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CAN GENAI BOOST STUDENT ACADEMIC PERFORMANCE: EXAMINING THE ROLE OF AI QUALITY

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Abstract

Generative Artificial Inteligence (GenAI) tools are becoming increasingly interesting and useful for the student population in higher education (HE). The rate of adoption of GenAI tools at the population level has surpassed all previous technologies in history. The use and adoption of GenAI tools in higher education represents a critical area of future research with profound scientific and practical implications. This new technology is characterized by significant impact on productivity so it becomes important to explore the way that it impacts student work habits and academic results. This paper contributes to the growing body of research on the application of GenAI tools in higher education. It builds on previous research focused on the application of new technologies. The starting point of the paper is the measurement scales necessary to assess the use of GenAI tools in the context of higher education. The primary goal of this paper is to investigate the role of GenAI quality in the dissemination process of GenAI tools primarily through measuring the adoption and use of GenAI. Additionally, the paper addresses the impact of adoption and use of GenAI on student academic performance. The research was conducted among students of a Croatian higher education institution during the winter semester of 2024, and approximately 340 responses were collected. Structural equation modeling (SEM) analysis was used to test the proposed hypotheses. The results of the study confirm that GenAI quality has a significant and positive effect on GenAI use and GenAI adoption. Furthermore, both GenAI adoption and GenAI use have a significant and positive impact on students' academic performance in higher education. The results of the study highlight the importance of GenAI quality in shaping students' experiences with GenAI tools and their broader educational outcomes.

Keywords: GenAI, AI quality, Academic performance

1. INTRODUCTION

Numerous technological revolutions have significantly reshaped the conditions and context in which modern businesses and organizations operate. However, previous revolutions seem nowhere near as transformative as the Artificial Intelligence (AI) revolution. When measured across key metrics – such as adoption rates, investment volume, computational efficiency, and integration into business processes – AI is demonstrating an unprecedented level of disruption. For example, AI-powered applications have reached millions of users at an unprecedented rate, with models like ChatGPT surpassing 100 million users within two months of launch (Menzies et al., 2024). Similarly, investment in AI has surged, with global funding exceeding $154 billion in 2023, driven by the private and public sectors (Enholm et al., 2021). Moreover, the computing power supporting AI models has grown exponentially, with AI hardware achieving significant performance improvements. For example, new AI chip architectures have enabled high computing performance while optimizing power consumption (Chen & Chen, 2024). These improvements significantly exceed Moore's Law, accelerating AI-driven innovation across industries. Given these trends, the integration of AI into various industries not only improves operational efficiency but also disrupts existing competitive relationships. From optimizing decision-making processes to automating complex business functions, AI is driving fundamental change in economic and organizational structures (Gurjar et al., 2024). As AI technology continues to rapidly develop, its role in redefining the nature of numerous industries is becoming an increasingly interesting research question.

The higher education sector (HE) is going through radical changes, driven by structural challenges and the need to integrate numerous new technologies. As a multi-stakeholder industry, higher education institutions must address a range of interests; however, students remain at the center as the primary users of educational services. From the perspective of service quality and institutional performance, students function as key stakeholders, as their engagement significantly affects institutional sustainability and competitiveness (Reynolds-Cuéllar, Stump, & Bagiati, 2020). Innovations aimed at students in higher education are particularly relevant considering the characteristics of students as lead users for the adoption of new technologies and inclusion in experimental learning models. Research highlights that digital transformation and personalized learning environments contribute to improved academic performance and institutional effectiveness (Miller, 2021; Zhienbayeva & Abdigapbarova, 2021). The shift toward student-centered learning, facilitated by emerging technologies and innovative pedagogical models, underscores the importance of integrating student feedback into strategic educational planning (Cañado, 2010). Additionally, universities that embrace digital transformation and adaptive learning models are better positioned to meet evolving educational demands, ultimately enhancing the overall quality of education (Chauca et al., 2021).

There are two research questions that are adressed in this paper:

- What is the impact of quality of GenAI tools on their usability and adoption among student population in HE?
- How does the disemination of GenAI technologies among student population really affect their academic performance?

To answer these research questions a primary research was conducted among students in HE and the results are presented in the next chapters.

