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The Influence of ChatGPT on Students' Opportunistic Behavior and Reduced Effort

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Master Thesis

presented as partial requirement for obtaining the Master Degree in Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

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**THE INFLUENCE OF CHATGPT ON STUDENTS' OPPORTUNISTIC BEHAVIOR AND REDUCED
EFFORT**

by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Knowledge Management and Business 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 or 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.

Beatriz Guita Grilo

Lisbon, 2024

DEDICATION AND ACKNOWLEDGEMENTS

This dissertation would not have been possible without the endless support and encouragement of several important people in my life.

Firstly, I want to dedicate this dissertation to my parents, Elsa and Rui. Their unconditional love and belief in me have been the rock of my academic journey. They have consistently supported me through every challenge and obstacle, and provided me with the opportunities that have allowed me to reach this milestone. I am especially thankful for their support during these difficult years, as well as their constant faith and belief in my work.

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ABSTRACT

This study challenges the assumption that students become less invested in tasks once they achieve an average grade using AI tools like ChatGPT, this leads to growing concerns about students overreliance on ChatGPT to complete their tasks leading to the decrease of their critical thinking. This study, draws data from 249 participants gathered through an online questionnaire and analyzes it using Partial Least Squares Structural Equation Modeling (PLS-SEM), proving that while students are using ChatGPT for quick answers, they often do not engage deeply to enhance their learning or to achieve their full potential, they tend to care less and less about their tasks when they achieve an average grade by just using AI. This leads to the fact that there is a growth of students opportunistic behavior in academic settings, where students settle for average when they could excel. The study points out the need for educational strategies that not only promote responsible use of AI tools but also encourage deeper engagement with learning materials to prevent a decline in academic rigor, reduce their lack of responsibility and promote academic success.

KEYWORDS

Artificial Intelligence; ChatGPT; Education; Students Opportunism; Students Performance; AI Tools; TTF

Sustainable Development Goals (SDG):

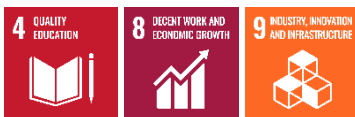


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LIST OF ABBREVIATIONS AND ACRONYMS

TEL	Technology Enhanced Learning
AI	Artificial Intelligence
LLMs	Large Language Models
TTF	Task-technology fit
PLS-SEM	Partial Least Squares Structural Equation Modeling
CA	Cronbach's Alpha
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait Ratio of correlations
VIF	Variance Inflation Factor

1. INTRODUCTION

Over time the students' have more and more tools, such as books, videos, notes, lectures, Artificial Intelligence (AI), etc., to aid them while performing a task, when it comes time to use one of these learning support tools, the introduction of new technology may or may not cause them confusion. As mentioned in Akkoyunlu & Soylu (2008) and Hatami (2013) studies we are aware that every individual learns differently and that every individual has unique learning strategies that are effective for them.

In education, technology-enhanced learning (TEL) has emerged as a transformative force, revolutionizing the way students' acquire knowledge, engage with concepts, and make informed decisions. TEL encompasses a wide range of digital tools and platforms that integrate seamlessly into the learning environment (Popenici & Kerr, 2017), empowering students' to personalize their learning experiences, enhance critical thinking skills, and develop a deeper understanding of complex subjects.

The increase of technological tools has brought an abundance of options for students', offering a range of resources to support their learning journey. From more interactive, virtual reality experiences to personalized learning plans and adaptive learning platforms, these resources offer students' individualized support to improve their knowledge and understanding while accommodating a variety of learning preferences and styles (Bilad et al., 2023; Grájeda et al., 2023).

However, among the abundance of technological tools, it is crucial to recognize the diversity among learners. Individual learning styles and preferences play a crucial role in determining the effectiveness of any learning tool. Some students' thrive in collaborative environments, while others prefer independent study, some retain concepts through visual representations, while others find auditory explanations more engaging.

Effectively selecting the most suitable tool requires a deep understanding of individual learning styles and preferences. Students' must be empowered to explore various tools, assess their fit with their learning styles, and identify those that align with their unique needs and learning objectives.

Recent research has focused on evaluating the effectiveness of various learning tools in supporting student development and performance. Studies by Baartman & De Bruijn (2011), Tsai et al. (2023) and Tynjälä P. (1997) have examined the use of constructivist learning environments, competence development, and large language models (LLMs) in education. While these studies provide valuable insights, they do not fully address the potential for students' opportunistic strategies, when using such tools to complete their educational tasks and also the potential extra work they can do to go beyond AI tools answers and achieve the best possible grade.

