education sciences

MDPI

Article

The Impact of Prompt Engineering and a Generative AI-Driven Tool on Autonomous Learning: A Case Study

Kovan Mzwri [1,*] and Márta Turcsányi-Szabo [2]

[1] Doctoral School of Informatics, Eötvös Loránd University, Pázmány Péter stny. 1/C, 1117 Budapest, Hungary
[2] Department of Media & Educational Technology, Faculty of Informatics, Eötvös Loránd University, Pázmány Péter stny. 1/C, 1117 Budapest, Hungary; tszmarta@inf.elte.hu
* Correspondence: kovan@inf.elte.hu

Abstract: This study evaluates "I Learn with Prompt Engineering", a self-paced, self-regulated elective course designed to equip university students with skills in prompt engineering to effectively utilize large language models (LLMs), foster self-directed learning, and enhance academic English proficiency through generative AI applications. By integrating prompt engineering concepts with generative AI tools, the course supports autonomous learning and addresses critical skill gaps in language proficiency and market-ready capabilities. The study also examines EnSmart, an AI-driven tool powered by GPT-4 and integrated into Canvas LMS, which automates academic test content generation and grading and delivers real-time, human-like feedback. Performance evaluation, structured questionnaires, and surveys were used to evaluate the course's impact on prompting skills, academic English proficiency, and overall learning experiences. Results demonstrated significant improvements in prompt engineering skills, with accessible patterns like "Persona" proving highly effective, while advanced patterns such as "Flipped Interaction" posed challenges. Gains in academic English were most notable among students with lower initial proficiency, though engagement and practice time varied. Students valued EnSmart's intuitive integration and grading accuracy but identified limitations in question diversity and adaptability. The high final success rate demonstrated that proper course design (taking into consideration Panadero's four dimensions of self-regulated learning) can facilitate successful autonomous learning. The findings highlight generative AI's potential to enhance autonomous learning and task automation, emphasizing the necessity of human oversight for ethical and effective implementation in education.

Keywords: generative AI-driven educational tools; prompt engineering; autonomous learning; generative AI Canvas LMS integration; AI-driven assessment; AI-driven feedback; educational technology; academic English proficiency; educational task automation; higher education

check for updates

Academic Editors: Mike Joy, Boban Vesin, Dunja Vrbaški and Aleksandra Klašnja-Milićević

Received: 10 December 2024
Revised: 31 January 2025
Accepted: 4 February 2025
Published: 7 February 2025

Citation: Mzwri, K., & Turcsányi-Szabo, M. (2025). The Impact of Prompt Engineering and a Generative AI-Driven Tool on Autonomous Learning: A Case Study. *Education Sciences*, *15*(2), 199. https://doi.org/10.3390/educsci15020199

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The integration of artificial intelligence (AI), particularly generative AI, into educational practices has opened new avenues for enhancing learning experiences and outcomes (Crompton & Burke, 2023; Xu & Ouyang, 2022). Among these advancements, AI-driven tools hold significant promise for personalized educational support. This study examines the potential of such tools through the case of a self-regulated course titled "I Learn with Prompt Engineering", designed to empower university students in creating precise instructions for large language models (LLMs). The course emphasizes the role of prompt

engineering in minimizing errors, biases, and distortions, ultimately enhancing LLM reliability and usability across various domains. Through iterative practice and inquiry, this approach also facilitates the development of scientific English proficiency, addressing a critical skill gap among students whose native language is not English.

Students in fields like informatics (C.S.) must possess a strong command of academic English to excel in their studies and make progress in their professional fields. In our country, universities are now mandated to improve professional second-language education, yet no additional resources have been allocated to meet this objective. To address this challenge, our university has introduced several initiatives, including the pilot elective course "*I Learn with Prompt Engineering*". The course is structured into basic, intermediate, and advanced levels to support autonomous learning and enhance academic English proficiency, particularly in reading comprehension, while also fostering self-directed learning (SDL) and market-ready skills. The course was designed to facilitate autonomous learning, automated grading, and feedback without involving direct teaching or teacher-led assessment, with the goal of enabling its broader implementation in the future.

This case study evaluates how teaching prompt engineering concepts and applying them through Generative Artificial Intelligence (GAI) tools enhance learning in general. By focusing on prompt patterns and techniques, it also investigates how these skills improve students' academic English comprehension. To measure the impact of prompt engineering on students' language skills, the study employs EnSmart, an AI-driven tool developed specifically for real-time reading comprehension assessments. Powered by GPT-4, EnSmart generates test content, auto-grades responses, and provides detailed, human-like feedback. GPT-4, a language model recognized for its accuracy, contextual adaptability, and advanced reasoning abilities (OpenAI, 2023), is well suited for such applications. Integrated with the Canvas Learning Management System (LMS) via Learning Tools Interoperability (LTI) and an Application Program Interface (API), EnSmart delivers an automated testing environment aligned with course objectives.

The research methodology involves structured questionnaires and surveys to collect data on student perceptions and experiences with the course including prompt engineering patterns and AI-driven educational technologies. These instruments specifically evaluate the course's impact on students' academic English proficiency and overall learning outcomes. Additionally, the study examines the usability of EnSmart in generating test content, performing assessments, and delivering real-time, human-like feedback.

By analyzing student interactions and performance data, this study explores the effectiveness of prompt engineering with GAI tools in enhancing learning and self-evaluating skills as well as academic language proficiency for non-native English speakers and supporting self-regulated learning (SRL). It also evaluates the effectiveness and usability of generative AI-driven tools like EnSmart. Ultimately, this case study highlights the transformative role of GAI in autonomous learning, task automation, and assessment, emphasizing the value of integrating prompt engineering techniques and AI-driven educational tools into modern education.

Research Objectives

This pilot study aims to evaluate the potential of GAI tools, particularly through teaching prompt engineering techniques, to support autonomous learning and enhance self-directed academic English proficiency among university students. The specific objectives of the study are as follows:

1. Assess the impact of prompt engineering patterns on students' SDL skills, particularly in improving academic English proficiency through the use of GAI tools.

2. Analyze the usability and effectiveness of EnSmart, an AI-driven tool powered by GPT-4, in automating assessments. This includes evaluating EnSmart's ability to generate academic reading comprehension tests, auto-grade responses, and deliver human-like feedback, all seamlessly integrated within Canvas LMS.
3. Explore students' perceptions and experiences with using GAI in education, focusing on its relevance, usability, and limitations.

2. Literature Review

The integration of artificial intelligence (AI) into educational contexts has introduced significant advancements, especially through large language models (LLMs) and AI-driven tools, providing opportunities to enhance personalized learning, automate tasks, and transform content creation and delivery. These technologies support language learning, improve assessment and feedback (Caines et al., 2023), and offer a more individualized learning experience. The rise of LLMs, such as OpenAI's GPT series, has notably impacted how educational tools can be deployed to support autonomous learning and self-regulation in students (Peláez-Sánchez et al., 2024).

A critical aspect of leveraging LLMs in education is prompt engineering, a technique that tailors input instructions to optimize model performance. Well-designed prompts are instrumental in minimizing errors, biases, and distortions that can arise due to the inherent limitations of the training data and model architecture. Research indicates that precise instructions can significantly enhance the reliability and usability of LLMs across various domains. For instance, studies have shown that prompt engineering can direct LLMs to produce more relevant and unbiased outputs by providing clear and specific instructions (Reynolds & McDonell, 2021). Similarly, carefully crafted prompts can mitigate model hallucinations and increase response fidelity (Brown et al., 2020). This precision is particularly important in educational contexts, where the accuracy and relevance of generated content directly impact learning outcomes.

AI-driven educational tools have transformed autonomous learning and self-regulated courses by offering personalized and adaptive learning experiences. These tools support various aspects of the learning process, from content creation to assessment and feedback. AI tools can provide real-time analytics and personalized feedback, empowering students to take control of their learning. Research suggests that SRL facilitated by AI promotes higher levels of motivation and self-efficacy among students (Zimmerman, 2008). Additionally, AI can adapt to individual learning paces and styles, enhancing the effectiveness of autonomous courses and making education more inclusive and accessible (Luckin & Holmes, 2016). Based on recent research (Panadero, 2017), several standardized tests have been developed or updated to evaluate SRL skills:

The Self-Regulated Learning Perception Scale (SRLPS) assesses four dimensions of SRL:

1. Motivation and action in learning;
2. Planning and goal setting;
3. Strategies for learning and assessment;
4. Lack of self-directedness.

The SRLPS uses a 5-point Likert scale and has been validated for use with university students (Turan et al., 2009).

While several standardized options exist, researchers emphasize that SRL assessment should ideally use multiple methods and be adapted to specific learning contexts. Combining self-report measures, behavioral observations, and performance tasks can provide a more comprehensive evaluation of students' SRL skills (Grüneisen et al., 2024; López-Angulo et al., 2024; Panadero, 2017). This approach aligns with the course's objectives

of fostering autonomous and SDL, and thus the course design was based on developing the above skills, and assessment integrated multiple ways of measuring SRL skills by implementing SRLPS.

GAI has shown significant promise in language-learning contexts, particularly in enhancing second-language acquisition. Studies have highlighted that AI-driven tools, such as ChatGPT, can improve students' L2 writing skills by offering personalized support and fostering engagement (Guo et al., 2023; Marzuki et al., 2023; Muñoz et al., 2023). These tools also contribute to psychological benefits, such as increased motivation, interest, and self-confidence in language learners (Cuiping Song, Yanping Song). ChatGPT, specifically, has been recognized for its ability to engage in human-like conversations that simulate real-world dialog, helping learners practice their language skills in a more authentic context and regulate their learning processes (Agustini, 2023; Zou et al., 2024). Moreover, these AI tools efficiently generate assignments, quizzes, and learning activities, saving time for EFL teachers (Koraishi, 2023). By integrating prompt engineering into the "*I Learn with Prompt Engineering*" course, students are empowered to improve their academic English comprehension through direct application of LLM prompts, building on existing studies that link generative AI and language-learning outcomes.

The automation of test content generation, assessment, and feedback processes through AI tools also represents a significant development. Traditional approaches to test generation often relied on rule-based systems and pre-defined templates or question banks (Dikli, 2003). These systems lacked adaptability, producing generic content unsuitable for diverse learning contexts. The subsequent adoption of machine learning (ML) and natural language processing (NLP) algorithms enhanced adaptability, though these methods often struggled to address contextual nuances and dynamic educational requirements (Heilman et al., 2006; Shermis & Burstein, 2013).

GAI represents a transformative leap in this domain by enabling the efficient creation of tailored study materials, quizzes, and practice problems, fostering more personalized educational experiences (Boscardin et al., 2024). It also has the potential to revolutionize grading and feedback processes, automating tasks traditionally seen as time-consuming and subjective. Large language models (LLMs) provide nuanced, scalable, and efficient solutions for assessment, delivering detailed feedback that extends beyond mere correctness (Fagbohun et al., 2024). For instance, leveraging GAI for grading, as proposed by Koraishi (2023), can streamline assessment workflows, allowing educators to focus more on pedagogical priorities. Unlike traditional methods, GAI feedback is detailed, actionable, and more akin to human tutoring (Ruwe & Mayweg-Paus, 2024), accelerating feedback delivery and enhancing the learning experience. AI-driven feedback promotes SRL by identifying knowledge gaps and aligning insights with students' learning progress. This improves engagement, motivation, and comprehension, particularly in language-learning contexts, where specificity and timeliness are crucial (Kılıçkaya, 2022; Molina-Moreira et al., 2023) The EnSmart tool analyzed in this study exemplifies these qualities, offering automated feedback that drives engagement, supports performance improvement, and mitigates instructor bias (Barana et al., 2018; Chen et al., 2019; Guei et al., 2020; Marwan et al., 2020).

