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Understanding the impact of ChatGPT and related AI tools in Education

Kjubra Menga

Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data-Driven Marketing

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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Understanding the impact of ChatGPT and related AI tools in Education

by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data-Driven Marketing, with a specialization in Marketing Intelligence

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism, any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, 14.07.2025

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ABSTRACT

Artificial Intelligence (AI) has experienced fast development and widespread application, which has revolutionized the education field dramatically. The present study discusses AI tools' impact, in our case ChatGPT, on the academic performance of students in a learning setting. Using a quantitative approach, we developed an innovative and integrated theoretical model, integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Resource-Based View (RBV), which was tested empirically with PLS-SEM and data from Macedonian students. Our findings illustrate a direct link between students' behavioral intention to utilize AI tools (influenced by performance expectancy, social influence, and facilitating conditions) and their academic performance, further mediated by actual use of AI tools and individualized learning experience. This research makes unique contributions by providing one of the first empirical investigations connecting AI tools usage and academic performance, with a new theoretical model that has not been empirically tested in the literature previously. The study offers also significant theoretical contributions to technology acceptance in education and provides action implications for students, educators, and universities on how to effectively utilize AI tools to enhance learning outcomes and foster a supportive educational environment.

KEYWORDS

Artificial Intelligence; Education; Academic Performance; ChatGPT; AI tools

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AP	Academic Performance
API	Application Programming Interface
BI	Behavioral Intention
C	Capability
ChatGPT	Chat Generative Pre-Trained Transformer
CISC	Complex Instruction Set Computer
CPU	Central Processing Unit
DENDRAL	A Program for Analyzing Chemical Structures and Inferring Molecular Structures from Mass Spectra
EE	Effort Expectancy
FC	Facilitating Condition
GAI	Generative Artificial Intelligence
HTMT	Heterotrait-monotrait ratio
ICT	Information and Communication Technology
LLMs	Large Language Models
LM	Learning Motivation
ML	Machine Learning
MYCIN	A Program for Diagnosing and Treating Bacterial Infections
PE	Performance Expectancy
PLE	Personalized Learning Experience
PLS	Partial Least Square
R	Resource
RBV	Resource Based View
SEM	Structural Equation Modelling

SI	Social Influence
STEM	Science, Technology, Engineering, and Mathematics
UB	Use Behavior
UNESCO	United Nations Educational, Scientific and Cultural Organization
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

1. INTRODUCTION

The fast development and improvement of AI technologies have changed the educational scenario, influencing researchers, educators and students to think what this could mean for the teaching and learning practises. The increased interaction with AI tools seen in the education sector in the last years reinforced the needto better understand AI tools capabilities, benefits, and challenges. Our work aims to understand and investigate the influence and impact of ChatGPT and related AI tools in education, devoting special attention on their potential to spread learning experiences while addressing ethical considerations. The relevance of studying AI stems from its universal reach and the rate at which it evolves. Its impact on teaching techniques, learning results, and the entire educational system also calls for an in-depth examination of its consequences. The rise of AI in education has already a long track record, marked by the development of different adaptive learning technologies and techniques which posit both positive and negative effects on student outcomes (Krumsvik, 2023). This type of tools provides opportunities for greater personalized learning and increased engagement, but they also bring important questions regarding academic integrity, bias, and the role of educators in managing these technologies. By investigating the capabilities and limitations of ChatGPT and related AI tools used in educational settings, we intend to provide a deeper understanding on how they can be manipulated while overcoming associated challenges. This study stands out by providing an unique theoretical model not yet tested in literature until now that sinegertically combines the theory of User Acceptance of Information Technology (UTAUT) from Venkatesh et al., (2003) with a resource-based view model adapted from Wernerfelt (1984) and Barney (1991) and two additional varibles, personalized learning experience and learning motivation, to analyze the impact of AI tools on students' academic performance in a more holistic and integrated way. Another important contribution to the scholarship is empirically testing these relationships in the educational context, enhancing the understanding of the academic performance influencing factors and providing a sound guidance for educators and policymakers on responsibly and productively integrating AI technology tools.

In the last few years, the usage of ChatGPT and related AI tools has raised an increasing number of debates regarding philosophy and ethical issues. According to Krumsvik (2023), there is related to uncertainty regarding what these tools could bring to teaching, and to student learning, especially in initial levels of education. In the research made in Digitale Læringsfelleskap group from the University of Bergen focused on the implementation of AI tools in Norwegian primary schools. The results were mixed, some of them showed positive effects on students' learning subjects like mathematics and English, others provided negative results (Krumsvik et al., 2018; Krumsvik et al., 2021).

AI usage in education is likely to change traditional views and approaches in the learning process. More precisely, usage of ChatGPT and related AI tools will provide opportunities for learners and practicers, shortening the time in classroom needed to perform tasks providing deeper learning experiences according to Moltudal et al., (2020). However, all AI related tools, including ChatGPT are dependent on successful implementation through teacher digital competence and good classroom management as well as data protection, ethics and privacy as Krumsvik (2023) underlined. Thus, as educational technology continues to shift and change, it should be clearly drawn the line between AI applications that are actually built for educational purposes, and then to make sure curricular alignment, also considering and student data security. The remaining sections of this document are organized as follows: In chapter 2, literature review is presented, regarding the historiography, features, advantages, obstacles, and ethics of artificial intelligence in the education sector. In chapter 3, the methods of research are described, which include the theoretical model set forth, the hypotheses, and the data collection methods . In chapter 4, the outcomes of data analysis are presented and the finding discussion is provided. Finally, in chapter 5, the conclusions of the study are presented , articulating its implications, limitations, and prospects for further inquiry.

2. LITERATURE REVIEW

2.1 The Rise of AI in Education

2.1.1 Historical Context

The development of artificial intelligence has influenced different fields. Historically, the origin of AI can be checked back to the mid-20th century, when researchers started exploring the mechanization of intelligence and the potential for machines to perform tasks associated with human cognition (Newell, 1982). The early years of AI were marked as a split between two types of systems: symbolic and continuous. Those divisions later helped to create basic ideas and methods that affects educational technology (Newell, 1982).

During the 1950s and 1960s, researchers were mostly focused on solving problems and on identifying new or improved AI models. At that time programs, instead of using algorithms, they used simple rules to guide problem-solving, that was called heuristic programming. (Newell, 1982). As AI started to be improved and developed, the education sector has started idealizing how these technologies could develop new learning experiences, personalized education, and how it would be support for teachers in their teaching methods (Holmes et al., 2021).

Meanwhile in the 1970s, has begun a shift towards expert systems and knowledge representation systems, that has changed AI's role in education. Programs such as MYCIN and DENDRAL (Newell, 1982). has showed that AI could change real-world problems, shape the way for its use in educational settings. The unification of AI with education was not only a technological advancement, and meanwhile it raised philosophical questions about intelligence, learning, and the role of teachers in education.

At the end of the 20th and the beginning of the 21st century, as AI continued to develop and grow, new forms of using it in education were identified such as smart tutoring systems,like Carnegie Learning's MATHia (Jaciw et al., 2007) and adaptive learning platforms, like ALEKS (Ma, et al., 2014) that aim to provide tailored educational experiences and support for teachers (Luckin et al., 2016). All of these inventions and innovations changed the educational environment by providing personalized learning and data-driven insights about student performance. In summary, all the AI historical context in education highlights the continuous interaction between technology and educational practices and the need for the educators to adapt and to implement those technologies into their teaching methods.

2.1.2 AI Tools and Their Capabilities

The unification of artificial intelligence with the education is at the center of the movement to change traditional learning models. There is a necessity to critically rethink lifelong learning frameworks in light of the fast advancement in technology. According to Poquet & de Laat (2021), continuous change aligned with the workplace' digitalization in an educational environment has quickened and highlighted the urgent need of changing educational systems,becoming even more important after recent global events such as the COVID-19 pandemic.

A critical argument is the fact that for the greater part traditional models of lifelong learning had neglected, among others, the transformative function of Technology in learning. The emergence of AI powered tools has profoundly transformed this perception though (Mhlanga, 2023). These tools are designed to not only promote information access, but also to facilitate ongoing interaction with human cognition and social behavior. As a result, the impact of AI is transforming how people learn, interface with information and work and, as a result, even the larger story of what education is about. In light of this, some authors advocate for a shift in skills development, emphasizing human development and individual empowerment (Poquet, & de Laat., 2021). This latter approach centers on equity, personal growth, and diverse learner needs in a way that suggests the design of AI tools should not only enhance efficiency but also promote learner autonomy and support varied learning experiences(Özer, 2024). By focusing on capabilities, educational practices can better address the systemic barriers that prevent individuals from fully realizing their potential.

Moreover, Poquet & de Laat (2021) highlight that AI-based tools can facilitate personalized learning pathways, enabling individuals to navigate their educational journeys in ways that align with their personal goals and values. Such personalization becomes imperative in a plural educational landscape where learners come from various locations, backgrounds and possess different learning styles. These authors have also reiterated that effective use of AI in education should be done with a focus on social and contextual factors influencing learning and on the design of AI systems allowing to engage in issues of power and equity in educational settings (Luckin et al., 2016).

They further contend that framing AI as a cogitative partner has the effect of enhancing human capabilities toward promoting inclusivity and equity in education. By embedding AI into education thoughtfully, educators and institutions can create supporting learning contexts not only related with skill gain but also with critical thinking and lifelong creativity (Holmes et al., 2021).Ultimately, Poquet & de Laat (2021) move on indicating a future in which technology would be an enabler of human development, whereby learners take responsibility for their learning processes and contribute to society. The working paper titled *Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development*, UNESCO (2019) examines the significant role that artificial intelligence (AI) can play in the educational systems transforming, particularly in developing countries. The paper argues that AI has the potential to enhance learning outcomes promote educational equity by facilitating personalized learning experiences and improving educational management through the use of advanced data analytics (Zawacki-Richter et al., 2019).It highlights various initiatives from

countries such as China, Uruguay, and Kenya, which serve as case studies demonstrating the successful integration of AI technologies into educational frameworks. Furthermore, the document identifies six critical challenges that must be addressed to ensure the effective implementation of AI in education. These challenges include: (i) the need for comprehensive public policy frameworks that govern AI use, (ii) the importance of ensuring equitable access to AI technologies, (iii) the necessity of preparing educators for the integration of AI into their teaching practices, (iv) the development of quality data systems to support AI applications, (v) the enhancement of research significance in the field of AI education, and (vi) the imperative to address ethical concerns related to data collection and usage (Pathak, 2023).
The paper concludes with a call for ongoing dialogue regarding the applications and potential risks associated with AI in education, emphasizing the need for a collaborative approach among stakeholders to harness AI's capabilities for sustainable development in the educational sector. This comprehensive analysis provides valuable insights for policymakers and educators seeking to navigate the complexities of AI integration in education (Rahman & Watanobe, 2023).