These are some of the previous studies, made to study the effectiveness of different tools in the last years, in this study we intend to fill the missing gap on these studies and evaluate students' potential opportunistic behavior when facing a task, and evaluate whether they just use ChatGPT, which is one of the most recent tools to aid students' in their learning process, to complete a task and get an average grade just using this tool, or whether they do some extra work of maybe a few more days or even an overnigher to get their best possible outcome (the maximum grade). By approaching these aspects, we will come up with valuable insights into the strong relationship between the use of AI tools, students' tasks and individual characteristics in educational contexts, and address the following research questions, RQ1: How does students' opportunistic use of ChatGPT affect their performance on academic tasks? RQ2: How does the additional effort performed by students' to improve their grades influence their performance on academic tasks when using ChatGPT?

The issue now lies in if students' know what's efficient for their learning or they just go with the new technologies independently of if that's the best for them or not, just to get a "good" grade without working harder than ChatGPT's answers, or if they just settle with these new technologies because it's convenient.

Thus far students' performance by just using ChatGPT in educational tasks has not yet been explored and that's what we intend to do. This could be an issue for students', as reliance on AI tools could suffocate their ability to critically think and form their own opinions and decrease their learning engagement.

By exploring the potential for students' opportunistic strategies in education with the use of ChatGPT, we can better understand the risks and benefits of this technology and develop strategies to reduce the negative impacts, and encourage students' to use ChatGPT and other AI tools in a responsible and critical way, so that they can maximize their learning potential.

To do so we will develop a theoretical background to better understand what's been done and develop a model to help us achieve these results, which will consist of a questionnaire that will be distributed among many university students', and where we will be able to determine whether the students' have made the decision to use ChatGPT for a task for an average grade based on their needs or whether they do extra work to get the best possible result and not settle for an average grade. And further evaluate if these new tools are not helpful for their learning and will lead them to opportunistic behaviors and sequentially cause them confusion, inefficiency, and lack of productivity.

The study will essentially fill the gap in the previous literature by exploring the potential for students' opportunistic strategies in education with the use of ChatGPT and will provide insights into how students' use ChatGPT to aid their learning.

2. THEORETICAL BACKGROUND

2.1. EVOLUTION OF EDUCATIONAL TECHNOLOGIES

Based on previous literature, various studies were made in order to evaluate whether new technologies were beneficial for students' development and performance in classes. We can see that different learning processes exist for every person, and that with time more and more technologies appear to aid students' (Akkoyunlu & Soylu, 2008; Hatami, 2013). Back in the days the traditional methods for learning were just traditional lectures and paper support, and then evolved to complementing the lectures and homework with what we call, TEL which is when technological tools are used to support and enhance learning. These tools can go from computers to AI itself. TEL has a positive effect on student achievement. As Woltering et al. (2009) said in their study that blended learning is the way to go because by doing it both, in person and virtual learning combined improves students' motivation, satisfaction and learning process, but this can take a different path that rather than taking a thorough approach to learning, students' focus on being able to answer the questions that were presented. This implies that giving clear instructions might not be the best way to induce a deep approach to learning. This topic leads to different opinions from diverse authors. The conception of learning by Tynjälä P. (1997) acknowledged how teachers see learning which is quite consistent with students' opinions: *"(a) accumulating more information to satisfy external demands, (b) acquiring concepts to satisfy external demands, (c) acquiring concepts to satisfy internal demands, (d) conceptual development to satisfy internal demands, (e) conceptual change to satisfy internal demands"* (p.278). This approach lacks on not knowing the individual development according to these conceptions and doesn't consider important factors that might influence their individual conceptions.

2.1.1. Traditional Learning

Traditional learning, commonly known as in-person or face-to-face education, is a time-honored approach that has stood the test of time. Under this model, students' physically attend classes, interact with their peers, and engage directly with their teachers. However, this model has been criticized for its tendency to isolate students' from each other and the lack of opportunities for self-expression. As argued in Castronova (2002) study this isolation can set back the learning process, as students' may not feel driven to fully engage with the material if they are not actively participating in the learning environment. Additionally, Vermunt (1998) pointed out that traditional instructional design theories often place control over the learning activities of the students', which runs against the idea that each individual learns differently and has unique learning strategies. In contrast, constructivist theories emphasize the active role of the learner in constructing their own knowledge, rather than

passively receiving information. This approach gives students’ more control over their learning activities, which has been shown to lead to better performance.

2.1.2. AI Tool Disruption in the Learning Process

This is a type of learning in which teachers use technology to teach and students’ learn with the aid of technology. This has come a long way, and it goes from the replacement of chalkboards to smartboards, the use of devices like phones and computers with the internet to the use of AI tools. These new tools have come to replace the traditional education tools. Nowadays, Large Language Models (LLMs), a type of AI exemplified by ChatGPT (Tsai et al., 2023), are in the spotlight in education and are trained on vast quantities of textual data. Enabling them to produce writing, translation between languages, create a variety of unique content, and provide useful answers to our questions with little instructions to perform tasks (Brown et al., 2020).