The integration of these AI-driven tools with Learning Management Systems (LMSs) like Canvas has the potential to further enhance their utility by allowing seamless tracking of student progress and personalized learning interventions. Research indicates that LMS integration facilitates a holistic approach to monitoring and improving student learning outcomes (Graf et al., 2009). This alignment between AI tools and LMS platforms strengthens the potential for enhanced learning experiences, especially in courses designed to foster autonomous learning.

In this study, we developed the EnSmart tool, which leverages the GPT-4 language model to integrate real-time test content generation, automated grading, and human-like feedback within Canvas LMS via LTI and API. EnSmart exemplifies the transformative potential of GAI technologies in automating educational tasks, particularly in SRL contexts such as the "*I Learn with Prompt Engineering*" course.

3. Development of EnSmart

This chapter details the development of EnSmart, an AI-driven tool designed to evaluate students' academic English reading comprehension. EnSmart was developed specifically for integration into the "*I Learn with Prompt Engineering*" course on canvas LMS, leveraging GAI to provide real-time content generation, auto-grading, and human-like feedback. The chapter will cover the conceptualization, design, technical integration, usability testing and deployment, and continuous improvement of EnSmart.

3.1. Conceptualization and Design

The development of EnSmart began with a clear vision: to create an AI-driven application capable of generating, evaluating, and providing feedback on reading comprehension tasks. The conceptualization phase involved identifying the key functionalities required to meet this goal. The design focused on creating a user-friendly interface that would seamlessly integrate with the Canvas Learning Management System (LMS) while ensuring the tool could effectively leverage GAI for real-time content creation.

The core objectives defined during this phase were the following:

1. Real-time generation of reading comprehension content.
2. Automated grading of student responses.
3. Provision of detailed, human-like feedback.
4. Full integration with Canvas LMS.

3.2. Integration with Generative AI—Test Content Generation

Central to EnSmart's functionality is its integration with the GPT language model. This integration necessitated a development process that effectively harnessed the capabilities of generative AI. We applied appropriate prompt engineering techniques to ensure that the AI generated reading comprehension passages and questions that were both relevant and contextually appropriate.

Given the complexity of controlling the output of a large language model (LLM), we used a low value for the temperature parameter. This decision minimized variability in the AI's responses, ensuring consistency and relevance in the generated content.

To achieve our goal of generating high-quality, consistent, and relevant educational content, we employed the task-oriented prompt pattern in conjunction with a low temperature setting. The task-oriented prompt pattern exemplifies a structured approach to generating educational content tailored for specific tasks. This particular prompt type guides the AI through a series of tasks aimed at assessing academic English reading comprehension for university students in the Faculty of Informatics.

It directs the AI to perform several key actions:

1. Passage Generation: The AI is tasked with creating a 380–400-word passage that is both informative and engaging. The passage must cover a diverse and random topic related to an area of computer science. Its purpose is to effectively evaluate students' academic English reading comprehension while exploring a unique aspect or application of computer science.

2. Question Design: The prompt instructs the AI to craft questions that assess various reading comprehension skills, including identifying main ideas, understanding details, making inferences, and recognizing the writer's opinions.
3. Structuring the Passage: The AI is prompted to provide a title for the passage and organize it into paragraphs, ensuring clear and logical presentation of information.
4. Multiple-Choice Questions: Five multiple-choice questions are to be meticulously designed to delve into and assess students' profound comprehension of academic English reading concepts demonstrated in the passage. The questions should follow a format similar to IELTS reading test questions, challenging students' understanding effectively.
5. Output Format: The generated passage and questions are required to be presented in the format of a JavaScript object. This structured output includes attributes such as passage.name, passage.paragraphs[], and questions[{questions[0].text,questions[0].options[],questions[0].answer}], facilitating easy accessibility and usability of the generated data by other components within the application.

3.3. Integration with Generative AI—Automated Grading and Feedback System

One of EnSmart's features is its ability to automatically grade student responses and provide detailed feedback. The system uses pre-defined criteria to evaluate answers accurately and consistently. Additionally, the feedback mechanism was crafted to deliver constructive, human-like insights, helping students understand their mistakes and enhancing their learning experience. This system was meticulously developed in alignment with a task-oriented prompt tailored for instructors of university students in Academic English proficiency. The prompt delineates a series of tasks aimed at evaluating students' comprehension within an academic context. These tasks encompass the following:

1. Accurate Grading: The system computes grades by comparing student responses to correct answers, adopting a binary representation where 1 denotes correctness and 0 signifies incorrectness. This methodical approach ensures precise evaluation of academic English reading comprehension, aligning with the overarching goal of the exercise.
2. Scoring Criteria: Each question carries a weightage of 8 points, with full credit awarded for correct responses. This standardized scoring mechanism enhances transparency and consistency in the grading process, adhering closely to academic standards.
3. Detailed Feedback: An integral component of the system is the generation of precise and detailed feedback for each student's response. Focused on academic English reading comprehension, the feedback provides nuanced assessments, emphasizing clarity and depth. By mimicking human-like insights, the feedback aids students in identifying and rectifying errors effectively, fostering a conducive learning environment.
4. Structured Output: The system presents its assessment outcomes in the format of a JavaScript object, adhering to the prompt's specifications. This structured format includes attributes such as assessment.feedback, assessment.totalGrade, and assessment.overallFeedback. This output format facilitates accessibility and ensures that the generated output is captured more easily, enabling seamless integration with other components of the system.

3.4. Integration with Canvas LMS

To ensure that EnSmart could be seamlessly incorporated into the existing course framework, it was integrated with Canvas LMS using Learning Tools Interoperability (LTI) and the Canvas API. The LTI and API were used to achieve full integration of the app with the Canvas LMS environment, ensuring full accessibility of the app inside the Canvas

platform and enabling data exchange between EnSmart and Canvas. This integration allowed for the exchange of student information such as student names and IDs, posting student grades to the course gradebook, and posting feedback from EnSmart to the students' gradebook for tests. The overall architecture of EnSmart and its interconnected components are illustrated in Figure 1.

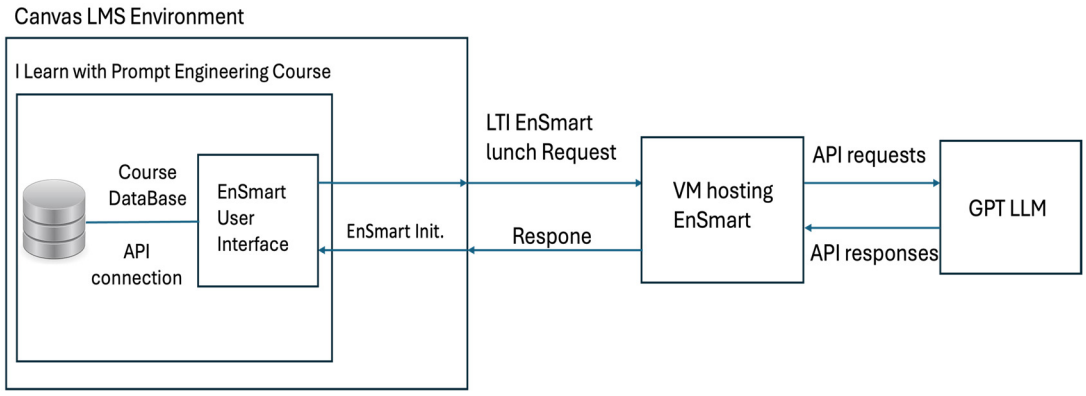


Figure 1. EnSmart architecture.

This integration enabled EnSmart to function as a cohesive part of the course, providing a unified platform for managing assessments and student interactions. The importance of such integration is supported by research indicating that seamless LMS integration enhances user experience, improves learning outcomes, and increases the efficiency of course management (Watson, 2007). Additionally, LTI integration is recognized for its role in facilitating interoperability between educational tools, thereby fostering a more cohesive and accessible learning environment (Galanis et al., 2017).

In this context, EnSmart acts as the tool provider, offering educational content and assessment functionalities, while Canvas LMS acts as the tool consumer, integrating these tools within its platform to deliver a seamless user experience to students. Figure 2 illustrates the seamless integration of EnSmart within the Canvas LMS environment, allowing students to access it directly from the course navigation menu.

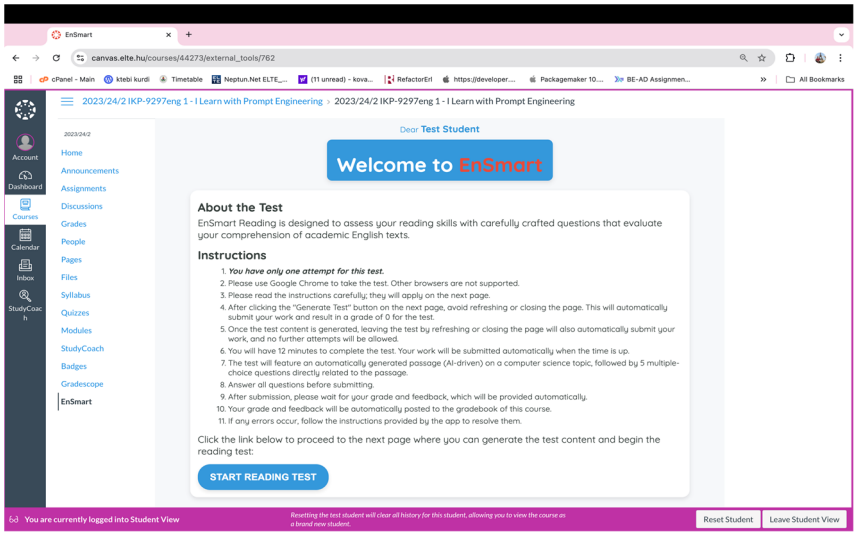


Figure 2. Seamless integration of EnSmart within the Canvas LMS interface.

3.5. Usability Testing, Refinement, and Deployment

Throughout the development process, we conducted usability testing to refine EnSmart's functionalities and user interface. Pilot tests involving a test student provided

feedback, which we used to identify and address potential issues. These iterative refinements ensured that EnSmart was both functional and user-friendly.