2.1.3 Potential Benefits of AI in Education

The integration of Artificial Intelligence (AI) in education offers numerous potential benefits that can significantly enhance the learning experience for students and streamline the teaching process for educators. AI systems, particularly generative models like ChatGPT, can facilitate personalized adaptive learning by monitoring students' real-time progress and emotional states, thereby tailoring educational resources to meet individual needs (Holmes et al., 2021; Luckin et al., 2016). These technologies enable teachers to create innovative and interactive learning environments, allowing for the development of customized lesson plans and assessments that cater to diverse learning styles (Özer, 2024; Baidoo-Anu & Owusu Ansah, 2023). Furthermore, AI can assist in automating administrative tasks, such as grading and feedback provision, which can reduce teachers' workloads and allow them to focus more on fostering student engagement and collaboration (Özer, 2024).In general, the successful integration of AI into educational settings has the potential to change how teaching is traditionally carried out and enhance learning outcomes

Some key features of the integration of artificial intelligence in education present countless potential benefits, thus contributing more to teaching and learning processes. The main one here will be the capability of artificial intelligence tools like ChatGPT to give personal tutoring or individual feedback that matches different student needs. This personalization can help address diverse learning styles and paces, allowing students to progress at their own speed and receive support precisely when they need it (Baidoo-Anu & Owusu Ansah, 2023). For instance, AI-driven platforms can analyze a student's performance in real-time and adjust the tasks’ difficulty accordingly, ensuring that learners remain engaged and challenged without becoming overwhelmed. Moreover, AI can facilitate automated essay grading, which allows educators to save time and focus on more critical aspects of teaching, such as fostering student engagement and developing curriculum (Baidoo-Anu & Owusu Ansah, 2023). This efficiency not only streamlines the assessment process but also provides students with timely feedback, which is essential for their learning and improvement. Additionally, AI technologies can support language translation, making educational materials more accessible to diverse student populations, including non-native speakers and those with varying levels of language proficiency (Baidoo-Anu & Owusu Ansah, 2023). This accessibility can help bridge educational gaps and promote inclusivity in the classroom. AI can create interactive learning environments where students engage with virtual tutors, fostering a more dynamic and engaging educational experience. These virtual tutors can simulate one-on-one interactions, providing students with a safe space to ask questions and explore concepts without the fear of judgment (Baidoo-Anu & Owusu Ansah, 2023). Additionally, AI can assist teachers in identifying students who may be struggling, allowing for timely interventions and support. The latter also implies analyzing data on learners' performance and engagement to let educators further adjust their instructional strategies to students' needs more effectively. The incorporation of AI in an educational setting may thus alter conventional pedagogical methodology in an effort to achieve better student learning outcomes and prepare these young minds for a future dependent on digital literacy and technology skills. As educators and policymakers consider how to integrate AI tools into the classroom, it's important to consider the ethical implications of such technologies and to ensure that they are enhancing, not replacing, the invaluable human elements of teaching and learning.

By utilizing AI, educators can track students' learning deficits and offer relevant feedback and supplemental materials, which can lead to improved learning outcomes (Luckin et al., 2016). Furthermore, AI can assist in identifying learning disabilities early on by analyzing patterns in students' responses and actions, allowing for timely interventions that can mitigate future challenges (Luckin et al., 2016). Additionally, AI can facilitate the development of critical skills in young learners through interactive and gamified learning experiences, which not only make learning enjoyable but also promote problem-solving and critical thinking abilities (Holmes et al., 2021).

2.2 The Impact of ChatGPT and Related Tools

2.2.1 ChatGPT's Capabilities and Limitations

ChatGPT is a generative artificial intelligence model developed by OpenAI that has become an important tool in educational contexts, where it has several capabilities and limitations that have to be considered with caution. Among the most important features is the possibility of creating personalized learning experiences at higher levels of difficulty, as educators can structure specific teaching activities and then give individual feedback to the students (Memarian & Doleck, 2023). Apart from that, ChatGPT can promote asynchronous communication in that students can be supported outside traditional classroom hours to solve time constraints for both learners and instructors (Memarian & Doleck, 2023). Its potentiality to improve English language skills, assist in the accuracy of research, and play the role of a student, teacher, or co-agent further asserts its flexibility in educational settings (Memarian & Doleck, 2023). Yet, despite these benefits, there are a number of limitations associated with the use of ChatGPT. There are concerns about academic integrity in that the model may inadvertently facilitate plagiarism and reduce students' critical thinking skills since it provides answers instead of encouraging independent thought (Memarian & Doleck, 2023). Moreover, the reliance on ChatGPT necessitates a certain level of technical expertise, which may not be accessible to all educators and students, potentially exacerbating existing inequalities in educational access (Memarian & Doleck, 2023). The model's tendency to generate inaccurate or misleading information, particularly in specialized fields, further complicates its application in education (Memarian & Doleck, 2023). Consequently, while ChatGPT creates real opportunities for improving teaching and learning, it also engenders a number of challenges that have to be overcome in developing its effective and ethical usage within educational contexts.

The ChatGPT capabilities are based on deep learning techniques that allow it to generate coherent and contextually relevant responses in conversational settings. According to Cong-Lem, et. al, (2024), despite the impressive performance of ChatGPT, there are still some limitations. A systematic review of empirical studies reveals several key concerns, particularly about accuracy and reliability. For example, ChatGPT has been found to produce misinformation or incorrect information, especially in critical fields like healthcare, where factual inaccuracies may have serious implications (Wagner et al., 2023). Moreover, deficiencies in critical thinking and problem-solving skills have also been noted, which point to the inability of the model to carry out complex tasks that require a deep level of understanding and independent analysis (Clark, 2023). Ethical considerations also arise, particularly concerning biases in responses and potential violations of privacy and academic integrity (Ibrahim et al., 2024). These limitations underscore the necessity for cautious and informed use of ChatGPT, particularly in educational settings where overreliance on the tool may hinder the development of critical thinking skills among learners (Alafnan et al., 2023). Thus, although ChatGPT has exciting opportunities that can enhance workflows and support educational practices, it is crucial that users be cognizant of the limitations to apply it responsibly and effectively (Cong-Lem et al., 2024).

ChatGPT is a further development of an AI text generator from OpenAI, which has both a lot of capabilities and some limitations, important for the application in education and professional settings. One of the most valuable features of this model is its ability to produce coherent and contextually relevant text based on the given prompt. This capability enables ChatGPT to support users in a range of applications, including draft writing, summarizing, and explaining complex topics. In the educational context of accounting, for example, ChatGPT has been shown to be capable of producing case requirement responses that require ethical judgments and the application of rules and regulations at levels commensurate with average students (Cheng et al., 2023). However, despite these strengths, ChatGPT also faces notable limitations. Its performance tends to decline when tasked with requirements that necessitate detailed calculations, the creation of financial statements, or the use of external software, as it lacks the ability to interact with databases or spreadsheets effectively (Cheng et al., 2023). Besides, there is a scarcity of subtlety and detailedness on different points in various responses generated through ChatGPT, as well as much potential to become misinformed or a generally sweeping answer found by clients with less specific experience, as stated by Wood et al., (2023). With its data-driven generation method, the output could either be outdated or incomplete regarding those areas wherein continuous innovation or other rapid, progressive fields happen. As such, while ChatGPT serves as a valuable tool for generating text and facilitating learning, users must remain vigilant and critical of its outputs, ensuring that they supplement its use with thorough research and expert guidance (Cano et al., 2023).

2.2.2 Applications of ChatGPT in Education

The integration of artificial intelligence (AI) technologies, particularly ChatGPT, into educational environments has sparked significant interest and concern among educators and researchers. Released in November 2022, ChatGPT has demonstrated remarkable capabilities in various academic tasks, including literature review, translation, and generating complex answers to exam questions (İpek et al., 2023). Its ability to produce articulate and contextually relevant responses has led to its application in diverse fields, from law and medicine to language education, where it has performed comparably to above average stu dents on assessments (Choi et al., 2023; Huh, 2023). However, the potential for misuse, such as academic dishonesty and plagiarism, has raised ethical concerns regarding its role in education (Rudolph et al., 2023). The literature indicates that while ChatGPT can enhance personalized learning experiences and assist in grading and assessment, it also poses risks related to bias, misinformation, and the erosion of critical thinking skills among students (Cotton et al., 2023; Zhai, 2022). As educators navigate the challenges and opportunities presented by AI, it is crucial to establish guidelines and training to ensure that these technologies are used responsibly and effectively, fostering an educational environment that prioritizes both innovation and integrity (İpek et al., 2023).

The integration of ChatGPT into educational settings has raised significant discourse on its potential benefits and challenges. As noted by several researchers, ChatGPT presents opportunities for improving teaching and learning processes, especially in language education and medical training. According to Kohnke et al., (2023) and Lee (2023), the tool can generate human-like text that may be used to facilitate personalized learning experiences, thus enabling educators to tailor content to meet diverse student needs. This increases a new set of ethical worries related to academic integrity and the detection of plagiarism that ChatGPT has created; by example, Khalil & Er 2023; Susnjak, 2022. Dual-use technology like ChatGPT-as a resource and possible cause of academic dishonesty-suggests the dual importance of carefully weighing what in this respect the role of the platform is in educational perspectives (Opara et al., 2023). Moreover, the consequences of adopting such technology go beyond simple educational repercussions, raising debates over the future of learning approaches and where educators' responsibilities lie in terms of directing students toward ethical use (Murgia et al., 2023; Zhang et al., 2023). In negotiating such complications, institutions have to provide frameworks that can advance responsible and effective usage of ChatGPT in a manner that its integration into education enhances learning and does not undermine it (Javaid et al., 2023; Rahman & Watanobe, 2023).