ChatGPT it’s an AI system that generates responses to our questions using natural language processing and has become very famous in little time (Lo, 2023). Despite its success, ChatGPT brings both benefits and challenges into student learning. In Esplugas (2023) and Fuchs (2023) studies were observed some benefits and challenges on how AI affects student learning, they are mentioned in the table 1.

Table 1 – Benefits and Challenges of AI in student learning

Benefits	Challenges
Personalized Learning	Overreliance on AI
Engaging and Interactive Learning	Increases the risk for cheating
Accessibility	Limited understanding of complex concepts
Extra guidance outside of the classroom	Reduces human interaction
Practical	Reduces critical thinking skills
	Reduces problem solving skills

As illustrated by the table 1, the implementation of AI into the learning process has brought a range of benefits and challenges for both teachers and students’. While AI tools like ChatGPT can with no doubt enhance personalized learning experiences by adapting its responses to the interests of each student, making learning more motivating because it connects new information to students’ existing knowledge and experiences, these tools can also make education more engaging and interactive, they also raise concerns about overreliance and potential negative impacts on critical thinking and problem-solving skills.

A study by Fuchs (2023) shows that ChatGPT can significantly improve student outcomes by adapting learning contents to individual interests and learning styles. This personalized approach can promote a deeper engagement and comprehension, leading to better academic performance. Additionally, ChatGPT's interactive features can improve the learning experience, making it more stimulating and motivating for students'.

However, some concerns have been raised about the potential for overreliance on AI learning tools. As students' grow used to relying on ChatGPT to provide answers and assistance, they may develop a decreased tendency for independent thinking and problem-solving. This reliance on external support could interfere with their development of critical thinking and analytical skills, which are essential for academic success and lifelong learning.

Therefore, it is crucial to find a balance between making use of the benefits of AI learning tools and fostering independent learning habits. According to Dwivedi et al. (2023) study students' should be guided in using ChatGPT as a tool to aid their learning, rather than relying on it as a replacement for their own critical thinking and problem-solving abilities.

ChatGPT is a product of OpenAI's GPT-3.5 architecture, which stands for "Generative Pre-trained Transformer 3.5.". Since it's a deep learning model it is trained on large textual datasets, including journals, web pages, and books, in this process the chat predicts something based on previous information given to him and because of this, the chat is able to understand and generate human-like text (Dutta & Chakraborty, 2023).

Before ChatGPT is used for a user's input, it undergoes a pre-training phase, in which, the chat learns a lot of factors from the given data, after that it can be tuned for a specific application given by the user, this allows ChatGPT to be more accurate in its responses (Baidoo-Anu & Owusu Ansah, 2023). Basically, once interacted with, ChatGPT analyzes the question or task, identifies the patterns based on the training previously done and then it generates a response.

2.1.3. Opportunism and Self-efficacy in Students' Learning

Most of the students' have the tendency to take on opportunistic behaviors, these behaviors are expressed under the form of lack of honesty, traditionally opportunism is translated in academic settings by cheating or by the distortion of information (Elias, 2013). Nowadays, because of the growing presence of AI tools like ChatGPT, students' opportunism now extends to exploit these AI tools to minimize effort and maximize their outcomes, by taking profit of something without being honest, for instance, by only relying on ChatGPT to complete their academic tasks, this can lead to average grades without them genuinely learn the contents of their tasks.

A study by Nagin et al. (2002) acknowledges the factors contributing to opportunistic behaviors. It proposes a model to examine opportunism in a work setting, particularly its

connection to cheating and opportunism alternative explanations. The model suggests that a person's effort level plays a significant role in determining their actions and opportunistic tendencies. This study findings demonstrate that opportunistic behavior can indeed positively influence individuals in achieving their goals.

Self-efficacy holds a significant role in shaping students' educational experiences, especially in the context of using AI as an aid in their learning process. It refers to an individual's belief in their ability to successfully complete tasks, meet their academic goals, and become an expert in a particular field, all with the support of AI tools (Drnovšek et al., 2010). As students' engage with AI-powered tools and platforms, they develop self-efficacy beliefs associated with their competence in using these technologies. But in the context of AI enhanced learning, the relationship between opportunism and self-efficacy offers a complex dimension to the learning process (Xiao & Song, 2022). Some students', driven by their self-efficacy beliefs, may actively embrace AI as a means to promote their learning autonomy and problem-solving skills. In contrast, some individuals may have opportunistic attitudes due to both personal and environmental factors, depending excessively on AI guidance while not fully using their own capacity for learning on their own. Thus, a more comprehensive study is required to better understand how AI's impact on education can either increase or decrease students' autonomy during the learning process because of the strong interaction between opportunism and self-efficacy.