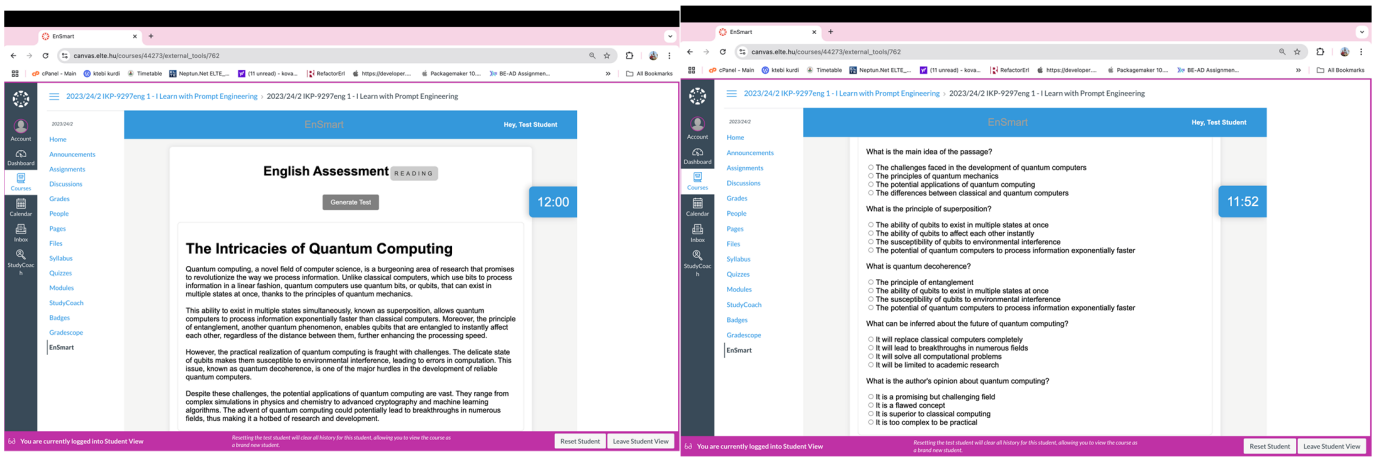
Our usability testing involved the following:

1. Formative Testing Phase: Initial testing with a sample student was conducted to gather feedback on usability and interface design. This phase aimed to evaluate EnSmart's functionalities, including usability, interface design, and overall performance, as a preparatory step before full-scale deployment. The term Formative Testing Phase was adopted to accurately reflect the purpose of this stage.
2. Iterative Refinements: Adjustments were made based on test results to improve functionality and user experience.

After development and testing, we deployed EnSmart on the specified virtual machine provided by the university as part of the "*I Learn with Prompt Engineering*" course. The deployment phase included student orientation, ensuring that students could easily access and navigate EnSmart within Canvas LMS.

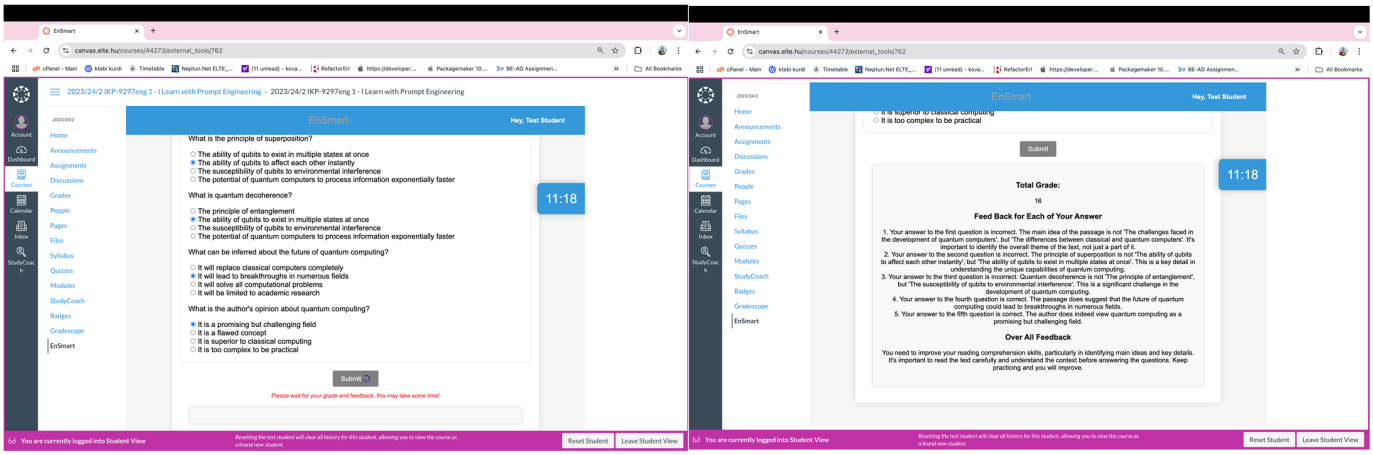
Figure 3a through Figure 4b showcase the complete process of taking a test using the EnSmart tool within Canvas LMS. Figure 3a,b illustrate the initial process in which test content is dynamically generated by configuring reading passages and corresponding questions. Upon clicking the "Generate" button, the application sends an API request to the GPT language model, which then creates passages and questions based on the specified configurations. The generated content is presented in a user-friendly interface, after which a 12 min countdown timer begins, allowing students a single attempt to complete the test. Security features are incorporated to uphold academic integrity, including disabling content copying and restricting advanced browser functions.

Figure 4a illustrates the submission stage, where students complete and submit their answers. Figure 4b depicts the final stage, which involves automated grading and real-time feedback. In this phase, EnSmart evaluates student responses, providing immediate grades and personalized, human-like feedback, while directly posting the results to the corresponding Canvas gradebook.



(**a**) (**b**)

Figure 3. (**a**,**b**) Describing dynamic test content generation.



(**a**) (**b**)

Figure 4. (**a**,**b**) Describing submission, automated grading, and dynamic personalized feedback.

4. Methodology

4.1. Course Design and Pedagogical Framework

The self-paced elective course "*I Learn with Prompt Engineering*" was designed within the framework of Education 4.0, focusing on three foundational principles (Peláez-Sánchez et al., 2024):

1. Promotes a student-centered approach to learning, emphasizing active engagement.
2. Provides students with real-world contexts and scenarios, enabling them to apply knowledge and skills in practice.
3. Encourages the development of research skills and complex thinking, allowing students to propose innovative solutions to current societal issues.

These principles draw on the theories of Heutagogy (grounded in humanistic and constructivist principles to foster self-directed learning practices), Peeragogy (collaborative learning processes), and Cyberpedagogy (integrating ICT with educational experiences) (Ramírez-Montoya et al., 2022).

The course content is organized around four core competencies:

1. Mastery of prompt engineering, enabling students to skillfully interact with LLMs using advanced prompt techniques.
2. Master purposeful Socratic conversations and the skill to build prompt constructs for self-directed learning in any discipline or seek guidance in any life situation. At the same time, students are cautioned on "hallucinations" in LLMs and prepared for fact checking and critical thinking.
3. Allowing them to improve their scientific English reading and writing skills, which are highly important skills for their advancement in informatics studies and workforce skills.
4. A methodology for learning involving peer reviews and discussions to help peers or share good practices.

The art of prompt engineering was divided into two levels:

1. Basic prompt patterns: question refinement, cognitive verifier, Persona, audience, and flipped interaction patterns.
2. Extended prompting techniques: prompt expansion, chain of thought, guiding prompts, optimizing, GPT confronts itself and discusses problem formulation as well as the parallel between prompt engineering and programming.

Each module was assessed through multiple-choice tests and an assignment requiring students to design prompt structures for creating precise contextualized content. The advanced level (the last two modules) provided a lot of examples of prompt structures that could be configured for developing the learning process:

- Prompt structures for language learning—assessment was performed using the developed EnSmart app.
- Prompt structures for general learning and self-development of various work–life skills—assessment was performed by requiring the development of a mega-prompt for dynamic assessment of knowledge level in a specified topic.
- The advanced level is fundamentally based on learner autonomy and self-directedness, enabling learners to take control of their learning process, set their own goals, and choose their learning strategies. This approach is grounded in humanistic and constructivist principles, fostering self-learning practices that promote student autonomy, capacity, self-efficacy, and non-linear learning (Peláez-Sánchez et al., 2024).

The effectiveness of SRLPS was monitored through the careful design of the course "*I Learn with Prompt Engineering*" containing purposeful elements that allow evaluation of the main features of Turan's SRLPS model, without using a direct questionnaire, but rather applying performance monitoring (Turan et al., 2009). Tests were automatically assessed, and the results could be immediately seen by participants, while assignments required peer-reviews using pre-defined rubrics. EnSmart used its own evaluation method.

4.2. Research Design

This study employs a mixed-method research design to evaluate the effectiveness of the "*I Learn with Prompt Engineering*" course and the EnSmart tool. The primary focus is on assessing how prompt engineering techniques, integrated with GAI tools, enhance students' academic English proficiency and overall learning outcomes. The study utilizes a survey that includes structured questionnaires to collect quantitative data and open-ended questions to gather qualitative feedback. This approach enables a detailed analysis of both measurable outcomes and nuanced participant perspectives.

4.3. Participants

The participants in the course for this study are 60 international students from various departments and different stages of study and qualifications within the Faculty of Informatics at Eötvös Loránd University (ELTE). These students, all aged 18 and above, enrolled in the "*I Learn with Prompt Engineering*" elective course, which was conducted over one academic semester from 15 February 2024 to the end of May 2024. The course was designed to promote autonomous learning, scientific English proficiency, market-ready skills, and self-improvement. The gender distribution among the participants included 34 males and 26 females. Most participants had basic familiarity with AI tools such as ChatGPT but no prior experience with prompt engineering or associated patterns. The diverse backgrounds of the participants ensure a broad perspective on the course's effectiveness and the usability of EnSmart.

4.4. Data Collection Instruments

Data collection for this study involved a survey that included structured questionnaires administered to students at the end of the course via the university's LMS, Canvas. These instruments are designed to gather quantitative and qualitative data on students' perceptions, experiences, and learning outcomes. The survey questions cover multiple aspects of the course and the EnSmart tool, providing detailed insights into their effectiveness. An

analysis of course performance using Turan's SRLPS dimensions (Turan et al., 2009) was used to evaluate the effectiveness of autonomous learning.

4.5. Survey Instrument

The survey instrument was meticulously designed to capture students' opinions, preferences, and experiences with prompt engineering patterns, autonomous courses, and AI-driven content in academic reading English proficiency. Developed specifically for this study, it addressed focus areas not fully covered by existing validated instruments, such as student perceptions of SRL, preferences for AI-driven educational tools, and experiences with prompting techniques. Its design was informed by principles from established instruments, including the Self-Regulated Learning Interview Schedule (SRLIS) (B. Zimmerman & Martinez-Pons, 1986), the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & De Groot, 1990), the Course Experience Questionnaire (CEQ) (Wilson et al., 1997), and the Student Course Engagement Questionnaire (SCEQ) (Handelsman et al., 2005). To ensure content relevance, clarity, and alignment with the study objectives, the survey underwent a review by two experts in educational technology and pedagogy. It comprised 29 questions organized into 5 key areas, each targeting specific aspects of the educational experience.

- Opinions on Autonomous Learning and improving self-direct learning:
  This section included questions to gauge students' attitudes towards autonomous courses and their suitability for different learning approaches. Likert-scale items assessed the degree of agreement with statements about the preference for instructor-led versus self-regulated courses. Additionally, it evaluated students' perceptions of the appropriateness and effectiveness of course content (prompt engineering) on improving their self-direct learning with GAI tools.
- Enhancement of Prompting Skills and Reflections on Academic Language Proficiency:
  This section assessed the extent to which the course improved students' prompting skills. It explored how the application of various prompt patterns enhanced students' ability to engage with GAI tools and how these skills contributed to improvements in their academic language proficiency.
- Effectiveness of AI-Driven Content and Tools:
  This section included questions on the quality, complexity, and effectiveness of AI-generated passages and questions provided by the EnSmart tool. It aimed to evaluate how well these AI-driven elements supported academic English reading comprehension and the accuracy of auto-grading and feedback.
- Interaction and Support Mechanisms:
  This section explored the potential benefits of live consultations and peer discussions in enhancing knowledge transfer. It included questions about the reasons for utilizing or not utilizing discussion areas in the LMS, as well as the perceived impact of these interactions on learning outcomes.
- Overall Satisfaction and Recommendations:
  The final section included a Net Promoter Score (NPS) question to determine the likelihood of students recommending the course to their peers. It also featured open-ended questions to gather additional feedback on the EnSmart tool and the overall reliance on AI-driven content, providing insights into areas for improvement and students' suggestions for future enhancements.