2.3 Challenges and Ethical Considerations

2.3.1 Academic Integrity Concerns

The emergence of generative artificial intelligence tools, particularly ChatGPT, has raised significant academic integrity concerns within higher education. Highlighted in the article by Sullivan, Kelly, & McLaughlan (2023), the misapplication of these technologies toward academic dishonesty has perhaps become a focal point for discussion among educators and institutions. Reports indicate that a large number of students have used AI tools for assessment tasks, and in some surveys, more than one-third of university students admit to having used ChatGPT to write assignments, even though most considered this cheating (Sullivan et al., 2023). This duality of awareness and action underlines a disturbing trend where students may choose the expediency of AI-generated content over the ethical implications of their academic conduct. The literature suggests that most universities have responded by imposing bans on the use of ChatGPT, viewed as a "threat" to the integrity of academic assessments (Sullivan et al., 2023). However, the discourse surrounding these concerns is not monolithic; while some academics perceive AI tools as detrimental to the educational process, others advocate for a more nuanced approach that emphasizes the need to adapt teaching and assessment practices to the realities of AI integration in academic settings (Sullivan et al., 2023). This is a debate that continues and shows that it is not only necessary to consider the risks associated with the misuse of AI but also to consider its potential to improve learning outcomes as a means to foster a deeper understanding of academic integrity in rapidly changing technological contexts.

Academic integrity is a cornerstone of higher learning that underscores the importance of honesty, trust, fairness, respect, and responsibility in students' academic undertakings. On the other hand, the rise of advanced technologies, especially artificial intelligence tools like ChatGPT, has brought into question some key concerns about academic integrity. These AI systems can generate essays, solve complex problems, and provide answers to exam questions, which may tempt students to submit work that is not their own, thereby undermining the educational process (Zeb et al., 2024). The potential for plagiarism and academic dishonesty is heightened as students may rely on these tools to produce assignments, leading to a devaluation of their learning experiences and the qualifications they earn (Cotton et al., 2023). Furthermore, the challenge of distinguishing between student-generated content and AI-generated text complicates the assessment process, making it difficult for educators to accurately evaluate a student's understanding and mastery of the subject matter (Dehouche, 2021). It is, therefore, the duty of institutions to be proactive in such matters by laying down clear policies on the use of AI tools, establishing effective plagiarism detection systems, and promoting a culture of academic integrity through education and awareness (Zawacki-Richter et al., 2019). By upholding academic integrity, the educational institutions ensure that the value of their degrees is maintained and that students are adequately prepared with the knowledge and skills to enter their respective professions.

The advent of advanced AI tools, especially generative models like ChatGPT, has raised a variety of concerns about academic integrity in research and publishing. As these tools continue to improve their ability to create coherent, contextually relevant text, their use within an academic context raises a set of ethical dilemmas challenging traditional notions of authorship and originality. Scholars have pointed out that this could create instances of plagiarism, given the blurred lines between the work of a human and a machine. Moreover, the capacity of AI to generate misinformation or inaccurate information increases the danger of spreading untruths in the disguise of academic work. These developments have grave implications, in that they threaten to compromise not only the integrity of academic publishing but also the trust that is basic to scholarly communication. Accordingly, institutions and researchers should develop clear guidelines and ethical frameworks within which the use of AI in academic writing can be governed to ensure that their contributions enhance rather than compromise the integrity of academic discourse. With the ever-evolving research landscape due to the increasing integration of AI, responsibility falls upon the academic community to ensure standards of integrity and accountability are upheld (Guleria et al., 2023; Jain et al., 2011; Liebrenz et al., 2023; Owens, 2023; Rahimi & Abadi, 2023; Thorp, 2023).

2.3.2 Future Directions

Future directions for ChatGPT and other LLMs are set to go toward significant use in different domains, mainly in enhancing the contextual understanding and ethical deployment of models. While such models continue to improve in their capabilities, researchers have focused on tackling the inherent biases arising from the large data sets used for training, which themselves often mirror societal prejudices (Bender et al., 2021). This therefore calls for more enhanced techniques for debiasing and the development of fairness-aware algorithms that can ensure AI-generated content is equitably representative of the diversity of views. Furthermore, embedding multimodal capabilities allows LLMs to process and generate visual content in addition to text, increasing their use in creative industries such as advertising, filmmaking, and education (Ray, 2023). Moreover, with the increasing demand for real-time information, improving the factual accuracy of these models will be imperative, especially in high-stakes domains such as healthcare and law, where misinformation can have serious consequences. Researchers are also considering the environmental impact of training large models, calling for greener practices in AI development to reduce carbon footprints associated with extensive computational resources (Sallam et al., 2023). By focusing on these areas, the next generation of LLMs will be in a position to improve performance and reliability while contributing to a more ethical and inclusive technological landscape, with the ultimate aim of fostering a society that benefits from the improvements in artificial intelligence while minimizing potential harms.

The future directions of AI in education are going to bring a sea change in the learning environment, offering personalized and adaptive learning experiences to meet individual students' needs. While AI technologies continue to evolve, they are bound to enhance educational practices by providing tailored learning materials, real-time feedback, and intelligent tutoring systems that can adapt to the unique learning styles and paces of students (Pathak, 2023). One significant advancement is the development of AI-driven platforms that can analyze vast amounts of educational data to identify patterns and trends, enabling educators to make informed decisions about curriculum design and instructional strategies (Pathak, 2023). Furthermore, AI can facilitate the creation of immersive learning environments through virtual and augmented reality, allowing students to engage with content in interactive and meaningful ways (Pathak, 2023). AI integration in education brings key ethical concerns regarding data privacy and potential biases in AI algorithms to the table, which shall be sorted to achieve the desired equitability of educational resource access (Pathak, 2023). It is a challenge for all stakeholders in the process-the educators, technologists, and policymakers who are concerned that continued research and collaboration can best unlock the complete possibilities of AI and diminish many of the challenges in learning. Eventually, the future of AI in education holds the promise of transforming traditional learning paradigms, fostering greater engagement, and improving educational outcomes for diverse learner populations.

2.3.3 Bias and Fairness

The integration of GAI models, like ChatGPT, into higher education in recent years has raised serious concerns about bias and fairness. Most GAI models are trained on very large datasets that tend to reflect existing social inequities and, therefore, have the potential for amplifying biases related to gender, race, nationality, and other social categories (Li et al., 2024). Research has shown that GAI can actually perpetuate stereotypes and discriminatory practices, especially in education, where fairness and equity are key (Kasneci et al., 2023). For example, studies have found that language models can generate biased responses that favor specific demographics at the expense of others, negatively impacting students' learning experiences and outcomes (Venkit et al., 2024). Furthermore, the predominance of English-language data in training these models exacerbates the issue, as it may lead to outputs that are culturally insensitive or irrelevant to non-English speaking populations (Sheng et al., 2021). The lack of empirical research specifically addressing the nuances of bias in higher education settings highlights a critical gap in the literature, necessitating more comprehensive studies that explore the intersectionality of various biases and their implications for educational equity (Li et al., 2024). As institutions increasingly adopt GAI technologies, it is essential to establish ethical guidelines and best practices that ensure these tools are used responsibly, promoting fairness and inclusivity while mitigating the risks of perpetuating existing societal biases (Ojha et al., 2024).

Bias and fairness of AI have emerged as pressing concerns in the higher education context, especially in regard to the increased integration of AI technologies into the curricula and administrative processes of higher education institutions. The recent proliferation of AI tools, particularly large language models, has begun to raise serious questions regarding the ethical use of such technologies, particularly around issues of discrimination and bias. Researchers have pointed out that AI systems can passively create a continuation of the bias found in the data used to train them, which often results in biased outcomes and unfair treatment, especially for groups that have been traditionally oppressed. The concern is also heightened because the inner operations of most AI algorithms remain obscure and make detection of biases complex. As education institutions grapple with creating equity and therefore inclusiviness, there must be solid structures that make equity a priority in AI applications. This will involve setting policies that would not just focus on the ethical use of AI but also mitigate bias by considering diverse representations of data and continuous monitoring of AI systems. In addition, including AI ethics in curricula can better position students to think critically about these technologies, creating a generation of teachers and practitioners who will be prepared to advocate for equity and accountability in the deployment of AI. Eventually, addressing bias and fairness in AI is not just a technical challenge but a moral imperative that calls for cooperative efforts from policymakers, educators, and technologists in order to make sure that AI serves as a tool for sial good and not as a mechanism of exclusion (Lee, S, 2024).

3. RESEARCH METHODOLOGY

The growing incorporation of Artificial Intelligence (AI) tools in education offers both benefits and challenges for student learning results. This study specifically examines how these tools affect student grades, which are a crucial measure of academic achievement, in both high schools and universities. For these reasons we developed an innovative theoretical model, as presented in Figure 1, seeking to elucidate the intricate connections between students' perceptions of AI tools, their real usage, and academic performance in high schools and universities settings.

3.1 Research Model

Our model aims to explore how elements such as smart adaptability, creativity, social impact, and effort expectations shape students' views and intentions towards AI tools, ultimately impacting their academic success. The model examines various AI-powered educational tools effects on student achievement in different fields. Independent variables consist of intelligent adaptability (the AI's skill in addressing personalized learning requirements), creativity (the AI's ability to encourage creativity), social influence (the impact of peers/teachers on AI acceptance), and effort expectancy (the perceived effort needed for using AI). Mediating variables consist of perceived ease of use (the simplicity of utilizing the AI), facilitating conditions (the resources and support that are accessible), and perceived task of use (the significance of AI for educational tasks). The dependent variables include performance expectancy (expected effect on performance), intention to utilize AI tools, and the actual usage of AI tools (both frequency and duration). This research model offers a structure for examining eleven particular hypotheses concerning these connections (H1-H11, as outlined in Figure 1).

