same time, it has the capability to process and search data similar to a search engine but in a more advanced manner.

Another outcome presented in this article is the proposed architecture, which includes both the aspects reported by students in the questionnaire and addresses a significant gap identified in existing adaptive learning platforms. In concrete terms, the methodology for integrating a generative AI component to enhance the capabilities of the platform's virtual assistant or chatbot is presented.

Our architecture directly answers the second research question posed at the beginning of this study. We have demonstrated the feasibility of integrating generative AI into personalized learning systems. In addition, we have illustrated how this integration can create substantial benefits for students and teachers as well.

The proposed learning platform, when implemented, offers a virtual learning assistant capable of providing comprehensive and unrestricted responses to user queries. It is capable of personalizing the provided content and delivering this content in a summarized form using language specific to a human being. This capability is enabled by a knowledge base enriched with content generated by generative AI, expanding the breadth and depth of information available to students beyond what current platforms offer.

The architecture's components are designed to provide a holistic learning experience, including intelligent lessons, an evolved learning assistant, and a user-friendly interface. This design serves as a practical blueprint for developers and institutions aiming to create effective and engaging educational systems.

Limitations and Future Research

There are several limitations that have been identified in this research, such as the fact that this article considers self-reports of the perspectives that students have without presenting a validation of academic performance and thus results of how efficient the proposed system is cannot be presented [138,139]. Another limitation that should be mentioned is that the system has not been tested in a real learning mode with users who would actually use this solution in the learning process [140].

Although it has been shown that generative artificial intelligence tools are useful for rapid learning, there are still drawbacks when it comes to acquiring long-term knowledge. The article [134] demonstrated how students performed worse with ChatGPT compared to those who used a traditional learning method.

Although this paper proposes a conceptual architecture that takes into account students' impressions of using an LLM, for future work this system can be validated in terms of its efficiency. This stage is foreseen as a direction in future research. Therefore, the evaluation plan takes into account significant and specific metrics of these solutions, such as the gains that students have in terms of learning, the effectiveness in completing tasks, the shortest time interval in which the learning assistant responds, and the degree of customization of the content for each user in relation to their needs [122]. Another way to test the proposed system would be to carry out a comparative analysis between experimental groups in order to see the real impact of generative artificial intelligence. It is also intended to explore intercultural differences in the perspective on AI tools [138].

This article contributes to research on information systems/software engineering and adaptive learning solutions in education by presenting a concrete architectural approach to incorporate AI and generative AI into learning, based on concrete results gathered from students who are generative artificial intelligence users, as well as on a rigorous analysis of existing platform architectures.

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