5. Data Analysis and Results

5.1. Analysis of Course Performance Using Turan's SRLPS Dimensions (Turan et al., 2009)

5.1.1. Motivation and Action to Learn

Since the pilot course "*I Learn with Prompt Engineering*" was an elective course, only those registered who were interested in challenging themselves with this emerging notion of prompt engineering, being curious, experimental, and willing to learn through new methodologies.

In total, 60 students registered on the course, but 4 did not even start it and 8 failed by dropping out in the first month, so the overall attrition rate was 20%. These students did not even check further exercises, so most probably they had a lack of time or lost motivation. Out of those 48 students who continued the course, all succeeded, 32 of which (67%) received excellent grades. Completing the course with such a high percentage of excellent grades implies that participants' motivation and action to learn were very high.

There is a strong relationship between motivation and academic performance, with intrinsic motivation having a higher impact than extrinsic motivation (Afzal et al., 2010), but well-designed courses with clear expectations, engaging relevant content, and appropriate support with effective use of technology can lead to higher completion rates, even if student motivation varies (Pittenger & Doering, 2010).

5.1.2. Planning and Goal Setting

The main feature of prompt engineering is actually problem formation, problem-solving through the creation of a plan to reach the goal needed and identify/utilize prompt patterns effectively, fulfilling the identified objectives to be achieved through experimentation by the end of the learning process. The assignment submission requirements were not the final prompt structures but the link to the full prompt window that showed what strategies lead to the results. Thus, we could analyze the process that led to developing the final prompt structure—the learning process. This allowed insight into the full inquiry and problem-solving process.

Since this was a self-paced course, participants had to plan their time-line of progress to utilize learning recourses effectively and identify the learning materials that would help them to learn.

Those who submitted intermediate assignments (creating precise contextualized content) received, on average, 84 percent as their grade. Completing the intermediate assignment with such a high percentage implies that participants succeeded very well with their undertaken challenge in planning and goal setting.

These findings are in line with recent research results, especially focusing on MOOCs (Handoko et al., 2019; Saks, 2024).

5.1.3. Strategies for Learning and Assessment

As a self-paced elective course, participants had to look for new ways to facilitate learning in new situations from the learning materials provided, fulfill the assignments with their own best problem-solving strategies, use the different learning strategies for the knowledge to be acquired in a meaningful way, and implement their plans adequately. After that, they should reflect on the results using the provided formal rubrics to objectively check if their solution met the goals to be accomplished and test the prompt to reflect on the meaningful results obtained. In case of encountering difficulties, they had to look for better strategies to accomplish goals and perfect the prompt structures accordingly, thus improving their learning process and even learning from mistakes.

Assignments were assigned randomly and anonymously for peer-review; thus, all participants could also explore other participants' methods of problem-solving, compare

that to their own, learn new methods, and evaluate others' results using the objective rubrics provided.

Those who submitted the advanced assignments (development of a mega-prompt for dynamic assessment of knowledge level in a specified topic) received, on average, 78 percent as their grade. Completing the advanced assignment with such a high percentage implies that participants succeeded very well with their strategies for learning and assessment.

The literature supports the notion that students who acquire effective learning strategies demonstrate improved planning, goal-setting, and self-monitoring skills, which are crucial components of SRL (Boulahmel et al., 2023), and learning to use various assessment strategies, including self-assessment and peer assessment, enhances students' ability to reflect on their learning process and make necessary adjustments (Nicol & Macfarlane, 2006).

5.1.4. Lack of Self-Directedness

Each module of the course had a discussion area, where students could ask questions to be answered or shared by others. Discussions contained only very few formal questions that needed to be answered, but none asked for further instructions on how to proceed, study, or learn.

As previously noted, 20% of the registered students disengaged from the course, including four who did not commence and eight who withdrew within the first month. This lack of engagement with subsequent exercises indicates potential challenges associated with self-directedness, as well as contributing factors such as time constraints or reduced motivation.

In total, 80% of students completed the course successfully, which implies that participants succeeded very well using their own self-directed skills.

A study of online distance learning and traditional university students found a positive correlation between SDL and academic achievement, with a stronger correlation for online learners (Khalid et al., 2020). On the other hand, there can be institutional, social and environmental, course-related, and personal factors for attrition in higher education; here, personal factors are in focus, including time pressures and poor time management skills, lack of motivation or clear goals for pursuing education, insufficient academic skills and abilities, limited prior experience with online learning, and procrastination tendencies (Shaw et al., 2016).

As an overall evaluation, we can conclude that most of those taking the "*I Learn with Prompt Engineering*" self-paced elective course were mostly ambitiously wanting to learn and perform well (32 received excellent grades) in this emerging topic; thus, those succeeding can be considered to score well in Turan's SRLPS dimensions (Turan et al., 2009).

5.2. The Survey

The survey responses from 48 students were analyzed to extract insights into each of the five key areas outlined.

5.2.1. Opinions on Autonomous Learning and Improving Self-Directed Learning

Survey responses indicate that 72% of learners find self-regulated courses suitable for their learning approach, suggesting that these courses generally align with their learning preferences. A smaller portion of respondents remained neutral or disagreed, indicating that while many learners appreciate the autonomy that self-regulation offers, some may find it less compatible with their needs, a finding consistent with research highlighting that while autonomy is valued, such courses may not suit all students (Bright & Vogler, 2024; Lee et al., 2019). Figure 5 provides a detailed breakdown of these responses.

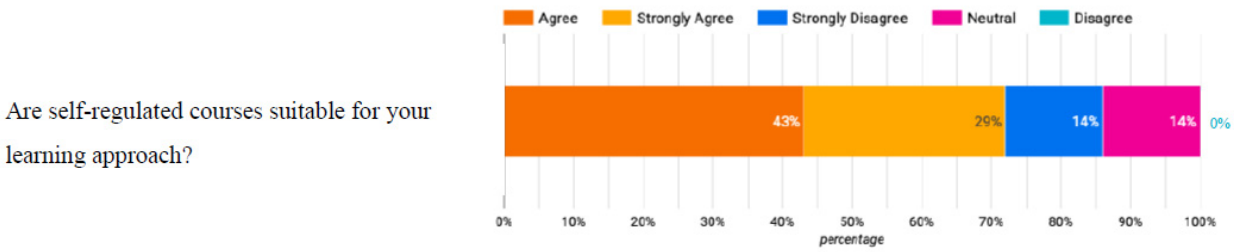


Figure 5. Learner perceptions of self-regulated courses.

In contrast, when asked about their preference for instructor-led versus autonomous courses, responses were more divided. While 43% preferred autonomous courses and 14% strongly preferred them, 29% indicated a preference for instructor-led courses, and 14% expressed no preference. Despite finding self-regulated courses suitable, learners' preferences are more varied when it comes to choosing between autonomous and instructor-led formats. This division suggests that, although many learners find SRL environments suitable and thrive in them, as also evidenced by Crosslin (2018), a significant portion still value the structure and guidance provided by instructor-led courses. Aligning with the findings of Raturi (2018) and Fujii (2024), these results underscore the importance of offering both types of learning environments to accommodate diverse learner preferences.

The course had a notably positive impact on fostering SDL and improving participants' ability to use GAI tools, particularly through the application of prompt engineering techniques. A majority of respondents (78.1%) rated the course as "Very Effective" or "Effective" in fostering SDL skills. Additionally, 80.6% of participants affirmed the usefulness of course materials, particularly those related to prompt engineering, in facilitating the mastery of GAI tools. Notably, 81.7% reported an enhanced ability to apply prompt engineering techniques in SDL tasks through the use of GAI tools after completing the course. These findings align with prior research, which highlights that structured prompts used with AI tools like ChatGPT have been shown to improve learning outcomes and motivate students to learn independently (Garg & Rajendran, 2024). Furthermore, targeted prompt engineering interventions have demonstrated positive effects on students' AI self-efficacy, knowledge, and prompt creation skills (Woo et al., 2024). Together these findings underscore the substantial impact of prompt engineering in achieving the course's pedagogical goals.

However, approximately 18–22% of respondents provided neutral feedback when evaluating the course's impact on fostering SDL and improving the ability to use GAI tools. This neutral feedback might reflect varying levels of experience or comfort with SRL, as well as a preference for instructor-led courses among certain learners. Overall, the results underscore the role of prompt engineering in enhancing SDL through GAI tools.

5.2.2. Improvement in Prompting Skills and Reflection on English Proficiency Improvement

The improvement in participants' prompting skills is evident, with 79.56% reporting either "Markedly Improved" or "Significantly Improved" abilities. This finding underscores the course's effectiveness in teaching essential prompt patterns that are critical for GAI proficiency. As White et al. (2023) and Knoth et al. (2024) highlight, prompt patterns provide reusable solutions that enhance prompt engineering, facilitating more effective interactions with large language model applications like ChatGPT and contributing significantly to improved AI literacy. Notably, the absence of negative feedback further highlights the course's positive impact on skill development. As shown in Figure 6, the distribution of responses reflects the program's success in enhancing participants' prompting skills, aligning with its goal of fostering self-directed learning through GAI tools.

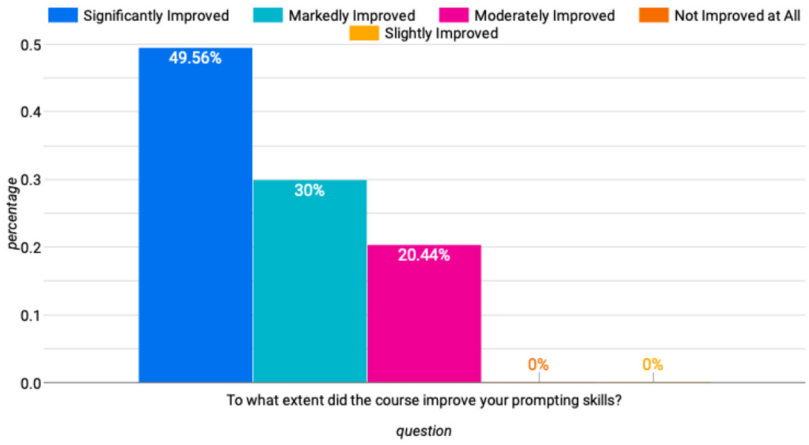


Figure 6. Distribution of participant improvements in prompting skills.

For instance, one participant highlighted the effectiveness of specific patterns, stating, "*The Persona pattern can really see the context of the situation and the suitable responses better*". This comment illustrates how certain patterns were perceived as particularly intuitive for understanding conversational contexts. Similarly, another respondent emphasized the utility of combining patterns, noting, "*All of them are useful because ideal results can be achieved by integrating them or at least some principles from them*". This reflects a holistic approach to applying the skills acquired during the course.

The "Persona pattern" emerged as widely regarded and beneficial, with participants consistently identifying it as the most helpful for practicing prompts. Similarly, recent research highlights that the Persona pattern is among the most effective approaches for engaging with LLMs (Olea et al., 2024). This consistency suggests that the Persona pattern was perceived as both accessible and practical, facilitating its application to real-world scenarios. Remarks such as "*easy to use and apply*" highlight its role in contextualizing situations for better responses. Despite the prominence of the Persona pattern, participants also recognized the value of other prompt patterns, including "Conditional", "Iterative", "Hypothetical", and "Problem-solving". These additional patterns reinforce the course's effectiveness in providing a comprehensive toolkit, enabling learners to tailor their approaches to specific tasks or contexts.