2. DEVELOPMENT AND DISEMINATION OF GENAI TECHNOLOGIES

Artificial intelligence (AI) can be defined as the ability of a machine to use algorithms to analyze its environment, learn from data, and apply the acquired knowledge to make decisions and take actions autonomously to achieve specific goals (Lodzikowski, Foltz, & Behrens, 2023). In the domain of artificial intelligence, general-purpose AI (GPAI) is a category of artificial intelligence capable of performing a wide range of tasks, such as text synthesis, image manipulation, and sound generation. Classic examples include OpenAI's GPT-4o and GPT-4.5 models that power applications such as ChatGPT and various other AI-driven platforms via OpenAI's application programming interface (API) (Mittal et al., 2024). GenAI on the other hand, encompasses AI systems – often built on top of GPAI models – that generate new content based on user input or queries. These systems enable the creation of text, images, video and sound, facilitating a wide range of applications in education and beyond (Singh, 2024).

The integration of GenAI into higher education creates significant opportunities for improving student experiences at all levels. Customization of education services, timely support, mentoring, and learning experiences are just some of the topics that can be radically improved. AI-powered tools enable personalized instruction, instant feedback, and inquiry support, fostering greater student autonomy and engagement (Maity & Deroy, 2024). Moreover, intelligent instructional systems powered by generative AI facilitate adaptive learning by tailoring educational content to student needs, thereby improving knowledge retention and overall academic success (Alali et al., 2024). On the other hand, these improvements also require a robust governance framework that includes ethical issues such as algorithmic bias, data privacy, and equitable access to AI-driven educational resources (Deng & Joshi, 2024). Ensuring the responsible use of AI in education is essential to mitigate risks while maximizing its transformative potential for students and teachers (Lodzikowski et al., 2023).

Issues of trust and mistrust, as well as the numerous ethical dilemmas surrounding the bias and false data delivered by GenAI, deserve additional attention in the higher education sector, where students form habits that they will use for years to come. The responsibility of regulators and institutions themselves cannot be overstated, given the perception that in this case the user is at least a few steps ahead of the creators and regulators. The diffusion of new technologies such as ChatGPT is a key factor in ensuring their effective adoption, integration, and social impact. The diffusion of technological advances enables industries, policymakers, and the public to understand, evaluate, and leverage innovations for economic and social progress. In particular, Artificial Intelligence (AI) and GenAI require structured diffusion strategies to mitigate risks, enhance ethical adoption, and maximize their transformative potential across sectors. For AI and GenAI, diffusion plays a key role in fostering trust, regulatory compliance, and strategic adoption patterns. Research shows that effective communication about the opportunities, limitations, and risks of AI is essential to ensure that organizations and individuals use these technologies responsibly (Reznikov, 2024). Without adequate diffusion, rapid implementation of GenAI risks increasing misinformation, ethical issues, and misuse in areas such as automated content creation and decision-making processes (Lorenz, Perset, & Berryhill, 2023). Furthermore, structured knowledge-sharing initiatives, such as academic research, policy discussions, and corporate transparency, enable the alignment of AI advances with human-centered values, supporting safe and productive technological integration (Bies et al., 2024).

3. APPLICATION OF GENAI IN HIGHER EDUCATION

Technologies emerging from the application of AI, especially Chatbots, leverage the capabilities of large language models (LLMs) to understand and generate human responses and show significant potential in improving student learning and educational outcomes. AI-powered technologies and applications engage students by providing interactive, context-aware learning experiences, offering timely academic support, and encouraging personalized learning paths (Yigci et al., 2024). In higher education, the integration of generative AI-powered chatbots enables students to better understand and instantly obtain clarification on complex topics, generate explanations tailored to their learning styles, and access personalized instruction at any time (Tzirides et al., 2023).

In addition to basic academic assistance, generative AI chatbots enable the development of adaptive learning environments that meet the unique needs of students. AI-based question answering systems, such as those using augmented search generation (RAG) techniques, improve the accuracy and reliability of chatbot responses, enabling deeper student engagement and more effective understanding of course material (Allen, Naeem, & Gill, 2024). Studies show that implementing these AI tools not only improves student learning efficiency, but also fosters independent problem-solving skills, helping students navigate complex academic challenges with minimal reliance on staff (Sarčević et al., 2024).