2.1.4. Effectiveness of Different AI Tools in Learning Tasks and What Influences Students' Choices

A growing number of studies has examined how different learning tools can support students' performance on multiple tasks. Studies have examined the impact of these tools on tasks such as problem-solving, critical thinking, and creative expression.

For instance, Alonso et al. (2005) found that blended learning, which combines traditional classroom lectures with e-learning, can increase students' motivation for learning and make it an active and interactive process. According to Shabiralyani et al. (2015) study is suggested that the use of audio-visual aids can improve consolidation of long-term memories and enhance the ability to recall information and learning outcomes. In Piccoli et al. (2001) study it is compared technology-mediated virtual learning environments to traditional classroom environments, concluding that the former can lead to better learning performance, higher levels of computer self-efficacy, satisfaction, and learning climate among students'. And Farhi et al. (2023) emphasizes the importance of formulating appropriate guidelines and addressing probable issues related to the use of ChatGPT, such as reliance on the tool for critical thinking and negative impacts on creative thinking and writing capabilities. Thus, different learning

tools can be effectively used to support students' performance on specific learning tasks, depending on the nature of the task and the specific learning objectives.

Building on prior research that has demonstrated the potential of AI tools to enhance student learning (Kooli, 2023), the table 2 aims to enlighten the impacts of commonly used AI tools in education. To achieve this, and going from Osamor et al. (2023) study, where it was presented a wide and developing range of AI-powered educational tools. Table 2 presents a focused analysis of the most frequently used AI tools and their anticipated effects on student learning process effectiveness.

Table 2 – Different AI tools for learning and their impact on students' learning process effectiveness

AI Tools	Impact on learning process effectiveness
ChatGPT	ChatGPT provides students' with personalized feedback, support, interactive learning experiences and has a big availability.
Gemini (formerly Google Bard)	Gemini also provides students' with personalized feedback, support, interactive learning experiences and has a big availability.
Grammarly	Grammarly improves writing skills, identifies grammatical errors, and provides suggestions for improvement.
QuillBot	QuillBot is very effective at summarizing texts and rewriting sentences.
Duolingo	Duolingo delivers engaging exercises and interactive games for language learning.
DeepL	DeepL provides accurate and natural-sounding translations, helping students' to read and understand foreign texts more effectively.
SciSpace	SciSpace can interpret a research paper and answer questions about it.

By assessing the effectiveness of various AI tools for learning tasks, it is crucial to recognize that students' choices of learning tools are influenced by a variety of factors. These factors go from individual preferences, experiences, self-efficacy, the nature of the learning task, the availability of tools and their perceptions of the tool's effectiveness.

A study by Kember et al. (2004) validates the Revised Two-Factor Study Process Questionnaire (R-SPQ-2F), which can assess students' preferences for deep and surface approaches to learning, which may influence their tool choices and validates the Revised Learning Process Questionnaire (R-LPQ-2F), which can provide insights into students' motives for choosing specific tools. In Dunn L (2002) study it is discussed the role of cognitive theories in learning, emphasizing that students' are more likely to choose tools that align with their cognitive preferences. And in Hu & Hui (2012) study it is examined the effects of technology-mediated learning, finding that students' are more likely to engage with tools that are interactive and provide immediate feedback. Basically, students' choices of learning tools are influenced by a combination of personal factors, task-related factors, and environmental factors.

2.2. INDIVIDUAL LEARNING STYLES

As previously discussed, individuals have different learning styles and strategies that work best for them. To elaborate, we will look into the different types of learning styles. Starting off by the older learning style the reading method, which is where students' read articles, research papers, textbooks, etc. that makes them internalize the information that they want to learn, another common type is the auditory which is when students' prefer to learn by lectures, recorded audio, videos, etc. (Moussa, 2014).

Subsequently, Shabiralyani et al. (2015), mentions that *"1% of what is learned is from the sense of TASTE, 1.5% of what is learned is from the sense of TOUCH, 3.5% of what is learned is from the logic of SMELL, 11% of what is educated is from the logic of HEARING and 83% of what is learned is from the sense of SIGHT"* (p. 1).

Thus, most common are the visual aids, these are students' that prefer visual aids such as, charts, diagrams, flashcards, etc. because these can illustrate the concepts in a clearer way and make learning more real and more accurate. Since visual aids in learning tend to be the most effective method, they are used in classrooms and other learning environments. This same study reveals that visual aids increase motivation, clarification, increase the vocabulary, saves time, avoids dullness, and promotes a direct experience.