Interestingly, while certain prompt patterns were favored, others proved more challenging to master. Responses regarding the most difficult prompt patterns revealed that the "Question Refinement", "Recursive", and "Flipped Interaction" patterns were particularly complex. One participant articulated this challenge, stating, "*The flipped interaction pattern requires a mix of IT and language skills to be successful*", reflecting the interdisciplinary nature of prompt engineering. This indicates that while some patterns are intuitive, others demand a higher level of cognitive flexibility, revealing a gap between learners' initial expectations and the complexity of certain concepts. The challenges associated with mastering recursive and flipped interaction prompts signal an opportunity for future iterations of the course to provide more targeted support and resources to help learners navigate these advanced ideas.

The use of prompt patterns with GAI tools was associated with noticeable improvements in participants' academic English proficiency. Participants were asked to estimate their proficiency on a scale from 0 to 100 before and after completing the course. Most participants rated their initial proficiency between 60 and 70, with post-course ratings typically ranging from 80 to 85. These improvements reflect the effectiveness of the course content, particularly the prompt patterns. Studies by Rusmiyanto et al. (2023), Ghafar et al. (2023), J and Rajakumari (2024), and Thi Quynh Anh (2024) affirm the role of GAI tools in en-

hancing English language proficiency by enabling self-directed, personalized learning environments, automated grading, and adaptive content delivery. Such tools become more impactful when combined with prompt patterns. One participant commented that the course "*opened new perspectives and techniques that can be used in the spirit of life-long learning*", further illustrating the impact of the course. These results underscore the potential of integrating prompt patterns with GAI tools to enhance SDL, as demonstrated in this research scenario focused on improving academic English language proficiency.

However, some participants reported no noticeable improvement in their proficiency, such as one respondent who indicated a score of "80–80" and another who noted "85 before and after". These responses suggest that the use of prompt patterns learned in the course to improve academic English proficiency through GAI tools, within the context of an autonomous course and self-directed learning, was particularly effective for learners with lower initial proficiency but had a diminished impact on those with higher levels of academic English. This observation aligns with related language-learning studies using AI tools. For example, findings from a study on grammatical error correction (GEC) using large language models suggested that advanced learners often face overcorrection issues, which may limit the effectiveness of AI-driven tools in addressing their nuanced language needs (Zeng et al., 2024). Similarly, research on GAI tools for English proficiency has demonstrated that learners with lower proficiency levels tend to experience more substantial gains. One study, for instance, reported a 9.53% improvement in lexical diversity for lower-proficiency learners, while higher-proficiency learners exhibited more modest gains (Cheon et al., 2025). These results underscore the significant benefits of GAI tools for learners with lower proficiency, suggesting that AI-powered environments can support personalized, self-directed learning that bridges gaps in language-learning outcomes.

Additionally, variability in practice time and engagement may have further contributed to this disparity. While some participants reported limited practice, such as "1–2 h" or "a few days", others consistently integrated prompt practice into their assignments. Such variability in practice likely hindered significant progress, particularly in academic contexts where consistent, focused practice is crucial for improvement (DeKeyser, 2007; Pesovski et al., 2024).

5.2.3. Effectiveness of AI-Driven Content and EnSmart

The quality and complexity of AI-generated passages received generally positive ratings from respondents, with 41% rating them as excellent and 37% as good. Similar trends have been observed in previous studies, where AI-generated content was found to be perceived as comparable in quality to human-created materials (Denny et al., 2023; Huschens et al., 2023). These responses suggest that users find the material suitable for assessing academic English reading comprehension. However, 20% rated the passages as fair, and 2% considered them poor, revealing opportunities for enhancement. This sentiment is echoed in the study by Zou et al. (2024), which highlights the necessity for critical evaluation of AI-generated content to ensure its relevance and challenge level. Addressing these concerns through targeted refinements could enhance the suitability of AI-generated passages for diverse educational applications. One effective approach to enhancing such content is prompt engineering and patterns, which Korzynski et al. (2023) identify as a crucial digital competence for optimizing language model performance. Similarly, Lo (2023) highlights that prompt engineering serves as a discipline that guides model outputs toward fairness, accuracy, and contextual relevance. Bevara et al. (2024) further underscore its role in mitigating biases in transformer-based models by ensuring that AI-generated content remains neutral, inclusive, and ethically aligned.

Survey responses regarding the effectiveness of AI-generated questions show a generally positive response, with the majority of users indicating the questions effectively or somewhat effectively tested their understanding. However, a portion of users remained neutral or dissatisfied, suggesting that while the questions are effective for many, there is room for refinement to better address diverse needs. These findings are illustrated in Figure 7.

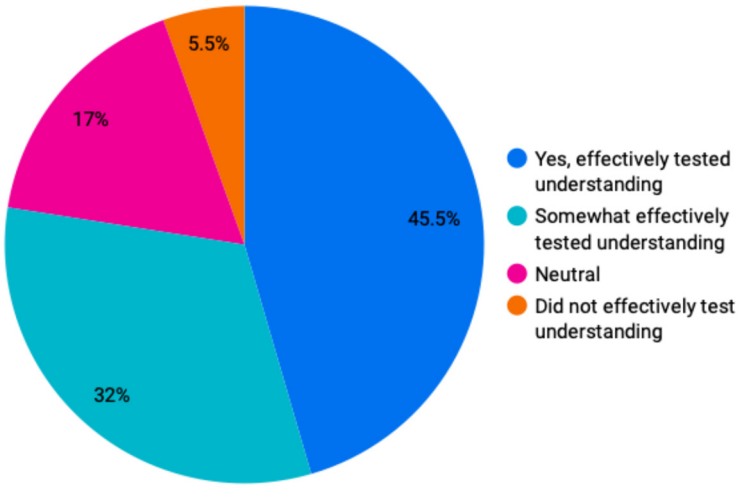


Figure 7. Distribution of survey responses on the effectiveness of AI-generated questions.

Importantly, dissatisfaction with the AI-generated questions appears to stem from a limitation of the EnSmart app developed for this case study, rather than from the capabilities of GPT-4 itself. EnSmart employed only multiple-choice formats to assess academic reading comprehension—a widely used method in English assessments but one that may not fully address the diverse needs of all students (Arnáiz, 1997). As Maity and Deroy (2024) suggest, while large language models have the potential to revolutionize automated question generation, broader question formats beyond multiple-choice are needed to better challenge learners' skills. This limitation may have contributed to user dissatisfaction, as some participants likely desired more varied question formats to better challenge their skills. We believe there is potential to address this limitation in future iterations of EnSmart, thereby enabling the full utilization of GAI models such as GPT-4. This would allow for the generation of a broader range of question types, enhancing the tool's overall effectiveness.

The accuracy of EnSmart'S auto-grading and feedback emerged as one of the tool's strongest features. An overwhelming 82% of respondents rated the auto-grading as either accurate or very accurate, with no users deeming it inaccurate. This high level of confidence reflects positively on the auto-grading mechanism, suggesting that users feel they receive fair evaluations of their submissions. In alignment with findings from Chai et al. (2024), which suggest that college students perceive AI algorithms as fairer evaluators than human teachers, this positive perception reinforces the growing trust in AI-driven grading systems. However, the 18% who rated it as neutral may indicate a lack of complete satisfaction or clarity regarding how grades are derived, highlighting the need for greater transparency in the AI grading process, a concern also emphasized by Ferrara and Qunbar (2022), who noted that increased transparency is essential for ensuring the validity and fairness of AI automated grading systems.

The survey also assessed whether auto-generated feedback from EnSmart helped users identify their strengths and areas for improvement in academic English reading comprehension. Responses revealed varied experiences: 44% of users reported that the feedback significantly helped, while 35% stated it somewhat helped. This suggests that the majority

found the feedback beneficial. Meanwhile, 16% of respondents were neutral, indicating neither positive nor negative impact. Only 5% felt the feedback did not help much, and no users reported that it was not helpful at all. These findings align with research highlighting the potential of GAI tools to provide personalized, real-time feedback and informal practice opportunities for L2 learners, enabling improvements in their language skills and overall learning outcomes (Joo, 2024; Pesovski et al., 2024). However, as Jansen et al. (2024) note, while GAI feedback is useful for students, it still lags behind expert feedback in quality, underscoring the need to refine these tools further to enhance their effectiveness. The neutral responses and the small percentage of less-satisfied users in this study suggest that improving the feedback's actionability and relevance could bridge this gap.

The user-friendliness of the EnSmart tool within Canvas LMS received positive feedback, with the majority of respondents rating it as "Very Friendly" or "Somewhat Friendly". A small percentage rated it as "Somewhat Challenging", and none found it "Very Challenging" (see Figure 8). This positive feedback suggests that integrating the EnSmart tool into Canvas LMS has been successful in providing an intuitive and seamless user experience. Such effective integration is crucial for fostering engagement and sustained usage, particularly in academic settings where ease of access and user satisfaction significantly influence adoption. Moreover, as Alotaibi (2024) highlights, the effective integration of AI within LMS platforms can enhance student engagement, facilitate personalized learning paths, and improve overall performance in higher education, reinforcing the broader potential of AI-driven tools in educational environments.

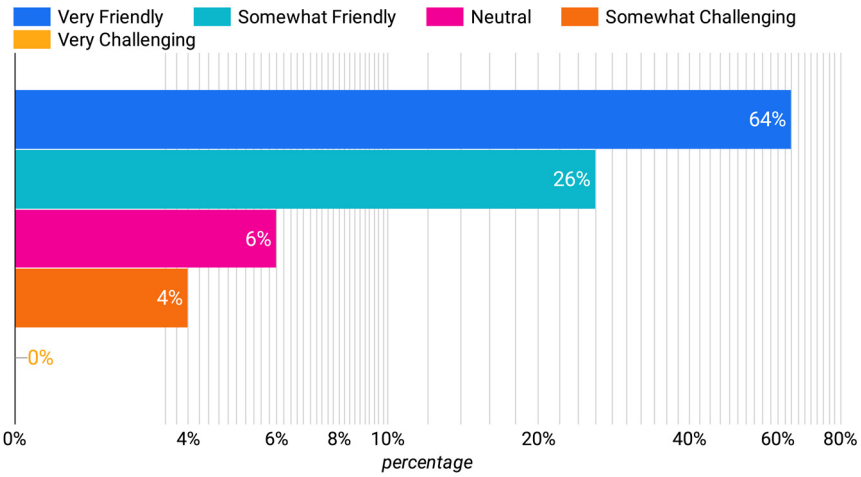


Figure 8. User-friendliness of EnSmart tool within Canvas LMS.

Open-ended responses regarding reliance on AI-driven content generation and assessments reflected a spectrum of perspectives. Many participants expressed positive sentiments, with one noting, "*It is really helpful*", indicating the perceived value of AI in enhancing educational experiences. Others appreciated the innovative approach, stating, "*I like this way of thinking*", which underscores a growing acceptance of AI in education. Participants also emphasized the importance of immediate feedback and personalized learning experiences facilitated by AI. One participant articulated this well, stating, "*I think it is beneficial for providing immediate feedback and personalized learning experiences*". This perspective is supported by research highlighting the potential of GAI to offer timely feedback to language learners while also creating tailored learning materials, which can foster a more customized and engaging educational experience (Pesovski et al., 2024; Xiao & Zhi, 2023).