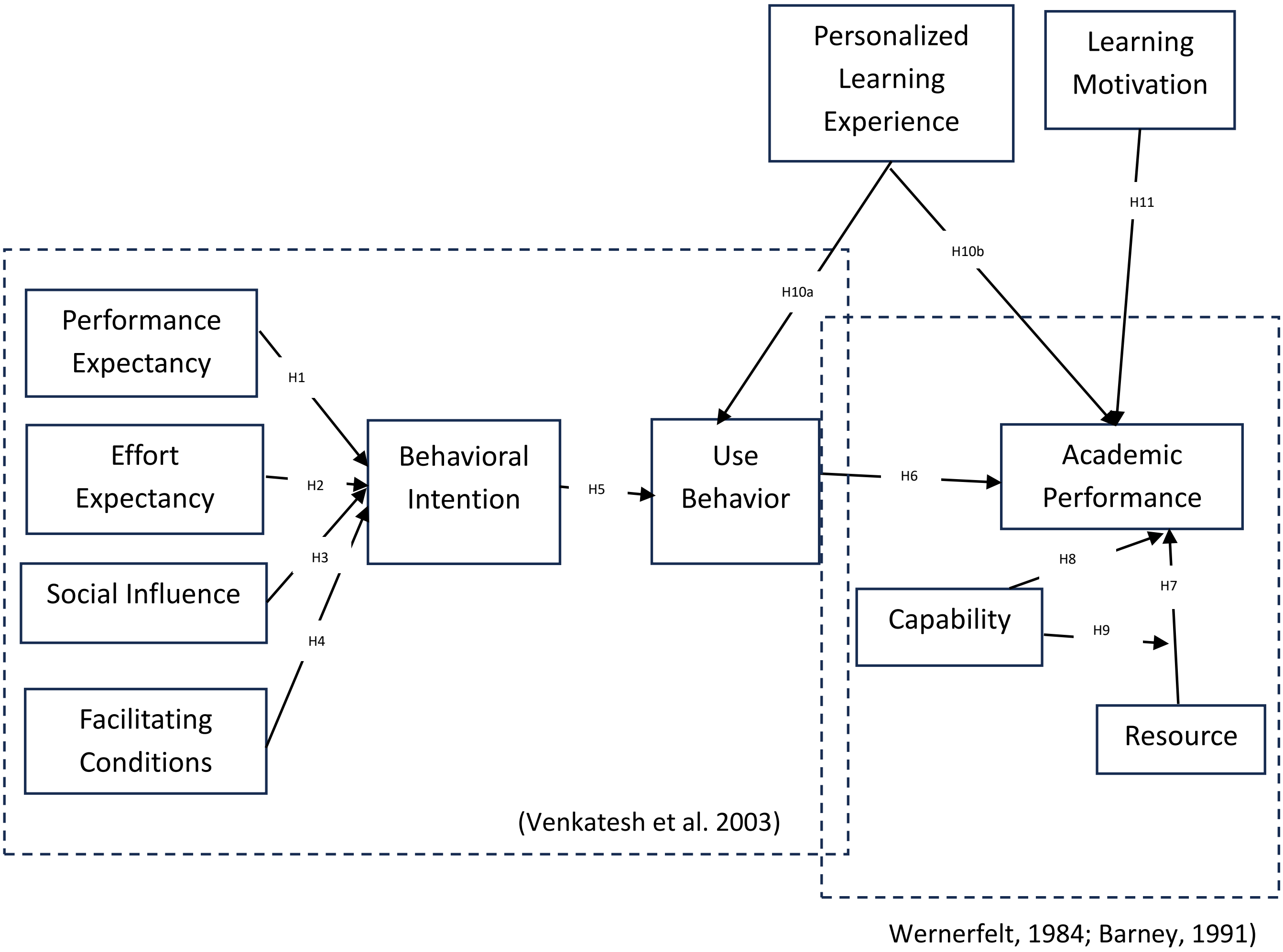

Figure 1 Hypothesis in research model.

3.1.1 Model Variables and their Relationships

The theoretical model developed for this research is graphically represented in Figure 1, an innovative model that attempts to explain the complex effect of AI tools on students' academic performance. This model combines constructs from Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the Resource-Based View (RBV) (Wernerfelt, 1984; Barney, 1991), extended with two specific variables of the education sector, namely personalized learning experience and learning motivation.

This synthesis enables a complete investigation of how attitudes, intentions of students, and the implicit characteristics of AI tools collectively impact on learning behaviors and academic performance. The independent and dependent variables used in the theoretical model are the following:

Variables

- **Independent Variables:**
  Performance Expectancy (PE): is the degree to which an individual believes that using AI tools will provide benefits in achieving gains in academic performance (Venkatesh et al., 2003).
  Effort Expectancy (EE): Represents the perceived ease associated with using AI tools for educational activities (Venkatesh et al., 2003).
  Social Influence (SI): Reflects the extent to which an individual perceives that important others (e.g., peers, teachers) believe they should use AI tools (Venkatesh et al., 2003).
  Facilitating Conditions (FC): Pertains to the degree to which an individual believes that organizational and technical infrastructure exists to support the use of AI tools (Venkatesh et al., 2003).
  Resource (R): Also rooted in the RBV, this variable denotes the perceived value and utility of AI tools as accessible resources for decision-making and task completion within the academic domain.
  Personalized Learning Experience (PLE): This variable measures the perceived effectiveness of AI tools in tailoring learning content, addressing individual learning needs, aligning with personal interests, and providing specific, customized feedback. It is conceptualized as an outcome influenced by the inherent capabilities of AI tools.
  Learning Motivation (LM): This variable assesses the extent to which students feel intrinsically driven to engage with course content, explore subjects further, and exhibit confidence in achieving learning objectives with the support of AI tools. It is hypothesized to be influenced by the Personalized Learning Experience.
- **Dependent Variables:**
  Use Behavior (UB): Refers to the actual frequency and duration of AI tool utilization by learners in their educational activities. This behavior is hypothesized to be directly influenced by Behavioral Intention and Personalized Learning Experience.
  Academic Performance (AP): The primary outcome variable, operationalized through student grades and their proactive engagement in continuous learning and skill development. Academic Performance is hypothesized to be directly influenced by Use Behavior, Resource, Capability, Personalized Learning Experience, and Learning Motivation.
  Behavioral Intention (BI): A core UTAUT construct, representing a student's intention to continue using AI tools in their educational activities in the future. This intention is hypothesized to be influenced by Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.
- **Moderator Variables:**
  Capability (C): Derived from the RBV, this variable signifies the student's inherent capacity to effectively leverage AI tools for academic problem-solving and adaptation to new learning circumstances.

3.1.2 Hypotheses

Students would use and intend to use a technology more if they are optimistic that it will help enhance their performance or aid them in achieving their sought-after outcomes. Venkatesh et al. (2012) point out that Performance Expectancy is an important antecedent to behavioral intention in technology acceptance theories. In the context of AI tools in education, if students believe that the use of such tools will increase their learning outcomes or effectiveness, they are more likely to use them (Zawacki-Richter et al., 2019) Therefore we hypothesize:

H1: Performance Expectancy (PE) will positively influence Behavioral Intention (BI) to use AI tools.

Subjective ease of technology use significantly impacts someone's intention to utilize it (Venkatesh et al., 2003). If students view AI tools as simple to work with and operate, they will be more likely to form a positive attitude towards their continued utilization in their learning process. This is consistent with the belief that easy interfaces and minimal perceived effort drive technology take-up (Krumsvik, 2023; Poquet & de Laat, 2021). Therefore, we hypothesize:

H2: Effort Expectancy (EE) will positively affect Behavioral Intention (BI) to use AI tools.

Social influence by peers, teachers, or significant others is a determinant to generate the intention to employ a new technology (Venkatesh et al., 2003). Students are likely to generate an intention to employ AI tools if they observe their peers or are encouraged by their teachers to do so. Khalil & Er (2023) highlight the significance of a harmonious learning environment in ensuring the effective application of AI technologies. Therefore, we hypothesize:

H3: Social Influence (SI) will positively influence Behavioral Intention (BI) in using AI tools.

Availability of resources and technical support (facilitating conditions) is fundamental for technology adoption and usage in the future (Venkatesh et al., 2003). If students have access to the necessary infrastructure, training, and support systems for AI tools, their future use of the tools will be more likely. Li et al. (2024) highlights the importance of proper infrastructure and support systems for successful integration of AI in education. Therefore, we hypothesize:

H4: Facilitating Conditions (FC) will have a positive impact on Behavioral Intention (BI) to employ AI tools.

One has a strong and direct association between intended use of a technology and actual technology use (Venkatesh et al., 2003). When students are going to use AI tools for learning activities, they will highly likely turn that intention into use. Therefore, we hypothesize:

H5: Behavioral Intention (BI) positively affects Use Behavior (UB) of AI tools.

The use of AI tools in actual life and continuous educational activities is expected to result in improved academic performance. This hypothesis suggests that the benefit of AI tools' usage, for example, improved learning experience and operating efficiency, will translate into improved grades and continuous skill advancement. Therefore, we hypothesize:

H6: Use Behavior (UB) of Artificial Intelligence tools will positively influence Academic Performance (AP).

Drawing on the Resource-Based View (RBV), this hypothesis presumes that perceived value and utility of AI tools as accessible resources to make decisions and accomplish work will have a positive influence on academic performance (Wernerfelt, 1984; Barney, 1991). As students are able to employ AI tools as valuable resources, it contributes to their academic success. Therefore, we hypothesize:

H7: Resource (R) will positively impact Academic Performance (AP).

Also derived from the RBV, this hypothesis suggests that a student's inherent capacity to effectively leverage AI tools for academic problem-solving and adaptation to new learning circumstances will positively influence their academic performance (Wernerfelt, 1984; Barney, 1991). Students with higher capability in utilizing AI are expected to achieve better academic results. Therefore, we hypothesize:

H8: Capability (C) will positively influence Academic Performance (AP).

This hypothesis posits a moderating effect, wherein the concurrent occurrence of a student's ability to use AI tools and availability of AI tools as helpful resources will have a synergistic impact that further enhances academic achievement. The resources' quality is generally improved by the users' ability to utilize them. Therefore, we hypothesize:

H9: Capability (C) will positively moderate the relathionship between Resource (R) and influence Academic Performance (AP).

Since AI tools can personalize learning material, respond to personal needs, and provide individualized feedback, learners will interact with such tools more frequently and for a longer duration. Perceived usefulness of AI in providing a personalized learning experience can directly encourage its use (Luckin et al., 2016; Özer, 2024). Personalized learning encourages students to be more motivated and well-supported, leading to improved accomplishments. Therefore, we hypothesize:

H10a: Personalized Learning Experience (PLE) will positively influence Use Behavior (UB) of AI tools.

H10b: Personalized Learning Experience (PLE) will positively influence Academic Performance (AP).

Intrinsically motivated students who want to pursue course content and explore deeper subjects, especially with the help of AI resources, are most likely to achieve their learning outcomes and demonstrate better academic performance. Higher motivation is one of the most significant predictors for successful learning outcomes (Cook & Artino Jr, 2016). Therefore, we hypothesize:

H11: Learning Motivation (LM) will have a positive effect on Academic Performance (AP).

3.1.3 DATA COLLECTION

Quantitative method approach will be employed, incorporating quantitative data (student grades, usage metrics, survey responses) to provide a comprehensive understanding of the impact of AI tools on student grades in diverse educational contexts. This method will enable a detailed analysis of the mediating functions of perceived task of use and intention to utilize AI tools in the connection between student perceptions, real AI usage, and academic results.