3. MODEL BUILDING AND HYPOTHESIS DEVELOPMENT

The main goal of this research is to investigate the impact of ChatGPT on students' opportunistic strategies and check if they only use it exclusively to complete their educational tasks or whether they work more to get the best possible performance. Since AI tools, more specifically ChatGPT continue to evolve and affect various aspects of education, understanding its potential influence on student learning outcomes and critical thinking skills is crucial. Thus, we will be focusing on the development of a conceptual model and its hypothesis. In which it will be able to provide an understanding of the relationships between ChatGPT usage, students' individual characteristics, and potential outcomes.

The model incorporates theoretical constructs inspired by previous studies Goodhue & Thompson (1995), Hoehle & Huff (2012) and Shaw & Gribbins (2005) including self-efficacy, effort expectancy, task-technology fit, and habit. Along with the constructs, different hypotheses were also developed based on the conceptual model, and will guide the implementation of data collection instruments and statistical analyses. The model was created based on the task-technology fit (TTF) theory, which based on previous studies aligns best with the goals and research problems that this study intends to address.

In Goodhue & Thompson (1995) study on task-technology fit established a theoretical framework that indicates the interaction between the alignment of information systems with specific tasks and the subsequent performance outcomes. With this, Shaw & Gribbins (2005) sum up in their study that *“(1) task-technology fit is a relevant concept to predict information systems success (e.g., performance impacts), and that (2) fit is determined by an appropriate interplay between tasks, technology, and individual, context-related characteristics”* (p. 4).

In this study, task-technology fit is defined as the match between the demands of the tasks assigned to students', the quality of AI technologies available like ChatGPT, and the individual characteristics in which students' use these technologies. The characteristics of the tasks are characterized by their nature. The technology, represented by ChatGPT, is defined by its functionalities, which include communication, information access, and data processing capabilities, and its adaptability to students' contexts. The individual use context is characterized by their self-efficacy, habits and effort expectancy. The conceptual model, as illustrated in the figure 1, proposes an ideal match among these three dimensions with them being task characteristics, technology characteristics, and individual characteristics (Shaw & Gribbins, 2005) which will facilitate a robust task-technology fit, leading to more effective use of ChatGPT in educational settings.

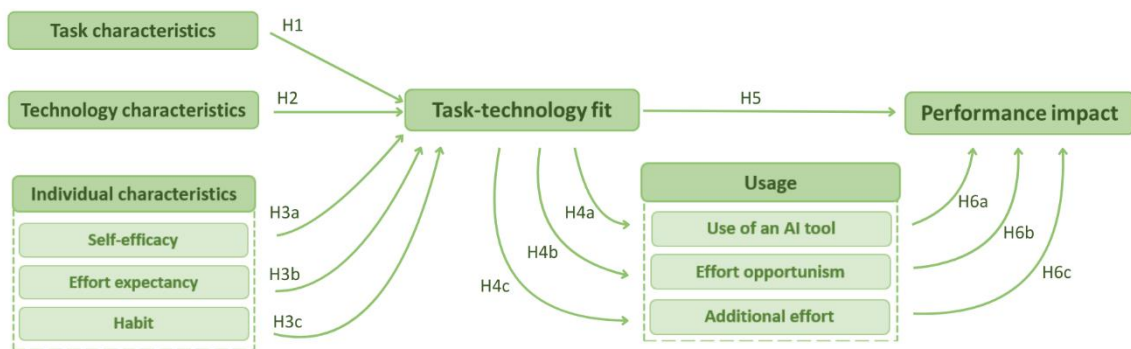


Figure 1 – Conceptual model

In order to create a base for this research, it is important to investigate the aspects of every variable in the model and the possible hypotheses that are associated with them. Firstly, by approaching each variable which are displayed by their meaning on table 3:

Table 3 – Meaning of each variable presented on the conceptual model

Variables	Meaning
Task Characteristics	The task characteristics encompass the attributes of the specific task or goal individuals are trying to achieve with ChatGPT. It considers factors like task complexity, ambiguity and required knowledge. Understanding these characteristics helps to assess how well the ChatGPT’s functionalities align with the demands of the task, ultimately influencing its effectiveness and student acceptance.
Technology Characteristics	This variable examines the features and functionalities of ChatGPT itself. It approaches aspects like ease of use, accessibility, reliability, flexibility, and the available information provided. Analyzing these characteristics helps to determine how well the tool matches the specific needs and capabilities of the students’, promoting potential success of ChatGPT integration and outcomes.