Despite the numerous advantages listed, there are still concerns regarding the ethical implications and potential misuse of generative artificial intelligence in educational settings. Issues such as social isolation, academic integrity, the risk of over-reliance on AI-generated content, and the spread of misinformation require well-defined guidelines for the responsible use of AI (Williams, 2024, Townsen Hicks et al., 2024). Higher education institutions must adopt a structured approach to the integration of artificial intelligence, ensuring that these technologies complement, rather than replace, traditional pedagogical methods. Effective governance frameworks, including AI literacy initiatives and transparency in AI-generated responses, are essential to mitigating risks while maximizing the transformative potential of generative AI in higher education (Chukwuere, 2024). An example of a potential concern is offered by Townsen Hicks et al., (2024) who describe false GenAI statements as "halucinations" because LLMs are simply not designed to accurately represent the way the world is. As can be seen from Figure 1. there are several key topics included under the umbrela of applying GenAI technologies in HE.

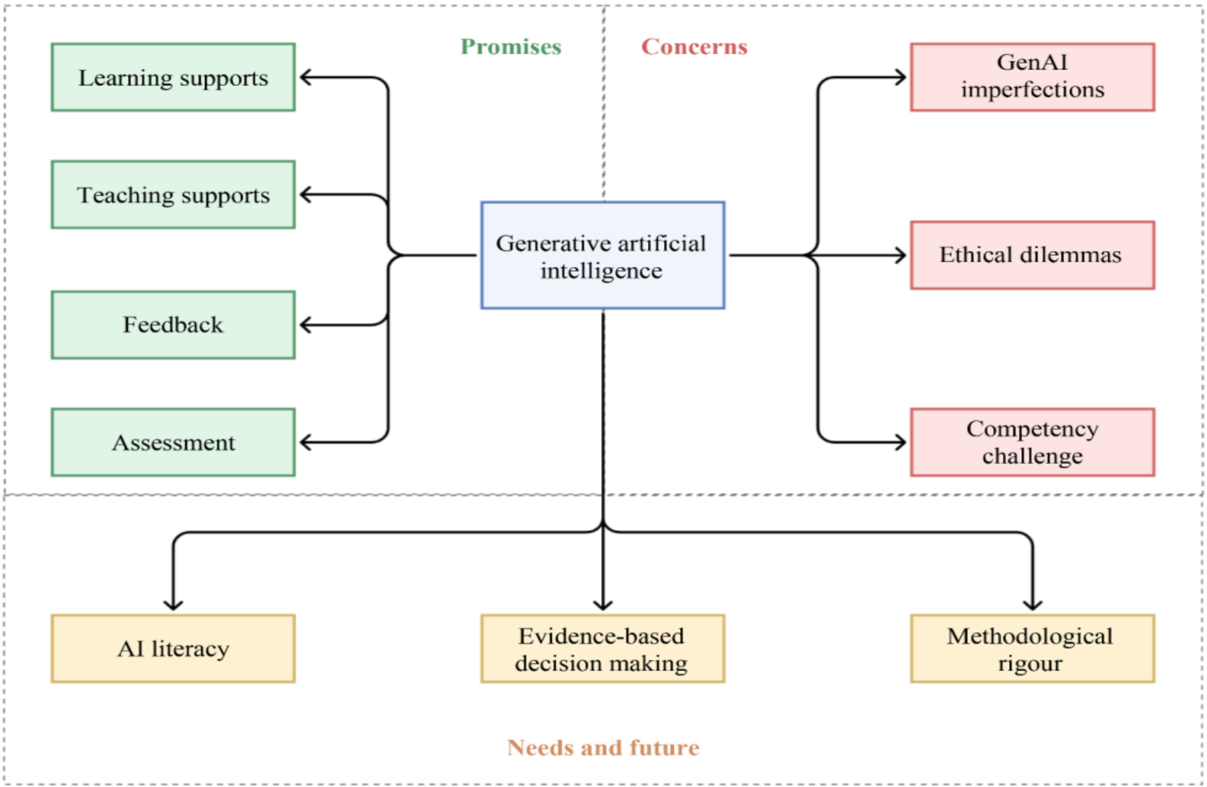

Figure 1 Framework of promises, concerns and future directions for GenAI in education