Sample:

The participants in this study will include students from different educational establishments throughout Macedonia, covering both secondary and post-secondary education levels. In the sample there were 200 participants joined the research. This demographic has been selected to ensure a varied representation of students who are actively using AI tools in their learning experiences. By incorporating students from various backgrounds, academic fields, and varying levels of digital proficiency, the study seeks to gain a thorough insight into how AI technologies, like ChatGPT, affect learning outcomes within the Macedonian setting.
The selection procedure will utilize stratified sampling to guarantee that different factors, including age, gender, and academic discipline, are properly represented. This method will enable a more detailed examination of the data, permitting the investigation of possible

variations in perceptions and utilization of AI tools across diverse student groups. Questionnaires will be disseminated to collect quantitative insights on students' experiences with AI tools, their views on these technologies, and their academic outcomes. The study targets a group of Macedonian students to offer insights pertinent to the local educational environment and also adds to the wider conversation about the incorporation of AI in education. Descriptive statistics regarding the attributes of the respondents has attached in the Table 1

Table 1 - Statistics regarding the attributes of the respondents.

Measure	Value	Frequency	%
AGE	18-22	62	30.8%
	23-27	76	37.8%
	28-32	27	13.4%
	33-40	19	9.5%
	41-50	12	6.0%
	51 or over	4	2.0%
	Don't Know / Prefer not to answer	1	0.5%
GENDER	Male	88	43.8%
	Female	107	53.2%
	Don't Know / Prefer not to answer	6	3.0%
EDUCATION	High school degree	58	28.9%
	Bachelor degree	94	46.8%
	Master or Postgraduate degree	40	19.9%
	Doctorate degree	4	2.0%
	Don't Know / Prefer not to answer	5	2.4%

The common method bias was also examined using the Harman's single factor test (Podsakoff et al., 2003) and Random dependent variable regression (Lindell & Whitney, 2001) confirming no significant common method bias in the data.

4. RESULTS

4.1 Data Analysis and Results

Structural Equation Modeling (SEM) is an advanced statistical method that allows researchers to explore intricate relationships between observed and latent variables by concurrently assessing multiple dependent and independent variables. This approach offers a thorough framework for evaluating theoretical models while considering measurement error, establishing SEM as a vital tool in fields such as social sciences, marketing, and behavioral research (Fan, Y., et al., 2016). The model was tested with the partial least square (PLS), with Smart PLS software (Hair, J.F., Hult, G., et al., 2017). The technique used for the analysis is the most convenient technique for the difficult and complex models. Analysis of the sample data has been done with the two steps, namely: (i) measurement to assess the reliability and validity of the measures and (ii) structural hypothesis testing to assess the structural relationships of the model, according to the Anderson and Gerbings (1988) guidelines.

4.1.1 Measurement Model

For the measurement model we tested the items reliability – loadings, internal consistency - composite reliability, Cronbach's Alpha, construct reliability and validity, convergent validity - Average variance extracted as shown in Table 2. In detail, for all the constructs Cronbach's Alpha is greater than 0.7 and have composite reliability. According to the (Churchill, G.A., 1979) the evaluation of the reliability should be more than 0.7. Therefore, C4 and UB1-D is removed from the model as they were less than 0.7. In order to ensure the items reliability, those two items needed to be removed. The rest of the loadings left as it is as they are higher than 0.7 and they indicate good reliability of the instruments. The test of convergent validity was done analysing if the AVE value is higher than 0.5. (Fornell & Larcker, 1981) as seen in Table 2 confirming the convergent validity.

Table 2 Quality criteria and factor loadings.

Construct	AVE	Composite reliability (rho_a)	Cronbach's alpha	Item	Loadings	t-value
Performance Expectancy (PE)	0.776	0.855	0.855	**PE1**	0.894	43.201
				PE2	0.904	49.960
				PE3	0.842	29.188
Effort Expectancy (EE)	0.728	0.829	0.813	**EE1**	0.863	30.494
				EE2	0.802	17.894
				EE3	0.891	50.806
Social Influence (SI)	0.653	0.75	0.733	**SI1**	0.849	31.809
				SI2	0.851	26.794
				SI3	0.717	11.492
Facilitating Conditions (FC)	0.675	0.76	0.758	**FC1**	0.795	20.691
				FC2	0.851	33.507
				FC3	0.817	23.789
Behavioral Intention (BI)	0.75	0.834	0.833	**BI1**	0.837	29.812
				BI2	0.874	38.720
				BI3	0.886	42.504
Use Behavior (UB)	0.603	0.876	0.869	**UB1-A**	0.796	26.656
				UB1-B	0.756	17.012
				UB1-C	0.789	21.719
				UB1-E	0.744	18.200
				UB2	0.777	24.597
				UB3	0.796	22.474
Academic Performance (AP)	0.677	0.773	0.76	**AP1**	0.859	37.834
				AP2	0.852	36.597
				AP3	0.752	17.699
Capability (C)	0.64	0.734	0.721	**C1**	0.825	27.852
				C2	0.755	14.852
				C3	0.818	20.142
Resource (R)	0.661	0.746	0.744	**R1**	0.816	23.594
				R2	0.825	23.877
				R3	0.797	18.559
Personalized Learning Experience (PLR)	0.662	0.749	0.744	**PLR1**	0.839	34.989
				PLR2	0.846	30.606
				PLR3	0.754	17.529
Learning Motivation (LM)	0.699	0.801	0.785	**LM3**	1	n/a

Discriminant validity was assessed using three measures, namely (i) Farnell-Larcker, (ii) Cross-loadings, and (iii) HTMT - heterotrait-monotrait ratio of correlations. For the Farnell-Larcker criterion test, the square root of AVE, in bold in the Table 3, confirmed that it exceeds the correlation between the constructs (Fornell & Larcker, 1981).

Table 3 Fornell Larcker criterion

Mean	AP	BI	C	EE	FC	LM	PE	PLR	R	SI	UB
AP	**0.822**										
BI	0.642	**0.866**									
C	0.496	0.445	**0.8**								
EE	0.38	0.573	0.47	**0.853**							
FC	0.432	0.607	0.461	0.657	**0.821**						
LM	0.678	0.616	0.525	0.448	0.44	**0.836**					
PE	0.409	0.595	0.378	0.743	0.555	0.445	**0.881**				
PLR	0.66	0.61	0.477	0.498	0.488	0.743	0.486	**0.814**			
R	0.642	0.56	0.543	0.379	0.435	0.658	0.435	0.613	**0.813**		
SI	0.484	0.506	0.261	0.42	0.444	0.402	0.487	0.415	0.409	**0.808**	
UB	0.657	0.476	0.388	0.261	0.322	0.454	0.258	0.43	0.523	0.44	**0.777**

Note: Square root of AVE and correlations between the constructs in the diagonal, highlighted in bold

For the cross-loading assess every item exhibits a greater loading on its respective factor compared to the cross-loadings on other factors. (Götz, O., 2009)), as presented in Appendix A. For the assessment of heterotrait-monotrait ratio, as presented in the Appendix D,the Personalized Learning Experience and Learning Motivation have failed the test and therefore two items have been removed, namely LM1 and LM2, according to the Henseler, et al., (2015) recommendations. The results of the measurement model demonstrate that the model possesses strong construct reliability, indicator reliability, convergent validity, and discriminant validity, confirming that the constructs are statistically distinct and suitable for testing the structural model.

4.1.2 Structural Model and Hypothesis Testing

The assessment of the structural model and testing the hypothesis has been based on the examination of standardized path. Significant levels of this path are estimated by using the bootstrapping method with 5000 iteration subsamples (Henseler, et al., 2015). We started with a collinearity testing analysing if all VIF are below the threshold of 5 (Kock & Lynn, 2012), as seen in Appendix C. The work main results are presented in the Figure 2, as follow. The model explains a variation in Behavior Intention of R^2 = 0.498, in Use behavior of R^2 = 0.258 and in Academic Performance of R^2 = 0.641.

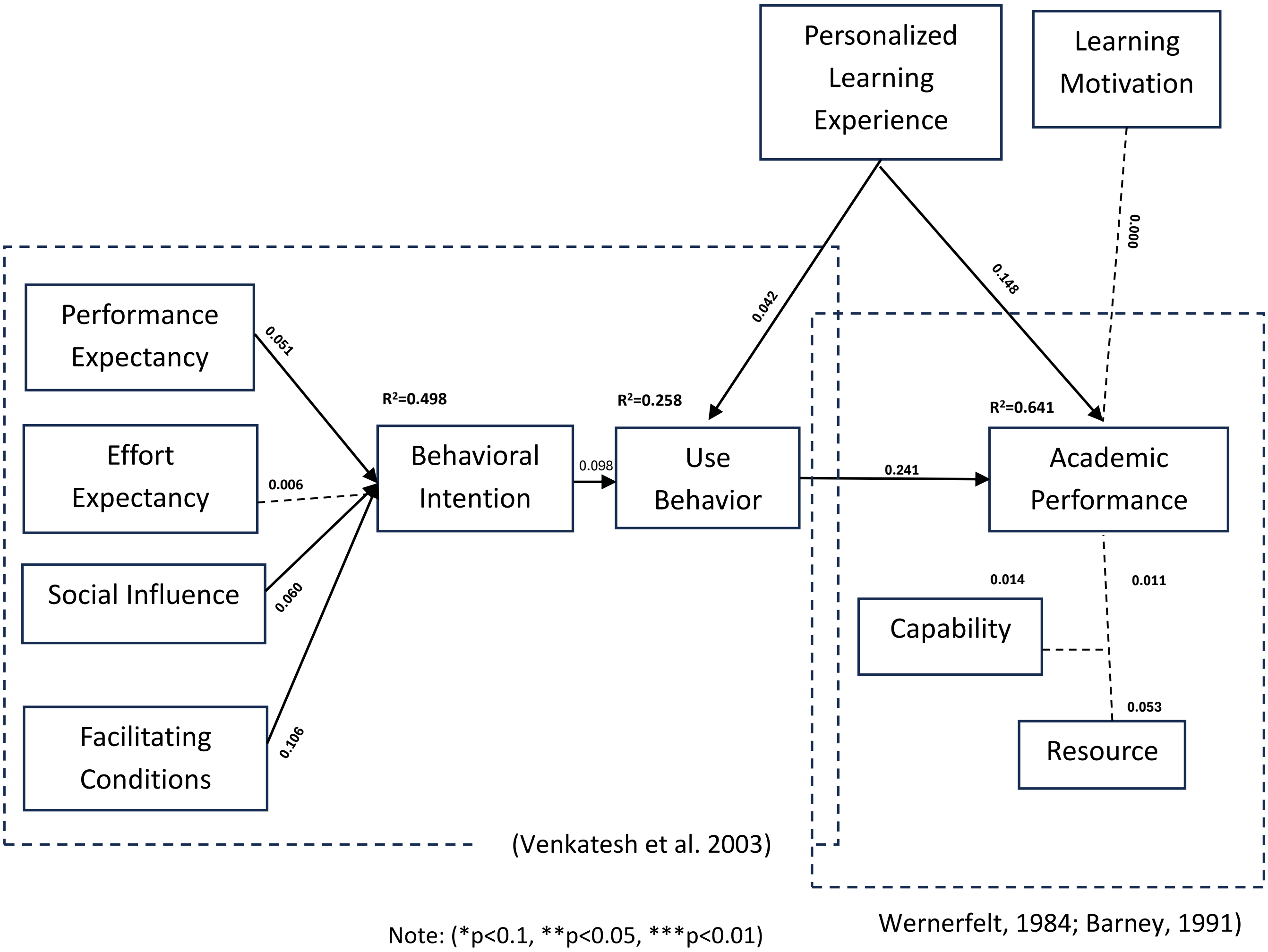

Figure 2 Structural model results.