Self-efficacy	This variable acknowledges individuals' confidence in their ability to successfully use ChatGPT and achieve their expected outcomes. High self-efficacy can lead to increased effort, determination, and positive expectations, leading to a greater use of ChatGPT.
Effort expectancy	This variable focuses on the perceived ease or difficulty of using ChatGPT to achieve the expected results. Lower effort expectancy indicates that the tool is complex or time-consuming, which can discourage its use and reduce its potential benefits.
Habit	This variable examines the frequency of using ChatGPT, often influenced by initial experiences and perceived value. Recurrent use can lead to increased student comfort and reliance on the tool, potentially promoting its impact on performance.
Task-technology fit	This variable combines many of the factors approached above, measuring the degree to which ChatGPT characteristics align with the demands of the specific task. High task-technology fit suggests a strong match between tool capabilities and student needs, which leads to improved performance and satisfaction.
Use of an AI tool	This variable measures the frequency of student engagement with ChatGPT, providing insights into the integration and potential impact of this tool.
Effort opportunism	This variable evaluates the level to which students' do their academic tasks with the aid of just ChatGPT itself, further providing insights on students' overreliance on the tool over their own understanding.

Additional effort	This variable refers to the extent students' are willing to improve their academic tasks, using their class materials and own understanding, over the use of ChatGPT.
Performance impact	This variable evaluates the effect of using the AI tool on individual performance measures, such as task completion time, accuracy, or overall productivity. Looking at this relationship helps to evaluate the effectiveness of ChatGPT.

Moreover, it is important to understand what type of relationships exist between the variables. To better understand them the following hypothesis have been created:

H1: The characteristics of a task are positively associated with the fit of the technology.

According to Shaw & Gribbins (2005) study, a task's compatibility with a given technology needs careful consideration of various key attributes, the complexity of the task, and the time constraint in which it must be executed. Basically, the effectiveness of the technology in question, ChatGPT, is significantly enhanced when there is a correspondent match with the task characteristics. Therefore, a bigger task-technology fit is achieved when the AI's capabilities are adapted to accommodate the task's complications, demands, and time constraints. This alignment is critical, as it directly influences the efficiency and efficacy with which the task can be completed, leveraging the full potential of ChatGPT.

H2: The characteristics of the technology are positively associated with the fit of the technology to the task.

The hypothesis H2 approaches the multifaceted concept of task-technology fit within the proposed model and acknowledges the positive association between technology characteristics and the task-technology fit. According to Hoehle & Huff (2012) study and the different concepts of fit. H2 takes a direct approach, hypothesizing a simple positive relationship between the features of the technology and the overall fit with the demands of a specific task. Thus, specific features like adaptability, interactivity, and ease of use contribute directly to a better "fit" by aligning with the requests of the task. In simpler terms, the more features a technology has that align with the demands of the task, the better suited it is for accomplishing that task.

H3: Individual characteristics, including self-efficacy, effort expectancy and habit are positively associated with the task-technology fit.

Fundamentally, if students' find the technology's features, functionalities, and overall design to be favorable and aligned with their individual preferences and values, they are more likely to take in a good "task-technology fit" (D'Ambra & Wilson, 2004). This is anticipated to influence the effectiveness of the learning process. Following Al-Rahmi et al. (2023) study, where the alignment between technology and personal values leads to technology adoption. It is hypothesized that a positive perception of technology characteristics will translate to a better fit for the learning task, potentially leading to enhanced learning outcomes. This positive impact could result from the self-efficacy, effort expectancy and habits taken from using ChatGPT which is related to the students' individual characteristics and preferences.

H4: A higher task-technology fit is positively associated with the usage of the technology, including the frequency of use of an AI tool, effort opportunism and additional effort beliefs.

Hypothesis H4 proposes a positive association between a higher task-technology fit and the increased use of an AI tool. In Howard & Rose (2019) study says that individuals are more likely to adopt and frequently use technologies that they perceive as valuable and well-suited to their needs. This hypothesis suggests that when an AI tool aligns with the demands and characteristics of a specific task, students' are more likely to find it useful and effective. Consequently, they are more likely to integrate it into their workflow and engage with it frequently. Thus, H4 emphasizes the importance of matching the capabilities of an AI tool to the specific needs of the task at hand.

This fit can also influence student beliefs about effort. Since these tools, ChatGPT, have features that make tasks easier and faster might lead students' to believe they require less effort to complete the task. On the other hand, these tools can also promote critical thinking, which requires the students' notes and class materials to believe that they need to make an additional effort to learn more effectively and get better results on their academic tasks. Thus, this fit can influence students' beliefs about the effort required. Tools that make tasks easier might promote beliefs about reduced effort (effort opportunism), while some students' might believe that additional effort will lead them to have a better performance. Basically, this "fit" acts as a key driver of student engagement and influences the adoption and use of the technology.

H5: A higher task-technology fit is positively associated with better outcomes in terms of performance impact.

H5 approaches the potential consequences of a strong task-technology fit. Taking up the understanding that this fit comes from the merge between task characteristics, technology characteristics, and individual characteristics (Al-Rahmi et al., 2023), it is hypothesized to have a positive association with performance impact. Basically, when students' perceive the technology as well integrated with the learning task and aligned with their needs and preferences, it likely leads to better learning outcomes and increased performance on their assignments.