Source: Zhang et al. 2024

There are many studies that analyse the impact of GenAI technologies in the context of higher education (Albadarin et a. 2024). Most of them identify positive impact on the learning process (Albadarin et a. 2024) but again stress some negative conotations such as: negative impact on innovative capacities and colaborative learning. GenAI is revolutionizing education by offering students new ways to learn, practice, and improve their academic skills. However, it is essential to consider the ethical implications of AI use, such as academic integrity, data privacy, and bias in AI-generated recommendations (Dwivedi et al., 2023). Institutions and policy makers need to implement robust governance frameworks to ensure that AI tools are used responsibly (Bender et al., 2021). To maximize the benefits of GenAI while mitigating the risks, institutions should develop clear policies for AI integration, promote transparency in AI systems, and ensure that students and faculty receive adequate training in its use (Townsen Hicks et al., 2024). Major developments in this area have occurred in areas such as the EU by adopting documents that define the framework for the use of GenAI technologies in higher education (Krpan & Mlađenović 2024). The EU is not the only region that has recognized the importance of this topic and there are already numerous other examples (U.S. Department of Education 2024). Efforts between educational institutions, AI developers, and policy makers will be needed to create an ethical, fair, and efficient AI-driven education system. Taking these considerations into account, GenAI can be used to enhance personalized learning, simplify administrative processes, and support students and teachers in achieving their goals in the evolving digital landscape (Kopp & Thomsen, 2023).

The application of GenAI tools in higher education, especially in the student population, has already taken on massive proportions, although the speed of adoption of these tools is not necessarily equal to the speed with which they will affect key study parameters such as: grades, realization of learning outcomes, employer satisfaction, etc. The application of GenAI in higher education is an example of how usability and adoption work together to influence technology diffusion. Students, as the primary end users, are increasingly using GenAI tools to enhance their learning experience. The intuitive design and accessibility of these tools have led to their wide application, allowing students to use artificial intelligence for a number of tasks such as: translating, generating ideas, brainstorming, summarizing and research assistance. This trend emphasizes the key role of usability in facilitating the acceptance and integration of new technologies in the educational environment (Hashmi & Bal, 2024). However, the successful incorporation of GenAI into the academic community goes beyond mere usability. This requires a comprehensive understanding of ethical considerations, the development of critical thinking skills, and the establishment of clear institutional guidelines. Educational institutions must proactively address these aspects to ensure that GenAI adoption is aligned with pedagogical goals and maintains academic integrity. Despite these challenges, GenAI is being integrated into educational technologies such as learning analytics and personalized learning experiences.

It is to be expected that the adoption of GenAI tools among teachers will expand even faster than among the student population. Teachers' responsibility is even greater as their example demonstrates the importance of promoting responsible use of AI while ensuring that students continue to develop critical thinking and writing skills. One ethical issue that is often raised in the context of GenAI technologies is bias in outcomes, which is also a topic that needs to be addressed by regulation (Krpan & Mladenović 2024). Similarly, concerns about meaningful writing in the era of AI-generated text highlight the need for strategies that balance AI assistance with original student work (Girdharry & Khachatryan, 2023). By implementing structured guidelines and ethical frameworks, universities can mitigate the risks associated with plagiarism and AI-generated content while maximizing the benefits of these tools. As usability continues to improve and educational institutions adapt to the evolving technological landscape, GenAI is poised to become an integral part of higher education. This advancement highlights the importance of aligning technological advances with the needs and expectations of students, ensuring that innovations like GenAI are effectively integrated to support and enhance learning outcomes (De Matas, 2023). Moreover, the impact of AI writing tools on student writing and development centers further illustrates the need for continuous evaluation and adjustment of AI policies in academic settings. By improving AI-driven educational tools and ensuring their responsible use, universities can create a balanced approach that fosters innovation while maintaining academic integrity. Like it or not, GenAI is a reality that higher education stakeholders cannot ignore, especially for the student population.