Performance Expectancy, Social Influence and Facilitating Condition are found to be statistically significant in explaining Behavior Intention in the same way Behavior Intention over Use Behavior and Academic Performance, thus supporting hypothesis H1, H3, H4, H5 and H6. However, Effort Expectancy is proven not statistically significant to support the hypothesis H2. The effect of Resource on Academic Performance is statistically significant that supports hypothesis H7 meanwhile effect of Capability and moderator effect of Capability and Resource are not statistically significant that doesn't support hypothesis H8 and H9. Nevertheless, effect of Personalized Learning Experience on Use Behavior and Academic Performance are statistically significant and supports H10a and H10b whereas the effect of Learning Motivation on Academic Performance is not statistically significant that doesn't support H11.

All in all, out of 11 hypotheses 8 of them are proven statistically significant and 4 of them not statistically significant (see **Table 4**).

Table 4 Hypotheses Testing

Hypotheses	f-square	P values	Results
H1: PE -> BI	0.051	0.008	Supported
H2: EE -> BI	0.006	0.416	Not supported
H3: SI -> BI	0.060	0.007	Supported
H4: FC -> BI	0.106	0.010	Supported
H5: BI -> UB	0.098	0.000	Supported
H6: UB -> AP	0.241	0.000	Supported
H7:R -> AP	0.053	0.015	Supported
H8: C -> AP	0.014	0.208	Not supported
H9: C x R -> AP	0.011	0.178	Not supported
H10a: PLR -> UB	0.042	0.006	Supported
H10b: PLR -> AP	0.148	0.000	Supported
H11: LM -> AP	0.000	0.839	Not supported

Hypotheses statistically supported 8

Hypotheses not supported 4

4.2 DISCUSSION

The integration of AI tools like ChatGPT in educational settings has sparked a transformative shift in teaching and learning methodologies. This research highlights not only the potential benefits of these technologies but also the complexities and challenges they introduce. The theoretical model of this research indicated below is unique, combining theory of acceptance and use of technology (UTAUT), of Venkatesh et al., (2003), with Resource based view (RBV) of Wernerfelt (1984) and Barney (1991) explaining the impact of ChatGPT and related AI tools in education.

4.2.1 MAIN FINDINGS

The main finding of this study is that Performance Expectancy (PE), Social Influence (SI) and Facilitating Conditions (FC) significantly influences the Behavioral Intention (BI) to use AI tools, which in return affects Use Behavior (UB) and Academic Performance (AP). Students who perceive and view AI tools as beneficial together with the encouragement from their peers and teachers are more into using those technologies, that concludes better academic results. The findings of the study indicate educational institutions needs to focus on enhancing student's view on the utility of AI tools create a nurturing atmosphere to boost their adoption and efficiency (Zawacki-Richter et al., 2019). The model's explanatory power is demonstrated by R^2 the values: it explains 49.8% of the variance in Behavioral Intention (R^2= 0.498), 25.8% of the variance in Use Behavior (R^2= 0.258), and a substantial 64.1% of the variance in Academic Performance (R^2= 0.641). Since there are no direct comparative data available from comparable studies, it is not possible to make a definite statement on equivalence.

Additionally, the research indicated that Facilitating Conditions, including availability of resources and support, significantly influence students' intentions to utilize AI tools. This discovery highlights the importance of educational organizations to ensure sufficient infrastructure and support mechanisms that enable the successful incorporation of AI technologies into the educational experience (Li et al., 2024). Another significant finding from this study is the increase in student engagement due to the application of AI tools. Studies show that AI-driven personalized learning experiences can enhance student motivation and engagement (Luckin et al., 2016). AI's capability to adjust to personal learning styles and speeds enables a more customized educational experience, potentially enhancing learning results significantly. AI-powered platforms can offer instant feedback and modify task difficulty according to student performance, making sure that learners are challenged but not overwhelmed (Özer, 2024). This corresponds with the results of Holmes et al., (2021), who contend that AI can create a more interactive and successful educational atmosphere by catering to various learner requirements.

4.2.2 OTHER SUPPORTED FINDINGS

Supported findings in line with the H1 is regarding the relationships between various factors and student performance.

The strong positive correlation between Performance Expectancy and Behavioral Intention **(H1)** ($\hat{\beta}$=0.051, p=0.008) indicates that students with the expectation that AI tools would improve their learning performance would be inclined to use AI tools. This finding is consistent with previous literature that cites perceived usefulness as one of the most important determinants of technology adoption, according to Venkatesh et al. (2003) in their influential paper on the Technology Acceptance Model (TAM) and extensions. Our results confirm that if students can see tangible academic benefits of AI tools, they plan to use them extensively.

Social Influence (SI) positively influences Behavioral Intention (BI) in using AI tools **(H3).** The significant and positive influence of Social Influence on Behavioral Intention ($\hat{\beta}$=0.060, p=0.007) supports the requirement of a motivating learning environment. When educators, peers, or other influential individuals encourage the use of AI tools, students are likely to create an intention towards using AI tools. This is consistent with the social influence construct of UTAUT (Venkatesh et al., 2003) and is also consonant with Khalil & Er (2023), who also emphasize the significance of a peaceful learning environment towards fruitful use of AI. Krumsvik (2023) also emphasizes the role of social context in the adoption of technology in educational settings.

Facilitating Conditions (FC) positively affect Behavioral Intention (BI) to employ AI tools **(H4).** Our findings show that Facilitating Conditions have strong and positive effects on Behavioral Intention ($\hat{\beta}$=0.106, p=0.010). This signifies that availability of necessary resources and technical support is significant for students' willingness to utilize AI tools. This result is consistent with the UTAUT model (Venkatesh et al., 2003) and is strongly supported by Li et al. (2024), who highlight the importance of adequate infrastructure and support mechanisms in the successful deployment of AI in education. Without adequate resources and support, even willing students can be brought back from adopting.

Behavioral Intention (BI) positively affects Use Behavior (UB) of AI tools **(H5).** There is a clear and strong association between Behavioral Intention and Use Behavior ($\hat{\beta}$= 0.098, p=0.000) is a general assumption of technology adoption models, e.g., UTAUT (Venkatesh et al., 2003). The present study affirms that if students have the intention to employ AI tools on learning activities, they are highly likely to translate such intention into action. Such a finding is common in most technology adoption research, confirming the explanatory power of behavioral intention on system adoption.

Artificial Intelligence tool Use Behavior (UB) positively impacts Academic Performance (AP) as mentioned in **(H6).** The strong positive impact of Use Behavior on Academic Performance ($\hat{\beta}$= 0.241, p=0.000)implies that the actual and persistent use of AI tools in educational activities leads to higher scholarly performance. This is in alignment with the hypothesis that the benefits derived from AI tool usage, such as higher grades of learning experiences and effectiveness of operations, will be augmented by higher grades and continuous skill acquisition. This finding aligns with the broader education technology literature, where productive tool use is linked to higher learning outcomes (Luckin et al., 2016; Özer, 2024).

Personalized Learning Experience (PLE) will positively influence Use Behavior (UB) of AI tools **(H10a).** Strong positive influence of Personalized Learning Experience on Use Behavior ($\hat{\beta}$= 0.042, p=0.006) indicates that whenever AI software can effectively learn material and provide personalized feedback, learners interact with them more frequently and for longer durations. This finding is consistent with the literature examining direct motivation of AI usage through perceived usefulness in the provision of customized learning (Luckin et al., 2016; Özer, 2024). Personalized Learning Experience (PLE) will positively influence Academic Performance (AP) **(H10b).** The high positive influence of PLE on AP ($\hat{\beta}$= 0.148, p=0.000) suggests that the possibility of AI in providing tailored learning experiences, according to students' practices and paces, reflects a direct influence on academic outcomes. This statement is also supported by Luckin et al. (2016) and Özer (2024), emphasizing that learning personalized supports greater motivation and help, which leads to improved achievements.

Resource (R) will positively affect Academic Performance (AP)**(H7)**. The statistically significant and positive effect of Resource on Academic Performance($\hat{\beta}$= 0.053, p=0.015) is supportive of the Resource-Based View (RBV) in the academic environment. It is that if the students are able to utilize AI tools as useful and available resources to aid decision-making and task fulfillment, this positively sums up to their educational success. This is according to the primary tenets of

RBV (Wernerfelt, 1984; Barney, 1991), which contends that valuable resources can lead to competitive advantage, in this context interpreted as improved scholastic performance.

4.2.3 ADDITIONAL FINDINGS

The research uncovered a few unexpected outcomes regarding hypotheses that were not statistically supported.

Effort Expectancy (EE) contrary to expectation, was not found to be statistically significant as a predictor of Behavioral Intention ($\hat{\beta}$= 0.006, p=0.416) **(H2).** This is in contrast to the usual assumption of UTAUT (Venkatesh et al., 2003), which is that perceived ease of use has a direct impact on intention. Even though earlier studies by Krumsvik (2023) and Poquet & de Laat (2021) suggest that simplicity of the interface results in adoption of technology, our finding indicates that in this specific AI tool learning environment, perceived ease of use may possibly not be one of the causes of intention not to use. This could imply that students will be willing to struggle with usability problems initially if they perceive other advantages (like performance expectancy) as high, or that the tools are sufficiently user-friendly already that effort is not a barrier. This finding implies a need for further research into what specifically motivates AI tool adoption in teaching beyond mere usability.