H6: The usage of an AI tool is positively associated with better outcomes in terms of performance impact.

Hypothesis H6 approaches the potential benefits of using an AI tool, proposing a positive association between its use and improved outcomes in terms of performance impact. This aligns with the research surrounding technology-enhanced learning and performance, suggesting that effective integration of AI tools can positively impact students' experiences and achievements, as performance is impacted by the tool's ability to display the information with the least amount of errors possible (Aljukhadar et al., 2014).

Firstly, by frequently using AI tools it can lead to increased cognitive abilities and optimize learning processes, providing capabilities like personalized feedback, automated data analysis, and adaptive content delivery. This can promote problem-solving skills, reduce the amount of information our memory can process at times, and ultimately lead to improved performance on tasks or assessments.

Secondly, AI-powered tools can raise or decrease our performance depending on our reduced effort behaviors to just use the tool to pass on an academic task and depending on the extra effort we are willing to make to get the best grade possible. Basically, the impact of AI tools on performance could be positive if it promotes a deeper learning, but negative if it encourages superficial use.

4. METHODOLOGICAL APPROACH

To assess the students' willingness to engage in additional work and their opportunistic tendencies, we created an electronic questionnaire, the questions for these questionnaire constructs were designed in accordance with the Portuguese grading system. This system evaluates student tasks on a scale from 0 to 20, where 20 represents the highest possible score and 15 is considered a "good" average grade.

This knowledge can then be used to inform educational institutions and guide the development of strategies to maximize the benefits of ChatGPT while reducing its potential negative effects. The research design employed in this study provides a rigorous and versatile approach to investigating the impact of ChatGPT on students' potential reduced effort. The model also enables rigorous variable exploration, controlled experimentation, and replication of real-world scenarios.

The primary tool used is a comprehensive electronic questionnaire incorporating a mix of self-reflective questions. This questionnaire is carefully designed to evaluate two distinct yet interconnected dimensions: student opportunism and potential additional effort. These questions are structured to bring out responses that reflect the students' practices, behaviors, and self-assessment in relation to their academic environment.

The constructs of the model are evaluated in the questionnaire through a numerical scale, each statement within the questionnaire is measured against a seven-point Likert scale, that ranges from 1 to 7, where 1 represents "Strongly Disagree" and 7 represents "Strongly Agree", this scaling mechanism helps students' to precisely quantify their level of agreement with each statement, ensuring an accurate reflection of their perspectives, as detailed in table 4.

Table 4 – Adapted questions for each construct

Construct	Source	Adapted Questions
Task characteristics	(Sarker & Valacich, 2010)	<ol style="list-style-type: none">1) Ideas for assignments to improve content.2) Review key concepts for quiz preparation.3) Summarize PDFs for faster understanding.

Technology characteristics	(Yang et al., 2013)	<p>1) Using ChatGPT aligns well with my learning style.</p> <p>2) ChatGPT provides helpful feedback.</p> <p>3) ChatGPT is a highly adaptable technology.</p>
Self-efficacy	(Sun et al., 2016)	<p>1) I can use ChatGPT to prepare for a task independently.</p> <p>2) I can use ChatGPT without relying on guidance from others.</p> <p>3) I can use ChatGPT effectively even without prior experience.</p> <p>4) I can use ChatGPT for a task with just the online help available.</p>
Effort expectancy	(Parthasarathy & Bhattacharjee, 1998; Wixom & Todd, 2005)	<p>1) It is easy for me to get the information I need from ChatGPT.</p> <p>2) I think mastering ChatGPT for tasks is simple.</p> <p>3) I feel that operating ChatGPT effectively is easy.</p>
Habit	(Bhattacharjee & Lin, 2015; Venkatesh et al., 2012)	<p>1) Using ChatGPT has become a habit for me.</p> <p>2) Using ChatGPT comes naturally to me.</p> <p>3) I automatically think of using ChatGPT when I need to complete a task.</p>
Task-technology fit	(Sun et al., 2016)	<p>1) ChatGPT's functionalities are compatible with my tasks.</p> <p>2) ChatGPT makes task preparation easier.</p> <p>3) ChatGPT facilitates the sequencing of tasks.</p>
Use of an AI tool	(Kositanurit et al., 2006)	<p>1) How frequently do I use ChatGPT for academic tasks.</p>
Effort opportunism	(Chen et al., 2022)	<p>1) I will accept to have 15 and not do the manual work.</p> <p>2) I prefer the 15 and dedicate my time to something else.</p> <p>3) It is okay to get 15 if only using ChatGPT.</p>

Additional effort	(Chen et al., 2022)	1) I prefer to do manual work for one more entire day and achieve 18. 2) I prefer to work overnight and achieve 18. 3) I prefer to work a few more days and achieve 18.
Performance impact	(Yang et al., 2013)	1) ChatGPT helps me be more effective. 2) ChatGPT has a positive impact on my productivity. 3) ChatGPT is an important aid to me in the performance of my tasks.