However, concerns were also voiced. One participant remarked that "*sometimes, it is unclear or confusing*", reflecting apprehension about the clarity and transparency of AI-generated assessments. This sentiment resonates with another participant who cautioned

that reliance on AI must be tempered with regular updates and human oversight to ensure "*accuracy and fairness*".

The complexities of integrating AI into education were further illustrated in comprehensive responses that elaborated on both opportunities and challenges. Participants recognized the efficiency AI brings to content generation and assessments, noting its capacity to tailor learning experiences to individual needs. However, they raised critical concerns about accuracy and reliability, emphasizing that "*AI-generated content and assessments may not always be accurate or reliable*", which raises significant questions about the validity and fairness of evaluations. Such apprehensions align with concerns raised by Misiejuk et al. (2024) about the reliability of AI-powered assessment tools and their potential to introduce errors, as well as recommendations from Kaldaras et al. (2024), who advocate for the development of validation approaches to ensure the credibility of generative AI-based assessments. Additionally, as Moorhouse et al. (2023) note, leading universities emphasize the importance of human oversight and the careful design of assessment strategies to address the limitations of GAI tools in higher education.

The potential for bias in AI algorithms was a recurring theme, with one participant warning that AI can inherit biases from its training data, potentially leading to inequitable outcomes in content generation and assessment. This concern is supported by research showing that GAI models in education can produce biased and inaccurate outputs, raising challenges in their application (Lye & Lim, 2024). Ethical implications, including privacy, consent, and the responsible use of technology, were also highlighted, reflecting the need for a balance between human oversight and AI utilization (Yang et al., 2024).

Participants expressed nuanced views on dependency risks, suggesting that overreliance on AI-driven tools could diminish critical thinking, creativity, and problem-solving skills. This perspective echoes Liang (2023), Walter (2024), and Sutton et al. (2018), who advocate for strategies such as AI literacy programs, adjustments to assessments, and fostering human–computer collaboration to preserve essential human skills and expertise. Walter (2024) further underscores the importance of integrating prompt engineering and critical thinking into educational practices. One response succinctly captured this sentiment: "*While AI-driven content generation and assessments offer undeniable benefits, it's essential to strike a balance between leveraging AI technology for efficiency and preserving the human element in education*". This statement reflects a desire for thoughtful integration of AI tools into the curriculum, ensuring opportunities for reflection, discussion, and human interaction remain paramount.

Interestingly, participants acknowledged AI's limitations. One noted that while AI is "*quite good and helpful*", it suffers from issues such as "*hallucinations*", indicating inaccuracies that can undermine trust in AI assessments. Another pointed out that although AI content generation holds promise, it is still "*not at the level of students, let alone lecturers*", suggesting that traditional assessment methods led by experienced educators should continue to play a vital role. This observation reflects the broader concern that overreliance on AI-driven tools in knowledge work could diminish human expertise and relevance, highlighting the importance of human–computer collaboration (Sutton et al., 2018).

5.2.4. Interaction and Support Mechanisms

In SRL environments, live consultations are particularly valuable as they offer structured, real-time feedback to support independent study. A significant 43% of respondents indicated that live consultations enhance knowledge transfer, suggesting that these sessions address a gap in guidance often present in self-paced courses. However, 21% of participants viewed consultations as unnecessary, while 35% remained neutral. This neutrality may

reflect a preference for self-guided study or a lack of awareness regarding the potential benefits of live support.

Peer discussions were identified as beneficial to knowledge transfer by 36% of respondents, highlighting their importance in fostering collaborative understanding. Discussion-based learning enables students to clarify ideas, engage with diverse perspectives, and deepen their comprehension through interaction. However, 57% of participants remained neutral, indicating that many students may prioritize solitary study over collaborative learning in a self-regulated course setting.

Patterns in responses also reveal low utilization of discussion features on the Canvas platform. Many students expressed a preference for real-time communication, citing the lack of immediacy in asynchronous discussions as a limitation. This aligns with Broadbent and Lodge (2021), who highlight live chat technology as a well-received, convenient tool for real-time support in SRL environments. Technical issues further contributed to dissatisfaction, with some students describing Canvas as "laggy" and expressing a preference for IRC-type communication, referring to Internet Relay Chat systems, which offer real-time text-based interactions that are fast, lightweight, and accessible. Notably, such interactions have been found to provide less negative feedback for language learning compared to face-to-face interactions, potentially fostering a more supportive and confidence-building environment for learners (Iwasaki & Oliver, 2003). Additionally, some students reported feeling self-sufficient within the course structure, describing the content as "self-explanatory" and not requiring further discussion. Conversely, students who valued discussions referred to them as "golden opportunities for improvement", illustrating the diverse needs and expectations within SRL contexts.

5.2.5. Overall Satisfaction and Recommendations

Participants' likelihood of recommending the course was assessed on a scale from 1 to 10. Notably, 56% rated it as "Extremely likely" (10), 29% rated it 8, and 15% rated it 7. The absence of ratings below 7 indicates general satisfaction, though some participants identified areas for improvement. Suggestions included incorporating diverse resources such as videos, academic articles, and interactive elements like live collaborative projects and varied assignments beyond quizzes to foster deeper engagement. While these suggestions highlight opportunities for enhancement, they do not appear to have significantly impacted overall satisfaction.

Feedback on the EnSmart tool was largely positive, with users valuing its simplicity, automation, personalized feedback, and immediate, accurate auto-grading. These features enriched the learning experience by providing timely evaluations. However, qualitative comments revealed areas for refinement, particularly the need for more diverse question types to cater to varied learning preferences and sustain engagement. As one participant noted, "EnSmart is a great tool, but it could be improved by incorporating more diverse types of questions".

Finally, 92% of respondents rated understanding AI-driven technology as either "Very Important" or "Somewhat Important" for educators and students (see Figure 9), underscoring the growing emphasis on technological literacy in education. As Kizilcec (2023) emphasized, educators' trust and perspectives are critical for the successful integration of AI into educational contexts. Similarly, students recognize the importance of understanding AI tools, not only to enhance their academic performance but also to prepare for future career opportunities (Thomson et al., 2024). Participants expressed enthusiasm for AI's benefits, such as automation, efficiency, and personalized learning, while also highlighting the ethical considerations and need for human oversight. These results reflect a balanced

perspective, acknowledging both the opportunities and challenges of integrating AI into educational contexts.

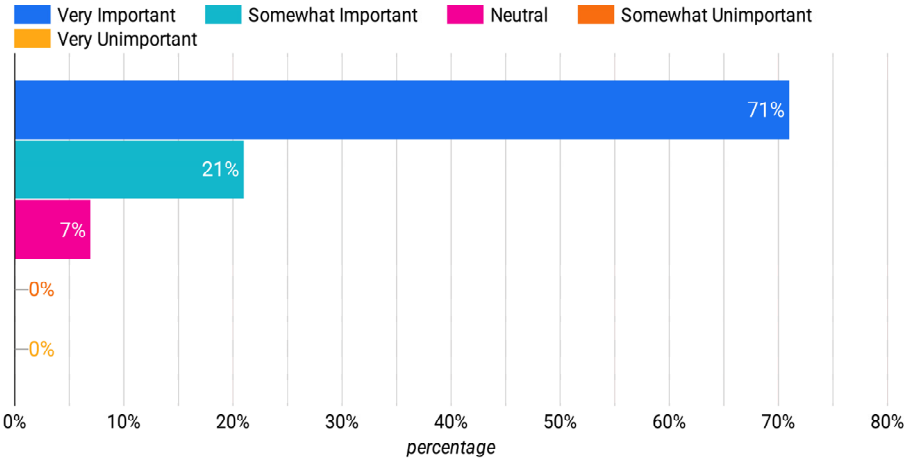


Figure 9. Importance of understanding AI-driven technology in education.

6. Conclusions, Limitations, and Future Works

6.1. Conclusions

The integration of GAI into educational practices, as demonstrated in this study, underscores its transformative potential for enhancing learning outcomes and addressing critical skill gaps. The self-regulated course "*I Learn with Prompt Engineering*" effectively empowered university students to craft precise instructions for large language models (LLMs), develop SDL skills, and enhance academic English proficiency through the use of GAI tools. By emphasizing prompt engineering techniques, the course not only improved students' ability to utilize LLMs effectively but also facilitated significant gains in academic English comprehension, particularly among non-native speakers with lower initial proficiency levels. However, learners with higher proficiency demonstrated minimal progress, likely due to the limitations of current GAI and the variability in practice time and engagement inherent in SRL environments, as well as the relatively short duration of the research. These findings suggest the need for personalized learning models that address individual abilities and goals, with technology playing a crucial role in facilitating tailored learning paths (Shemshack & Spector, 2020). Beyond academic proficiency, the course equipped participants with practical, market-ready skills, demonstrating the scalability of GAI tools in autonomous and SDL environments.

From the analysis of performance, we can conclude that those taking the "*I Learn with Prompt Engineering*" self-paced elective course were mostly ambitiously wanting to learn and perform well in this emerging topic; thus, those succeeding can be considered being good at SDL even though this is not a practice used at university.

Participants reported substantial improvements in their ability to apply prompt patterns, with the "Persona" pattern emerging as particularly intuitive and effective. However, advanced patterns such as "Flipped Interaction" and "Recursive" presented challenges, highlighting opportunities for refining instructional materials and providing targeted support for complex concepts.

The course's reliance on AI-driven tools, particularly EnSmart powered by GPT-4, further demonstrated the potential of GAI technologies for automated assessment and personalized feedback. The EnSmart tool, implemented in this pilot, was effective in autograding and providing immediate feedback—both essential for supporting SRL. Students generally endorsed EnSmart's grading accuracy and fairness, affirming its potential as a reliable assessment tool. Additionally, students appreciated its integration into Canvas

LMS, which has largely succeeded in delivering an intuitive user experience with seamless functionality within the LMS environment. This implementation exemplified successful GAI integration within the LMS platform to enhance automation and enable collaborative human–AI interactions.

However, limitations in question variety and content adaptability, attributed to pilot-specific constraints rather than inherent limitations of GAI technology, highlight areas for future development. Enhancing EnSmart with diverse assessments would better address varied learning needs.

While distinguishing between app-specific limitations and broader challenges with AI technologies, occasional inaccuracies or "hallucinations" in AI-generated content underscore the need for ongoing refinement in educational applications. Participants acknowledged the benefits of AI-driven tools but emphasized the importance of human oversight to enhance reliability and mitigate risks. Concerns around AI accuracy, potential bias, and the risk of overreliance on automated feedback highlight the necessity of responsible AI integration in education.

In conclusion, this study demonstrates the transformative role of GAI and prompt engineering techniques in education, advocating for their balanced integration with human oversight to ensure ethical, transparent, and effective applications in modern learning environments.

6.2. Limitations

Despite the positive outcomes reported in this study, two primary limitations warrant consideration.

First, as a pilot, this study implemented EnSmart specifically for generating test content, creating multiple-choice questions, grading student submissions, and providing immediate, human-like feedback on English reading proficiency. These functionalities, though effective, were constrained by a limited range of question types and lacked adaptability, likely impacting student engagement and satisfaction. The focus on multiple-choice assessments, combined with the limited adaptability of content, restricted EnSmart's potential to fully meet and assess the diverse proficiency levels and learning preferences observed among participants. This limitation underscores the need for further development to expand EnSmart's assessment capabilities beyond reading comprehension and to incorporate a wider range of question types that can address varying skills and learning needs. Diversifying AI-generated test questions could enhance student performance and learning outcomes in English language assessments (Anggoro & Pratiwi, 2023; Marandi & Hosseini, 2024).