Capability had a weak association with Academic Performance ($\hat{\beta}$= 0.014, p=0.208) **(H8)**. This is a counterintuitive finding, as the Resource-Based View (RBV) would suggest that a student's natural capability to operate AI tools would have a direct impact on academic accomplishment. This finding might be understood to indicate that while individual capacity is important, its direct influence on academic success could be moderated by other unmeasured factors, or that measurement of "capability" against currently used AI tools is not yet sufficiently discriminative. It can also mean that the presence of capability is not enough to guarantee improved performance unless optimized or fitted.

The interaction effect between Capability and Resource on Academic Performance was not significant ($\hat{\beta}$= 0.011, p=0.178) **(H9)**. This contradicts our hypothesis that the synergistic effect of a student's capability to take advantage of AI tools and how readily these tools are available as helpful resources would enhance academic performance even more. While the RBV assumes that resource quality is improved by their usability by users, our findings do not provide a strong moderating effect. This could imply that capability and resource effects are additive rather than synergistic, or that the interaction is more contingent and subject to other contextual factors. This surprising outcome calls for a closer examination of how student ability and availability of resources together influence academic performance in AI-enhanced learning environments.

The impact of Learning Motivation on Academic Performance was statistically non-significant ($\hat{\beta}$= 0.000, p=0.839) **(H11)**. The finding is contrary to expectations because intrinsic motivation is typically seen as a key predictor of successful learning outcomes (Cook & Artino Jr, 2016). This outcome can generate the conclusion that while learning is aided by AI tools, the overall learning motivation and performance can be affected by intervening variables in the case of AI integration, or that the measurement of learning motivation in this study did not do justice to its complexity regarding AI-aided learning. It could also indicate that AI software might not always make students more motivated in a way that is directly equatable to measurable academic achievement in all students. Further research is needed to explore the complex interaction between AI tool use, motivation to learn, and academic performance. Lastly, in line with earlier studies of (Sullivan et al., 2023; Zeb et al., 2024) the ethical considerations regarding academic honesty and the risk of abusing AI tools, like plagiarism, are significant issues that educational institutions need to confront in order to promote a culture of integrity while utilizing the advantages of AI technologies.

4.2.4 IMPLICATIONS FOR RESEARCH AND PRACTICE

This study enhances the comprehension of social influence by demonstrating that a supportive environment can boost interaction with AI tools, indicating that educational institutions ought to promote collaborative learning settings to optimize the advantages of technology. The research also questions current theories, especially those concerning effort expectancy. Unexpectedly, the study revealed that effort expectancy did not have a significant relationship with student grades, questioning the belief that perceived ease of use directly affects technology adoption and participation. This difference might arise from the difficulty of incorporating AI tools into current curricula, where students could encounter obstacles that are linked not only to the technology but also to the teaching methods used by instructors. This suggests a necessity for additional investigation into how teaching methods can adjust to promote easier incorporation of AI technologies. Additionally, the study emphasizes the significance of enabling factors, like resource availability and assistance, in affecting students' intentions to utilize AI tools. This result corresponds with Li et al., (2024), who highlighted the importance of sufficient infrastructure for effective technology integration. The findings indicate that technology adoption theories in education ought to consider a wider array of contextual elements, such as institutional backing and resource accessibility, to achieve a more thorough comprehension of how AI tools can be effectively applied in educational environments. The consequences for practical application are significant. The results highlight the necessity for educational establishments to foster environments that promote the utilization of AI tools. This involves offering training for teachers on how to successfully incorporate AI into their instructional methods and making certain that students have access to the essential resources. Organizations ought to think about creating professional development initiatives centered around the educational effects of AI tools, empowering teachers with the abilities to utilize these technologies to improve student learning results. Additionally, the study highlights significant ethical concerns about academic honesty and the likelihood of misusing AI tools, including plagiarism. This matches the worries expressed by

Sullivan et al., (2023) regarding the effects of AI on academic integrity. Educational institutions need to create defined policies and guidelines for the utilization of AI tools, fostering a culture of integrity while leveraging the advantages of technology. This involves establishing efficient plagiarism detection tools and promoting conversations on ethical usage with students. Alongside these theoretical and practical implications, the study presents various applicable strategies that educators and institutions might adopt. By acknowledging the significance of performance expectancy and social influence, schools can create focused interventions that improve students' views on AI tools. This might include highlighting effective case studies of AI implementation in educational settings or offering avenues for peer-to-peer learning where students can exchange their favorable experiences with AI resources. Additionally, the results indicate that organizations ought to focus on creating accessible AI tools that reduce entry obstacles for students and teachers alike. By streamlining the user experience, institutions can promote increased adoption and use of AI tools, which will ultimately enhance educational results.

4.2.5 Limitations and Future Research

There are several limitations that needs to be acknowledged that may affect the generalization and reliability of our results. The findings' applicability is constrained by the particular setting in which the research took place. The study centered on a group of students from diverse educational establishments in Macedonia, which might not represent the experiences of students in other geographical or cultural contexts. Additional studies are necessary to determine the relevance of these findings in various educational environments, encompassing both urban and rural areas, in addition to different nations or regions. Subsequent research ought to focus on replicating this investigation into diverse cultural and educational settings to improve the applicability of the results.

The reliability of our results is influenced by the self-reported aspect of the survey employed to collect data. Participants might have given answers that were socially acceptable or may not have genuinely portrayed their encounters with AI tools. To enhance reliability, upcoming research should consider employing mixed methods, integrating quantitative surveys with qualitative interviews or focus groups. This method would enable researchers to obtain a more profound understanding of students' experiences and perceptions, thus improving the validity of the data gathered. Owing to insufficient data regarding the long-term impacts of using AI tools on academic performance and student involvement, the findings cannot validate the durability of the noted advantages. Additional studies are necessary to determine the lasting effects of AI tool integration on educational results. Longitudinal research must be performed to evaluate the impact of AI tools on student performance and engagement over time, offering a more accurate understanding of the enduring effects of these technologies. The available resources and time constraints limited the methodological options. The research utilized a quantitative method, which, although useful for assessing connections between variables, might not fully reflect the intricate nature of students' engagement with AI tools. Future research should consider the possible advantages of qualitative methods, like case studies or ethnographic research, to offer a deeper insight into how students and educators manage the challenges and opportunities posed by AI technologies. This may involve examining particular case studies of effective AI implementation in classrooms to better determine best practices. This study does not aim to thoroughly examine the ethical implications associated with the use of AI tools. Additional studies are required to develop thorough ethical standards for implementing AI tools in educational environments. Future research must examine the ethical aspects of AI incorporation, focusing on creating frameworks that encourage responsible usage and tackle issues concerning privacy, bias, and academic integrity.

5. CONCLUSION

In conclusion, a thorough investigation of the influence of ChatGPT and similar artificial intelligence (AI) tools within education was done, highlighting their transformative capabilities and the intricate challenges they bring to teaching and learning practices. The primary contributions of this research encompass an in-depth examination of how AI technologies can improve customized learning experiences, increase student involvement, and simplify administrative duties for teachers. The research findings indicate that crucial elements like performance expectancy, social influence, and facilitating conditions greatly impact students' intentions to utilize AI tools, subsequently influencing their academic performance. The research showed that students who view AI tools positively and obtain assistance from peers and teachers are more inclined to use these technologies, resulting in enhanced learning results. This highlights the significance of cultivating a nurturing educational atmosphere that promotes the efficient use of AI tools. The core of the findings of the research reveal that Academic Performance (AP) is highly influenced by many noteworthy factors involved in AI tool usage and implementation. That is, students' Behavioral Intention (BI) to use AI tools depending on their Performance Expectancy, Social Influence, and Facilitating Conditions positively leads to higher Use Behavior (UB), which contributes significantly to Academic Performance (AP). One key and distinctive outcome is the substantial positive impact of a Personalized Learning Experience (PLE) enabled by AI tools on Use Behavior (UB) as well as directly on Academic Performance (AP), validating AI's capability to personalize content and feedback for improved academic performance. Perceived value of AI tools as accessible Resources (R) also contributes positively to Academic Performance (AP). Interestingly, Effort Expectancy did not significantly predict Behavioral Intention, suggesting that ease of use perceptions are less relevant than other factors to influencing AI tool adoption here, and neither Capability (C) (or its interaction with Resource) nor Learning Motivation (LM) had a statistically significant direct impact on Academic Performance (AP). This master review confirms that constructing positive attitudes, providing favorable conditions, and employing AI to facilitate individualized learning are among the most important ways of enhancing the academic achievements of students through integrating AI tools.

Educational Institutions must adapt teaching methods for them to use AI technologies, providing teachers with necessary resources and capacity building. This involves developing collaborative learning environments that utilize AI to provide adaptive support and developing policies to address ethical concerns like academic integrity and data protection. Encouraging regular dialogue among policymakers, educators, and technologists should help develop standards that ensure responsible and accessible AI use to enhance learning outcomes for all students. This collaborative effort is necessary to navigate the trajectory of AI in education amidst the shifting landscape, and make technological advances work equally for learners and teachers. By acting on both potential and challenge at the right time, institutions will be able to prepare students better for the technology-driven world ahead. All in all, the effective incorporation of AI technologies such as ChatGPT in education offers the potential to revolutionize conventional learning models, enhance student involvement, and elevate educational results for varied groups of learners. As we progress, it is essential for educators, researchers, and policymakers to collaborate effectively to utilize AI's potential in an ethical, inclusive way that supports the overall development of students. This joint endeavor will enhance the educational environment and enable future generations to succeed in a progressively digital society.