There are already many authors that focused on application of GenAI in HE context (Ravšelj et al. 2025, Aristovnik 2024, Das & Madhusudan 2024). Most of these studies measure student perceptions when it comes to how and why they are using GenAI but they lack the insight into what actualy changes from the standpoint of student academic performance. However this paper contributes to the discussion primarily by clearly defining key constructs that should improve student academic performance. The key variables defined were:

- GenAI Quality (Jaborov et al. 2023, Noor et al. 2022)
- GenAI Adoption (Lazar et al. 2020, Grassini 2023, Westman et al. 2021)
- GenAI Usability (Westman et al. 2021)
- Student academic performance (Verner-Filion & Vallerand, 2016)

4. RESEARCH RESULTS AND DISCUSSION

The research was conducted on a sample of students from the Faculty of Economics and Business, University of Zagreb. The questionnaire was created using an online platform and distributed to students who actively attended classes during the winter semester of the academic year 2024/2025. The sample includes students from undergraduate and graduate programs. The questionnaire was distributed to 1000 students, and after sending two reminders, 340 properly completed questionnaires were collected. The survey responses allowed us to carry out Structural Equation Modeling (SEM) analysis with the JASP software.

When it comes to measuring GenAI quality paper uses several questions covering elements such as: accuracy, reliability, efficiency, objectivity, compatibility, adaptability, context and bias. Usability was measured by using Gen AI for the purposes of: learning foreign languages, having social conversations, teaching, developing new ideas, assisting with career choice, providing additional materials, providing quick answers, helping with exam preparations and simplifying complex information. Adoption was measured with wanting: to pay for additional AI features, to know more after AI interaction, universities to offer more AI related courses, to have more AI related course topics, to work in AI related jobs. Academic performance was measured with: teaching preparation, class attendance, teaching results, classroom activity, interest for assignments, developing new skills and knowledge, putting effort into studying and solving difficult tasks.

Table 1 Reliability analysis of the proposed variables

Reliability

	Coefficient α	Coefficient ω
quality	0.823	0.813
adoption	0.841	0.848
usability	0.814	0.806
acad_performance	0.821	0.824
total	0.858	0.808

Source: Own research

The reliability analysis demonstrates strong internal consistency across all constructs, with Cronbach's alpha (α) values exceeding 0.80, indicating a well-validated measurement model. The total reliability estimate (α = 0.858) further supports the robustness of the instrument. Given that values above 0.70 are considered acceptable and above 0.80 indicate strong reliability (Nunnally &

Bernstein, 1994), these results confirm that the scale is well-constructed and suitable for further analysis. The slight differences between α and McDonald's ω suggest minor variations in item contributions, but since α remains consistently high across all constructs, the scale demonstrates strong internal consistency. The lowest α value (0.814 for usability) still surpasses conventional reliability thresholds, reinforcing the stability of the instrument. Overall, the findings validate the reliability of the measurement model, confirming that the constructs are measured consistently. Given the widely recognized role of Cronbach’s alpha as a standard reliability metric, these results provide confidence in the robustness and applicability of the scale.