Second, the generalizability of the findings is limited by the small sample size and the specific educational context. With only 48 students from a single course and institution, the findings may have limited applicability across broader educational settings. Additionally, the relatively short duration of the study may have restricted the depth of student engagement and the full potential for skill development, especially for more advanced prompt patterns and academic English proficiency. Future research with larger, more diverse samples and extended study periods is necessary to validate these results and assess AI-driven tools like EnSmart's broader applicability in supporting autonomous learning across varied academic contexts.

6.3. Future Works

Building upon the insights and limitations of this study, several avenues for future research and development are proposed.

First, expanding EnSmart's capabilities to include a broader array of question formats and more adaptive assessment options could enhance its effectiveness in addressing diverse student needs. Incorporating question types beyond multiple-choice and adding interactive assessments would enable a more holistic evaluation of student proficiency across various skill domains, fostering deeper engagement and more comprehensive learning assessments.

Further research should also investigate EnSmart's potential to assess a wider range of academic skills beyond English reading comprehension. Extending its functionalities to evaluate proficiency in additional domains, such as academic writing, could validate its adaptability and broaden its educational applications. With advancements in generative AI, there is significant potential to make the course fully automated, encompassing personalized content, assignments, assessments, and real-time, human-like feedback.

Additionally, the findings indicate that customizing AI-driven assessments based on students' initial proficiency levels could optimize learning outcomes (Castro et al., 2024; Villegas-Ch et al., 2024). Future work could develop individualized learning paths within EnSmart, tailoring content and assessments to align with students' unique needs, thereby fostering differentiated learning experiences.

Finally, to increase the generalizability of the findings, subsequent studies should involve larger, more diverse samples across varied educational contexts. Such research could provide more robust data on the role of AI-driven tools in supporting self-directed and autonomous learning at scale, offering valuable insights into their effective implementation across different academic settings.

Author Contributions: Conceptualization, K.M. and M.T.-S.; methodology, K.M. and M.T.-S.; software, K.M.; validation, K.M.; formal analysis, K.M.; investigation, K.M.; resources, K.M. and M.T.-S.; data curation, K.M.; writing—original draft preparation, K.M.; writing—review and editing, K.M. and M.T.-S.; visualization, K.M.; supervision, M.T.-S.; project administration, K.M. and M.T.-S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of ELTE Faculty of Informatics (Approval Code: IK/7043/1(2024)). Approval Date: 8 January 2024.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this article are available within the text. Additional data can be requested from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

Afzal, H., Ali, I., Aslam Khan, M., & Hamid, K. (2010). A study of university students' motivation and its relationship with their academic performance. *International Journal of Business and Management*, *5*, 80–88. [CrossRef]

Agustini, N. P. O. (2023). Examining the role of ChatGPT as a learning tool in promoting students' English language learning autonomy relevant to Kurikulum Merdeka Belajar. *EDUKASIA: Jurnal Pendidikan Dan Pembelajaran*, *4*(2), 2. [CrossRef]

Alotaibi, N. S. (2024). The impact of AI and LMS integration on the future of higher education: Opportunities, challenges, and strategies for transformation. *Sustainability*, *16*(23), 10357. [CrossRef]

Anggoro, K., & Pratiwi, D. (2023). Fostering self-assessment in English learning with a generative AI platform: A case of Quizizz AI. *Studies in Self-Access Learning Journal*, *14*, 489–501. [CrossRef]

Arnáiz, F. J. (1997). Assessment of knowledge. *Journal of Chemical Education*, *74*, 1384. [CrossRef]

Barana, A., Conte, A., Fioravera, M., Marchisio, M., & Rabellino, S. (2018, July 23–27). *A model of formative automatic assessment and interactive feedback for STEM*. 2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC), Tokyo, Japan. [CrossRef]

Bevara, R. V. K., Mannuru, N. R., Karedla, S. P., & Xiao, T. (2024). Scaling implicit bias analysis across transformer-based language models through embedding association test and prompt engineering. *Applied Sciences*, *14*(8), 3483. [CrossRef]

Boscardin, C. K., Gin, B., Golde, P. B., & Hauer, K. E. (2024). ChatGPT and generative artificial intelligence for medical education: Potential impact and opportunity. *Academic Medicine: Journal of the Association of American Medical Colleges*, *99*(1), 22–27. [CrossRef] [PubMed]

Boulahmel, A., Djelil, F., Gilliot, J.-M., & Smits, G. (2023, September 4–8). *Towards a skill-based self-regulated learning recommendation system*. Doctoral Consortium of the 18th European Conference on Technology Enhanced Learning, Aveiro, Portugal. Available online: https://imt-atlantique.hal.science/hal-04285013 (accessed on 13 January 2025).

Bright, K., & Vogler, J. (2024). Learning online vs. learning in person: A mixed-methods approach to understanding how student preferences and perceptions have evolved since the pandemic. *Online Learning*, *28*(4), 4565. [CrossRef]

Broadbent, J., & Lodge, J. (2021). Use of live chat in higher education to support self-regulated help seeking behaviours: A comparison of online and blended learner perspectives. *International Journal of Educational Technology in Higher Education*, *18*(1), 17. [CrossRef]

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., . . . Amodei, D. (2020, December 6–12). *Language models are few-shot learners*. Proceedings of the 34th International Conference on Neural Information Processing Systems, Vancouver, BC, Canada.

Caines, A., Benedetto, L., Taslimipoor, S., Davis, C., Gao, Y., Andersen, O., Yuan, Z., Elliott, M., Moore, R., Bryant, C., Rei, M., Yannakoudakis, H., Mullooly, A., Nicholls, D., & Buttery, P. (2023). On the application of Large Language Models for language teaching and assessment technology. *arXiv*, arXiv:2307.08393. [CrossRef]

Castro, G. P. B., Chiappe, A., Rodriguez, D. F. B., & Sepulveda, F. G. (2024). Harnessing AI for Education 4.0: Drivers of personalized learning. *Electronic Journal of E-Learning*, *22*(5), 5. [CrossRef]

Chai, F., Ma, J., Wang, Y., Zhu, J., & Han, T. (2024). Grading by AI makes me feel fairer? How different evaluators affect college students' perception of fairness. *Frontiers in Psychology*, *15*, 1221177. [CrossRef]

Chen, Q., Wang, X., & Zhao, Q. (2019). Appearance discrimination in grading?—Evidence from migrant schools in China. *Economics Letters*, *181*, 116–119. [CrossRef]

Cheon, G., Choi, Y., Lee, D., & Baek, J. (2025). *Generative AI agents in language learning: A randomized field experiment*. Available online: https://hdl.handle.net/10125/109443 (accessed on 12 January 2025).

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. [CrossRef]

Crosslin, M. (2018). Exploring self-regulated learning choices in a customisable learning pathway MOOC. *Australasian Journal of Educational Technology*, *34*(1), 1. [CrossRef]

DeKeyser, R. (2007). *Practice in a second language: Perspectives from applied linguistics and cognitive psychology*. Cambridge University Press. [CrossRef]

Denny, P., Khosravi, H., Hellas, A., Leinonen, J., & Sarsa, S. (2023). Can we trust AI-generated educational content? Comparative analysis of human and AI-generated learning resources. *arXiv*, arXiv:2306.10509. [CrossRef]

Dikli, S. (2003). Assessment at a distance: Traditional vs. alternative assessments. *The Turkish Online Journal of Educational Technology*, *2*(3), 2.

Fagbohun, O., Iduwe, N. P., Abdullahi, M., Ifaturoti, A., & Nwanna, O. M. (2024). Beyond traditional assessment: Exploring the impact of large language models on grading practices. *Journal of Artificial Intelligence, Machine Learning and Data Science*, *2*(1), 1–8. [CrossRef]

Ferrara, S., & Qunbar, S. (2022). Validity arguments for ai-based automated scores: Essay scoring as an illustration. *Journal of Educational Measurement*, *59*(3), 288–313. [CrossRef]

Fujii, A. (2024). Exploring autonomy support and learning preference in higher education: Introducing a flexible and personalized learning environment with technology. *Discover Education*, *3*(1), 26. [CrossRef]

Galanis, N., Mayol, E., Casany, M. J., & Alier, M. (2017). *Tools interoperability for learning management systems* (tools-interoperability-for-learning-management-systems). IGI Global. [CrossRef]

Garg, A., & Rajendran, R. (2024). Analyzing the role of generative AI in fostering self-directed learning through structured prompt engineering. In A. Sifaleras, & F. Lin (Eds.), *Generative intelligence and intelligent tutoring systems* (pp. 232–243). Springer Nature Switzerland. [CrossRef]

Ghafar, Z. N., Salh, H. F., Abdulrahim, M. A., Farxha, S. S., Arf, S. F., & Rahim, R. I. (2023). The role of artificial intelligence technology on English language learning: A literature review. *Canadian Journal of Language and Literature Studies*, *3*(2), 17–31. [CrossRef]

Graf, S., Kinshuk, D., & Liu, T.-C. (2009). Supporting teachers in identifying students' learning styles in learning management systems: An automatic student modelling approach. *Educational Technology & Society*, *12*, 3–14.

Grüneisen, L., Dörrenbächer-Ulrich, L., Kapsali, E., & Perels, F. (2024). Assessing knowledge about self-regulated learning: Validation of a measurement tool for preschoolers. *Frontiers in Education*, *9*, 1332170. [CrossRef]

Guei, H., Wei, T.-H., & Wu, I.-C. (2020). 2048-like games for teaching reinforcement learning. *ICGA Journal*, *42*, 1–24. [CrossRef]

Guo, K., Zhong, Y., Li, D., & Chu, S. (2023). Effects of chatbot-assisted in-class debates on students' argumentation skills and task motivation. *Computers & Education*, *203*, 104862. [CrossRef]

Handelsman, M. M., Briggs, W. L., Sullivan, N., & Towler, A. (2005). A measure of college student course engagement. *The Journal of Educational Research*, *98*(3), 184–191. [CrossRef]

Handoko, E., Gronseth, S. L., McNeil, S. G., Bonk, C. J., & Robin, B. R. (2019). Goal setting and MOOC completion: A study on the role of self-regulated learning in student performance in massive open online courses. *The International Review of Research in Open and Distributed Learning*, *20*(3), 39–58. [CrossRef]

Heilman, M., Collins-Thompson, K., Callan, J., & Eskenazi, M. (2006, September 17–21). *Classroom success of an intelligent tutoring system for lexical practice and reading comprehension*. INTERSPEECH 2006—ICSLP, Ninth International Conference on Spoken Language Processing, Pittsburgh, PA, USA. [CrossRef]

Huschens, M., Briesch, M., Sobania, D., & Rothlauf, F. (2023). Do you trust ChatGPT?—Perceived credibility of human and AI-generated content. *arXiv*, arXiv:2309.02524. [CrossRef]

Iwasaki, J., & Oliver, R. (2003). Chat-Line interaction and negative feedback. *Australian Review of Applied Linguistics. Supplement Series*, *17*(1), 60–73. [CrossRef]

J, A. J., & Rajakumari, R. (2024, July 24–26). *Harnessing AI: Enhancing English language teaching through innovative tools*. 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT) (pp. 1–7), Trichirappalli, India. [CrossRef]

Jansen, T., Höft, L., Bahr, L., Fleckenstein, J., Möller, J., Köller, O., & Meyer, J. (2024). Empirische Arbeit: Comparing generative AI and expert feedback to students' writing: Insights from student teachers. *Psychologie in Erziehung Und Unterricht*, *71*(2), 80–92. [CrossRef]

Joo, S. (2024). Generative AI as writing or speaking partners in L2 learning: Implications for learning-oriented assessments. *Studies in Applied Linguistics and TESOL*, *24*(1), 12865. [CrossRef]

Kaldaras, L., Akaeze, H. O., & Reckase, M. D. (2024). Developing valid assessments in the era of generative artificial intelligence. *Frontiers in Education*, *9*, 1399377. [CrossRef]

Khalid, M., Bashir, S., & Amin, H. (2020). Relationship between Self-Directed Learning (SDL) and academic achievement of university students: A case of online distance learning and traditional universities. *Bulletin of Education and Research*, *42*, 131–148.