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APPENDIX A. CROSS-LOADINGS

	AP	BI	C	EE	FC	LM	PE	PLE	R	SI	UB	
AP1	**0.86**	0.614	0.383	0.37	0.425	0.613	0.385	0.599	0.575	0.391	0.596	0.197
AP2	**0.853**	0.498	0.408	0.224	0.296	0.58	0.292	0.563	0.546	0.405	0.556	0.17
AP3	**0.75**	0.463	0.445	0.349	0.343	0.467	0.331	0.454	0.455	0.403	0.458	0.213
BI1	0.504	**0.837**	0.487	0.594	0.59	0.581	0.595	0.533	0.511	0.376	0.345	0.024
BI2	0.558	**0.874**	0.332	0.428	0.5	0.495	0.482	0.506	0.466	0.464	0.412	0.1
BI3	0.605	**0.886**	0.336	0.465	0.487	0.521	0.468	0.545	0.477	0.475	0.48	0.165
C1	0.421	0.469	**0.825**	0.439	0.522	0.478	0.42	0.437	0.448	0.24	0.292	0.103
C2	0.322	0.297	**0.755**	0.351	0.303	0.411	0.252	0.362	0.36	0.131	0.248	0.061
C3	0.433	0.294	**0.818**	0.338	0.273	0.374	0.229	0.347	0.482	0.239	0.378	-0.027
EE1	0.271	0.454	0.42	**0.863**	0.549	0.347	0.643	0.414	0.281	0.267	0.135	0.046
EE2	0.326	0.441	0.402	**0.802**	0.517	0.444	0.6	0.395	0.361	0.395	0.274	-0.041
EE3	0.368	0.559	0.388	**0.891**	0.609	0.364	0.657	0.461	0.329	0.407	0.254	0.005
FC1	0.268	0.482	0.346	0.531	**0.795**	0.349	0.487	0.422	0.326	0.296	0.167	0.121
FC2	0.411	0.508	0.419	0.617	**0.851**	0.407	0.458	0.452	0.361	0.416	0.292	0.118
FC3	0.381	0.506	0.37	0.472	**0.817**	0.329	0.424	0.328	0.384	0.378	0.329	0.142
LM1	0.588	0.55	0.47	0.42	0.433	**0.839**	0.447	0.666	0.561	0.353	0.333	0.127
LM2	0.625	0.537	0.411	0.298	0.32	**0.881**	0.352	0.582	0.563	0.393	0.443	0.113
LM3	0.472	0.449	0.442	0.424	0.357	**0.785**	0.311	0.627	0.527	0.246	0.358	0.02
PE1	0.352	0.508	0.363	0.659	0.515	0.379	**0.894**	0.418	0.377	0.429	0.272	-0.025
PE2	0.299	0.507	0.303	0.693	0.531	0.347	**0.904**	0.376	0.369	0.397	0.183	-0.039
PE3	0.422	0.552	0.331	0.611	0.423	0.444	**0.842**	0.482	0.398	0.456	0.226	-0.018
PLR1	0.595	0.552	0.403	0.415	0.417	0.617	0.428	**0.839**	0.55	0.342	0.345	0.154
PLR2	0.546	0.504	0.388	0.392	0.398	0.675	0.433	**0.846**	0.501	0.353	0.331	0.162
PLR3	0.463	0.426	0.373	0.411	0.374	0.518	0.319	**0.754**	0.44	0.318	0.378	0.1
R1	0.553	0.535	0.56	0.388	0.402	0.598	0.421	0.508	**0.816**	0.376	0.401	0.082
R2	0.519	0.433	0.423	0.275	0.366	0.571	0.351	0.534	**0.825**	0.292	0.428	0.078
R3	0.491	0.39	0.329	0.253	0.287	0.427	0.28	0.451	**0.797**	0.326	0.451	0.031
SI1	0.419	0.471	0.238	0.357	0.351	0.384	0.43	0.34	0.37	**0.849**	0.358	0.114
SI2	0.395	0.377	0.157	0.338	0.353	0.321	0.378	0.302	0.34	**0.851**	0.353	0.215
SI3	0.353	0.364	0.234	0.321	0.376	0.255	0.366	0.367	0.273	**0.717**	0.36	0.21
UB1-A	0.525	0.415	0.335	0.314	0.306	0.33	0.311	0.332	0.415	0.439	**0.796**	0.195
UB1-B	0.456	0.338	0.306	0.215	0.276	0.342	0.161	0.306	0.332	0.217	**0.756**	0.218
UB1-C	0.494	0.233	0.284	0.079	0.168	0.264	0.072	0.259	0.326	0.348	**0.789**	0.194
UB1-E	0.457	0.256	0.287	0.086	0.158	0.273	0.066	0.284	0.379	0.31	**0.744**	0.219
UB2	0.57	0.513	0.317	0.302	0.34	0.476	0.335	0.429	0.508	0.332	**0.777**	0.147
UB3	0.534	0.396	0.274	0.163	0.213	0.381	0.184	0.356	0.435	0.386	**0.796**	0.178

APPENDIX B. SURVEY QUESTIONS

Constructs	Item	#	Sources
Performance Expectancy	*Using ChatGPT and AI tools in my educational activities increases my chances of achieving things that are important to me	PE1	(Venkatesh et al., 2003)
	*Using ChatGPT and AI tools in my educationa l activities helps me accomplish things more quickly	PE2	
	*Using ChatGPT and AI tools in my educational activities enhances my overall learning productivity.	PE3	
Effort Expectancy	*Learning how to use ChatGPT and AI tools in my educational activities is easy for me.	EE1	(Venkatesh et al., 2003)
	*My interaction with ChatGPT and AI tools in my educational activities is clear and understandable	EE2	
	*I find ChatGPT and other AI tools easy to use in my educational activities	EE3	
Social Influence	*People who influence my behavior think that I should use ChatGPT and AI tools in my educational activities	SI1	(Venkatesh et al., 2003)
	*People whose opinions I value prefer that I use ChatGPT and AI tools in my educational activities	SI2	
	*My friends and family encourage me to utilize ChatGPT and AI tools in my educational activities	SI3	
Facilitating Conditions	*I have the necessary resources to use ChatGPT and AI tools in my educational activities	FC1	(Venkatesh et al., 2003)
	*I have the knowledge necessary to use ChatGPT and AI tools in my educational activities	FC2	
	*I can get help from others when I have difficulties using ChatGPT and AI tools in my educational activities	FC3	
Behavioral Intention	*I intend to continue using ChatGPT and AI tools in my educational activities in the future	BI1	(Venkatesh et al., 2003)
	*I will always try to use ChatGPT and AI tools in my educational activities	BI2	
	*I plan to frequently use ChatGPT and AI tools in my educational activities	BI3	
Use Behavior	* Please choose your usage frequency for each of the following AI tools in your education: a) AI-based tutoring systems b) AI-driven research tools c) AI for content creation d) AI for language translation e) AI for data analysis	UB1	(Venkatesh et al., 2003)
	*How often do you use ChatGPT for educational purposes?	UB2	
	*How frequently do you access online learning resources using AI tools?	UB3	
Academic Performance	*I regularly use ChatGPT and AI tools to keep my competencies up to date	AP1	Charbonnier-Voirin, A., & Roussel, P. (2012)
	*I actively seek out the latest AI innovations in education to improve the way I study	AP2	
	*I prepare for change by participating in every educational project or assignment that enables me to do so	AP3	
Capability	*I can quickly decide on the best actions to take to resolve the academic problems or questions	C1	Charbonnier-Voirin, A., & Roussel, P. (2012)
	*I analyze the solutions and their ramifications quickly to select the most appropriate for my studies	C2	
	*I do not hesitate to go against established ideas to propose an innovative solution	C3	
	*I can easily reorganize my study to adapt to the new circumstances	C4	
Resource	*I use ChatGPT and related AI tools in situations where i am required to make many decisions	R1	Charbonnier-Voirin, A., & Roussel, P. (2012)
	*I feel at ease using ChatGPT and related AI tools even if my tasks change and occur at a very fast pace	R2	
	*I look for solutions by having ChatGPT and related AI tools in discussions with peers	R3	
Personalized Learning Experience	*How effectively do you feel that ChatGPT and AI tools address your individual learning needs in your educational setting?	PLE1	Madhani, P. M. (2010)
	*To what extent do you agree that the educational materials supported by ChatGPT and AI tools align with your personal interests and academic goals?	PLE2	
	*To what extent you agree that you receive personalized feedback that is specific to your learning progress and challenges?	PLE3	
Learning Motivation	*Do you feel motivated to engage with the course content with the support of ChatGPT and AI tools?	L1	Madhani, P. M. (2010)
	*Do you agree that the learning activities with the support of ChatGPT and AI tools encourage you to explore further?	L2	
	*To what extend you agree that you are confident in your ability to achieve your learning objectives with the support of ChatGPT and AI tools in your studies?	L3	

APPENDIX C. VIF TABLE

	VIF
AP1	1.695
AP2	1.708
AP3	1.372
BI1	1.677
BI2	2.142
BI3	2.207
C1	1.456
C2	1.403
C3	1.393
EE1	2.004
EE2	1.565
EE3	2.010
FC1	1.460
FC2	1.696
FC3	1.518
LM3	1.000
PE1	2.774
PE2	2.909
PE3	1.676
PLR1	1.602
PLR2	1.697
PLR3	1.331
R1	1.436
R2	1.548
R3	1.475
SI1	1.640
SI2	1.816
SI3	1.280
UB1-A	1.960
UB1-B	1.785
UB1-C	2.099
UB1-E	1.810
UB2	1.707
UB3	1.951
C x R	1.000

APPENDIX D. HTMT TABLE

	Heterotrait-monotrait ratio (HTMT)
BI <-> AP	0.802
C <-> AP	0.668
C <-> BI	0.569
EE <-> AP	0.483
EE <-> BI	0.689
EE <-> C	0.617
FC <-> AP	0.566
FC <-> BI	0.764
FC <-> C	0.617
FC <-> EE	0.834
LM <-> AP	0.54
LM <-> BI	0.492
LM <-> C	0.523
LM <-> EE	0.472
LM <-> FC	0.41
PE <-> AP	0.504
PE <-> BI	0.702
PE <-> C	0.477
PE <-> EE	0.891
PE <-> FC	0.692
PE <-> LM	0.334
PLR <-> AP	0.868
PLR <-> BI	0.772
PLR <-> C	0.651
PLR <-> EE	0.639
PLR <-> FC	0.649
PLR <-> LM	0.723
PLR <-> PE	0.603
R <-> AP	0.848
R <-> BI	0.707
R <-> C	0.725

	Heterotrait-monotrait ratio (HTMT)
R <-> EE	0.484
R <-> FC	0.575
R <-> LM	0.608
R <-> PE	0.539
R <-> PLR	0.82
SI <-> AP	0.65
SI <-> BI	0.64
SI <-> C	0.348
SI <-> EE	0.54
SI <-> FC	0.597
SI <-> LM	0.284
SI <-> PE	0.61
SI <-> PLR	0.565
SI <-> R	0.548
UB <-> AP	0.796
UB <-> BI	0.541
UB <-> C	0.481
UB <-> EE	0.302
UB <-> FC	0.385
UB <-> LM	0.378
UB <-> PE	0.282
UB <-> PLR	0.527
UB <-> R	0.641
UB <-> SI	0.549

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