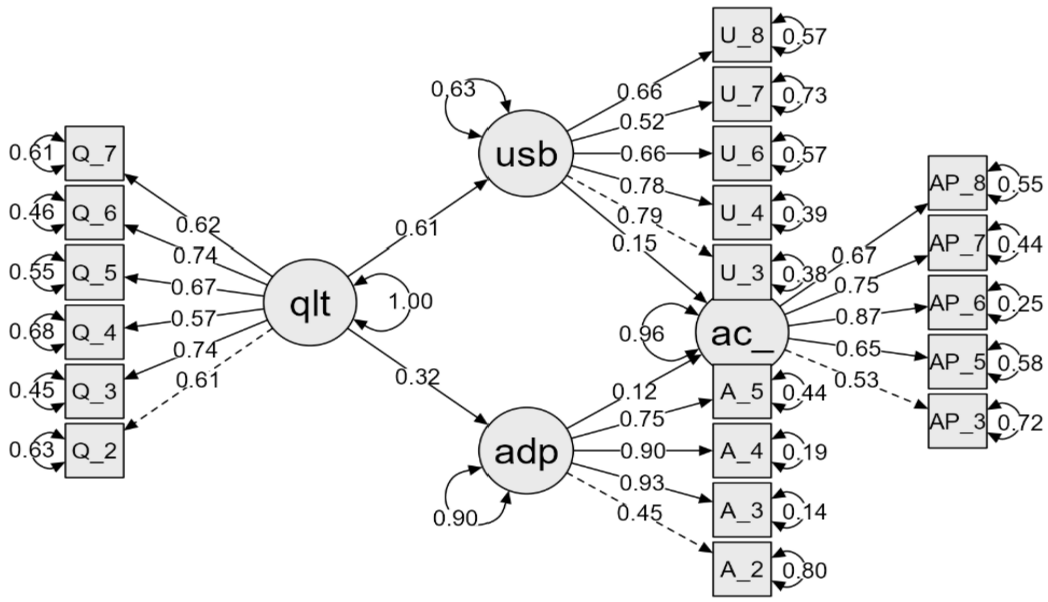

Figure 2 Path diagram of the proposed variables

Source: Own research

SEM is a widely used statistical approach in social sciences, psychology, and related fields, allowing researchers to test complex theoretical models while accounting for measurement error and latent constructs. The evaluation of model fit is a crucial step in SEM analysis, as it determines how well the proposed model represents the observed data. This study assessed the fit indices of a specified SEM model and found an overall acceptable fit, supporting its theoretical and empirical validity.

The chi-square test ($\chi^2 = 356.965$, df = 166, $p < .001$) traditionally serves as a goodness-of-fit measure, but its sensitivity to sample size often necessitates a broader evaluation of fit indices. Given its tendency to produce significant values even for well-fitting models, it is not considered a definitive measure of fit. Instead, alternative indices provide a more nuanced assessment. The information criteria, including Akaike Information Criterion (AIC = 13,559.597) and Bayesian Information Criterion (BIC = 13,791.302), offer comparative insights, with lower values suggesting better-fitting models (Burnham & Anderson, 2004). The sample-size adjusted BIC (SSABIC = 13,588.369) further accounts for model complexity and sample size considerations.

Incremental fit indices indicate the extent to which the model improves upon a null model where no relationships are specified. The Comparative Fit Index (CFI = 0.914) and Tucker-Lewis Index (TLI = 0.902) surpass the commonly accepted threshold of 0.90, signifying an acceptable fit (Hu & Bentler, 1999). These results suggest that the hypothesized model explains a substantial portion of the variance in the observed data. Similarly, the Incremental Fit Index (IFI = 0.915) supports this conclusion, reinforcing the model’s capacity to account for meaningful relationships.

Although the Bentler-Bonett Normed Fit Index (NFI = 0.853) falls slightly below the recommended 0.90 cutoff, it remains within a reasonable range, particularly given the model's complexity.

Absolute fit indices further substantiate model adequacy by assessing how well the model replicates observed data patterns. The Root Mean Square Error of Approximation (RMSEA = 0.065, 90% CI [0.055 – 0.074]) suggests a reasonable fit, as values below 0.08 are generally deemed acceptable, with values below 0.05 indicating excellent fit (Steiger, 2007). The confidence interval further supports the robustness of this finding, as the upper bound remains well within conventional acceptability. Additionally, the Standardized Root Mean Square Residual (SRMR = 0.077) aligns with the recommended threshold of ≤ 0.08, confirming minimal residual discrepancies between observed and predicted correlations (Hu & Bentler, 1999). While the Goodness-of-Fit Index (GFI = 0.889) is marginally below the conventional standard, its proximity to the acceptable range suggests a sufficiently strong fit.