Kizilcec, R. (2023). To advance AI use in education, focus on understanding educators. *International Journal of Artificial Intelligence in Education*, *34*, 12–19. [CrossRef]

Knoth, N., Tolzin, A., Janson, A., & Leimeister, J. M. (2024). AI literacy and its implications for prompt engineering strategies. *Computers and Education: Artificial Intelligence*, *6*, 100225. [CrossRef]

Koraishi, O. (2023). Teaching English in the age of AI: Embracing ChatGPT to optimize EFL materials and assessment. *Language Education and Technology*, *3*(1), 1. Available online: https://langedutech.com/letjournal/index.php/let/article/view/48 (accessed on 11 August 2024).

Korzynski, P., Mazurek, G., Krzypkowska, P., & Kurasinski, A. (2023). Artificial intelligence prompt engineering as a new digital competence: Analysis of generative AI technologies such as ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(3), 25–37. [CrossRef]

Kılıçkaya, F. (2022). Pre-service language teachers' online written corrective feedback preferences and timing of feedback in computer-supported L2 grammar instruction. *Computer Assisted Language Learning*, *35*, 62–87. [CrossRef]

Lee, D., Watson, S. L., & Watson, W. R. (2019). Systematic literature review on self-regulated learning in massive open online courses. *Australasian Journal of Educational Technology*, *35*(1), 28–41. [CrossRef]

Liang, Y. (2023). Balancing: The effects of ai tools in educational context. *Frontiers in Humanities and Social Sciences*, *3*(8), 7–10. [CrossRef]

Lo, L. S. (2023). The art and science of prompt engineering: A new literacy in the information age. *Internet Reference Services Quarterly*, *27*(4), 203–210. [CrossRef]

López-Angulo, Y., Sáez-Delgado, F., Gaeta, M. L., Mella-Norambuena, J., González-Robaina, Y., & Muñoz-Inostroza, K. (2024). Validation of the self-regulation of learning instrument for undergraduates. *Frontiers in Education*, *9*, 1464424. [CrossRef]

Luckin, R., & Holmes, W. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.

Lye, C. Y., & Lim, L. (2024). Generative artificial intelligence in tertiary education: Assessment redesign principles and considerations. *Education Sciences*, *14*(6), 569. [CrossRef]

Maity, S., & Deroy, A. (2024). The future of learning in the age of generative AI: Automated question generation and assessment with large language models. *arXiv*, arXiv:2410.09576. [CrossRef]

Marandi, S. S., & Hosseini, S. (2024, February 27–29). *AI-driven assessment in Iranian high school English classes*. 2024 11th International and the 17th National Conference on E-Learning and E-Teaching (ICeLeT) (pp. 1–3), Isfahan, Iran. [CrossRef]

Marwan, S., Gao, G., Fisk, S., Price, T. W., & Barnes, T. (2020, August 1–5). *Adaptive immediate feedback can improve novice programming engagement and intention to persist in computer science*. Proceedings of the 2020 ACM Conference on International Computing Education Research (pp. 194–203), Virtual Event New Zealand. [CrossRef]

Marzuki, Widiati, U., Rusdin, D., & Darwin. (2023). The impact of AI writing tools on the content and organization of students' writing: EFL teachers' perspective. *Cogent Education*, *10*, 2236469. [CrossRef]

Misiejuk, K., Kaliisa, R., & Scianna, J. (2024). Augmenting assessment with AI coding of online student discourse: A question of reliability. *Computers and Education: Artificial Intelligence*, *6*, 100216. [CrossRef]

Moorhouse, B. L., Yeo, M. A., & Wan, Y. (2023). Generative AI tools and assessment: Guidelines of the world's top-ranking universities. *Computers and Education Open*, *5*, 100151. [CrossRef]

Molina-Moreira, A. A., Velásquez-Orellana, O. J., Zambrano-Murillo, D. J., & Zambrano-Villamil, M. E. (2023). Importance of feedback in the student evaluation process. *International Journal of Social Sciences*, *6*(3), 3. [CrossRef]

Muñoz, S., Gayoso, G., Huambo, A., Domingo, R., Tapia, C., Incaluque, J., Nacional, U., Villarreal, F., Cielo, J., Cajamarca, R., Enrique, J., Reyes Acevedo, J., Victor, H., Huaranga Rivera, H., Luis, J., & Pongo, O. (2023). Examining the impacts of ChatGPT on student motivation and engagement. *Przestrzeń Społeczna (Social Space)*, *23*, 1–27.

Nicol, D., & Macfarlane, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, *31*, 199–218. [CrossRef]

Olea, C., Tucker, H., Phelan, J., Pattison, C., Zhang, S., Lieb, M., Schmidt, D., & White, J. (2024, June 22–23). *Evaluating persona prompting for question answering tasks*. 12th International Conference of Security, Privacy and Trust Management (p. 81), Sydney, Australia. [CrossRef]

OpenAI. (2023, March 14). *GPT-4*. Available online: https://openai.com/index/gpt-4-research/ (accessed on 25 November 2024).

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422. [CrossRef]

Peláez-Sánchez, I. C., Velarde-Camaqui, D., & Glasserman-Morales, L. D. (2024). The impact of large language models on higher education: Exploring the connection between AI and Education 4.0. *Frontiers in Education*, *9*, 1392091. [CrossRef]

Pesovski, I., Henriques, R., & Trajkovik, V. (2024). Generative AI for Customizable Learning Experiences. *Sustainability*, *16*, 3034. [CrossRef]

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33–40. [CrossRef]

Pittenger, A., & Doering, A. (2010). Influence of motivational design on completion rates in online self-study pharmacy-content courses. *Distance Education*, *31*, 275–293. [CrossRef]

Ramírez-Montoya, M. S., Castillo-Martínez, I. M., Sanabria-Z, J., & Miranda, J. (2022). Complex thinking in the framework of Education 4.0 and open innovation—A systematic literature review. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(1), 4. [CrossRef]

Raturi, S. (2018). *Understanding learners preferences for learning environments in higher education*. Available online: https://api.semanticscholar.org/CorpusID:150509330 (accessed on 11 January 2025).

Reynolds, L., & McDonell, K. (2021, May 8–13). *Prompt programming for large language models: Beyond the few-shot paradigm*. Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1–7), Yokohama, Japan. [CrossRef]

Rusmiyanto, R., Huriati, N., Fitriani, N., Tyas, N., Rofi'i, A., & Sari, M. (2023). The role of Artificial Intelligence (AI) in developing English language learner's communication skills. *Journal on Education*, *6*, 750–757. [CrossRef]

Ruwe, T., & Mayweg-Paus, E. (2024). Embracing LLM Feedback: The role of feedback providers and provider information for feedback effectiveness. *Frontiers in Education*, *9*, 1461362. [CrossRef]

Saks, K. (2024). The effect of self-efficacy and self-set grade goals on academic outcomes. *Frontiers in Psychology*, *15*, 1324007. [CrossRef]

Shaw, M., Burrus, S., & Ferguson, K. (2016). Factors that influence student attrition in online courses. *Online Journal of Distance Learning Administration*, *19*(3). Available online: https://www.westga.edu/~distance/ojdla/fall193/shaw_burrus_ferguson193.html (accessed on 13 January 2025).

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments*, *7*(1), 33. [CrossRef]

Shermis, M. D., & Burstein, J. (Eds.). (2013). *Handbook of automated essay evaluation: Current applications and new directions*. Routledge. [CrossRef]

Sutton, S. G., Arnold, V., & Holt, M. (2018). How much automation is too much? Keeping the human relevant in knowledge work. *Journal of Emerging Technologies in Accounting*, *15*(2), 15–25. [CrossRef]

Thi Quynh Anh, L. (2024). AI chatbots in English language learning: A critical review. *Journal of Knowledge Learning and Science Technology*, *3*(2), 185–195. [CrossRef]

Thomson, S. R., Pickard-Jones, B. A., Baines, S., & Otermans, P. C. J. (2024). The impact of AI on education and careers: What do students think? *Frontiers in Artificial Intelligence*, *7*, 1457299. [CrossRef]

Turan, S., Demirel, Ö., & Sayek, İ. (2009). Metacognitive awareness and self-regulated learning skills of medical students in different medical curricula. *Medical Teacher*, *31*(10), e477–e483. [CrossRef]

Villegas-Ch, W., Govea, J., Albuja, R., Buenaño-Fernández, D., & Mera-Navarrete, A. (2024). Optimizing automated educational systems: Adaptive syllabus generation and precise assessment using artificial intelligence. *IEEE Access*, *12*, 173390–173409. [CrossRef]

Walter, Y. (2024). Embracing the future of Artificial Intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*(1), 15–29. [CrossRef]

Watson, W. (2007). An argument for clarity: What are learning management systems, what are they not, and what should they become. *TechTrends*, *51*, 28–34.

White, J., Fu, Q., Hays, S., Sandborn, M., Olea, C., Gilbert, H., Elnashar, A., Spencer-Smith, J., & Schmidt, D. C. (2023). A prompt pattern catalog to enhance prompt engineering with ChatGPT. *arXiv*, arXiv:2302.11382. [CrossRef]

Wilson, K., Lizzio, A., & Ramsden, P. (1997). The development, validation and application of the course experience questionnaire. *Studies in Higher Education—STUD HIGH EDUC*, *22*, 33–53. [CrossRef]

Woo, D. J., Wang, D., Yung, T., & Guo, K. (2024). Effects of a prompt engineering intervention on undergraduate students' AI self-efficacy, AI knowledge and prompt engineering ability: A mixed methods study. *arXiv*, arXiv:2408.07302. [CrossRef]

Xiao, Y., & Zhi, Y. (2023). An exploratory study of EFL learners' use of ChatGPT for language learning tasks: Experience and perceptions. *Languages*, *8*(3), 212. [CrossRef]

Xu, W., & Ouyang, F. (2022). A systematic review of AI role in the educational system based on a proposed conceptual framework. *Education and Information Technologies*, *27*(3), 4195–4223. [CrossRef]

Yang, Z., Wu, J. G., & Xie, H. (2024). Taming Frankenstein's monster: Ethical considerations relating to generative artificial intelligence in education. *Asia Pacific Journal of Education*, 1–14. [CrossRef]

Zeng, M., Kuang, J., Qiu, M., Song, J., & Park, J. (2024). Evaluating prompting strategies for grammatical error correction based on language proficiency. *arXiv*, arXiv:2402.15930. [CrossRef]

Zimmerman, B., & Martinez-Pons, M. (1986). Development of a structured interview for assessing student use of self-regulated learning strategies. *American Educational Research Journal*, *23*, 614–628. [CrossRef]

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166–183. [CrossRef]

Zou, X., Su, P., Li, L., & Fu, P. (2024). AI-generated content tools and students' critical thinking: Insights from a Chinese university. *IFLA Journal*, *50*(2), 228–241. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.