Table 2 Total effects for proposed variables

Total effects

					95% Confidence interval	
	Std. estimate	Std. Error	z-value	p	Lower	Upper
quality → acad → performance	0.130	0.044	2.939	0.003	0.043	0.217
quality → adoption	0.323	0.063	5.167	< .001	0.201	0.446
quality → usability	0.612	0.052	11.711	< .001	0.510	0.715
adoption → acad → performance	0.124	0.075	1.661	0.097	-0.022	0.270
usability → acad → performance	0.147	0.078	1.900	0.057	-0.005	0.299

Source: Own research

The table presents total effects in a Structural Equation Modeling (SEM) analysis, highlighting the standardized estimates, standard errors, statistical significance (p-values), and confidence intervals for various relationships among the constructs. The quality- adoption (β = 0.323, p < .001) and quality - usability (β = 0.612, p < .001) paths are both strong and highly significant, suggesting that quality has a substantial positive effect on both adoption and usability. These results indicate that improvements in quality lead to greater adoption and usability, aligning with theoretical expectations in technology acceptance and system evaluation models. The quality - academic performance (indirect effect via other constructs, β = 0.130, p = .003) is also statistically significant, suggesting that the impact of quality on academic performance is mediated through other variables.

Given that the confidence interval does not include zero, this indirect relationship appears robust. However, the adoption - academic performance (β = 0.124, p = 0.097) and usability - academic performance (β = 0.147, p = 0.057) paths show marginal significance with confidence intervals that include zero. This suggests that while adoption and usability may contribute to academic performance, their effects are not strongly supported in this model. The borderline significance (p-values near 0.05) indicates that these relationships may require further investigation with a larger sample or refined model specification. Overall, the findings highlight the central role of quality in influencing adoption and usability, which in turn shape academic performance. While the direct effects of usability and adoption on academic performance are weaker, their indirect contributions might still be meaningful. Future research could explore alternative model specifications to better capture these relationships, potentially incorporating additional mediators or moderators to explain the weaker effects. Also it needs to be stated that using GenAI tools from student perspective is a new phenomenon and it will probably take some time for it to show its full effects. Also as sugested earlier the clear guidance on how to productively and effectively use these tools is lacking. It would be especialy interesting to look into variables like trust and mistrust and their potential effects on quality, disemination and performance.

The results of the SEM analysis show that the proposed model fits the collected data, confirming its theoretical correctness and empirical usefulness. CFI, TLI, RMSEA, and SRMR values together support the model's ability to represent the observed relationships among key variables. Although some indices, such as NFI and GFI, fall slightly below the optimal thresholds, they do not significantly undermine the overall fit of the model. Considering the results, the model shows great potential for improving knowledge in the field of application of GenAI technologies by students. Future research could explore alternative refinements of individual variables or theoretical modifications to further optimize the quality of the model, although the current results confirm its validity and applicability.

4. CONCLUSIONS

In the context of higher education, the increasing use of GenAI technologies opens new chapters in learning support. High-quality AI tools, such as generative models, can be crucial in improving educational outcomes. They offer the possibility of personalized learning, improved access to information, and support in complex academic tasks. However, the successful adoption of these technologies depends on several key factors. First, it is important to ensure that the tools are designed to be intuitive and easily accessible to students. Second, it is necessary to provide adequate support and training to maximize the benefits they offer. Finally, continuous monitoring and evaluation are important to ensure that the technologies have a positive impact on academic performance. This work makes a significant contribution to the implementation of monitoring the quality and effectiveness of GenAI tools and technologies, the number of which is growing day by day. From a theoretical perspective, this study advances the understanding of GenAI integration in education by empirically validating key constructs related to quality, adoption, and usability. The findings align with prior research indicating that technology acceptance is driven by perceived benefits and usability, further emphasizing the importance of AI tool reliability and accuracy in educational settings.

On a practical level, the study provides actionable insights for educators, policymakers, and technology developers. Institutions should prioritize the implementation of high-quality AI tools while ensuring adequate governance frameworks that address ethical concerns such as academic integrity, data privacy, and the risk of AI over-reliance. Overall, this research contributes to the ongoing debate on the role of AI in higher education and provides a foundation for optimizing AI-driven learning experiences. By fostering responsible AI adoption and emphasizing quality-driven implementation, academic institutions can leverage GenAI tools to enhance student learning, engagement, and overall educational outcomes.

At the end several limitations of the study need to be addressed. First of all study was conducted on a single institution and it is advisable to expand same research on other institutions and countries. Future research should also explore potential moderators, such as students' digital literacy levels and subject-specific AI applications, to provide a more nuanced understanding of GenAI's impact on academic success. Also the role od GenAI trust and mistrust as separate constructs needs to be further explored.

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