The data collection process follows the ethical standards and comply with data protection regulations. Personal identifiers, such as names and contact information, are not collected and are not stored at any stage of the research. This ensures the anonymity of all participants, thereby respecting their privacy and aligning the study with ethical research principles. The data is collected to comprehensively assess student performance, potential opportunism and additional effort. This includes an analysis of students' beliefs and interactions with ChatGPT, which provides insights into their engagement with AI learning tools. Thus, students' overall learning experiences are evaluated through their responses to the questions in the questionnaire.

We ended up getting 249 valid responses. As revealed in table 5, 50% of the participants were male, 53% were between ages 21 and 23, 16% were between ages 18 and 20 and the rest were comprehended between ages 24 to 36 and more. 59% of the participants are from a masters program, while 34% are from bachelors and the rest are from post graduate and doctoral programs.

Table 5 – Sample characteristics

Distribution (n= 249)		Frequency	Frequency (%)
Gender	Female	119	49%
	Male	121	50%
	Other	4	1%
Age	18-20	38	16%
	21-23	129	53%
	24-26	39	16%
	27-29	11	5%
	30-32	8	3%
	33-35	6	2%
	36 or more	13	5%
	Education	Bachelor Program	83
Master Program		143	59%
Post Graduate Program		15	6%
Doctoral Program		3	1%

For the analysis of the data received from the questionnaires, this study will employ the Partial Least Squares Structural Equation Modeling (PLS-SEM) statistical method. PLS-SEM will be important to the analysis, especially when it comes to profiling the students' who responded to the questionnaire and understanding their unique characteristics. PLS-SEM's versatility in handling complex relationships and latent constructs makes it a suitable choice for modeling the complex connections between different profiling variables (Basbeth et al., 2018).

5. RESULTS

This chapter presents the results and findings from the questionnaires delivered to many students' with diverse fields of study. The analysis of the results will help to define the conclusions drawn from the methodology. Building on the methodological approach section, this chapter uses PLS-SEM for data analysis. PLS-SEM is particularly suited for the research as it is ideal at predicting the impact of ChatGPT on students', besides that this study's data doesn't follow a normal distribution. SmartPLS 4 software will be used to test the proposed model, examining the relationships between variables and evaluating the hypotheses against the collected data since its main objective is to apply model statistics and methods that have been validated and documented in scientific journals and show its results in a transparent way (Hair et al., 2019).

5.1. MEASUREMENT MODEL EVALUATION

Before looking into the results, it's crucial to establish the validity and reliability of this study's measurement model. Following Hair et al. (2019) study, validity ensures the measures accurately capture the intended constructs, while reliability signifies the consistency and dependability of these measures. Assessing these qualities is important for building trust in the drawn findings and that will result in meaningful conclusions.

5.1.1. Internal Consistency

Internal consistency of the measurement model was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR). Both metrics should ideally exceed 0.7 for all latent variables to indicate good reliability (Hair et al., 2019). As shown in table 6, the CA and CR values in this study are all above 0.7, demonstrating strong internal consistency within the constructs.

5.1.2. Convergent Validity

Convergent validity assures that the indicators within each latent construct capture a significant amount of variance specific to that construct. To assess this, we examined the Average Variance Extracted (AVE) for each construct. In PLS-SEM, an ideal AVE value is generally considered to be above 0.50 (Hair et al., 2019; Salloum et al., 2019). As shown in table 6, all constructs display AVE values exceeding 0.50, indicating strong convergent validity. This suggests that the measures successfully capture the intended latent variables.

5.1.3. Discriminant Validity

Discriminant validity assures that this study's constructs are distinct, and this was achieved through an elaborate approach. First, as proposed by Fornell-Larcker criteria, the square root of each construct's AVE to exceed its correlations with other constructs. As shown in Table 7, this requirement is demonstrably satisfied.

Then, the cross-loadings parameter was examined, this requirement ensures that indicator loadings are consistently higher for their intended construct compared to their loadings on other constructs. The bold values in table 8 confirm this condition, indicating stronger loadings for intended constructs.

Finally, the Heterotrait-Monotrait Ratio of correlations (HTMT) criterion was used, this criterion compares the correlations between constructs with the average shared variance between their indicators. HTMT values below 0.9 are generally considered indicative of good discriminant validity. As shown in table 9, all HTMT ratios fall below this threshold, which further supports the distinctiveness of the constructs.

Table 6 – Construct reliability and validity measures

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Additional effort	0.868	2.136	0.892	0.736
Effort expectancy	0.879	0.889	0.925	0.805
Effort opportunism	0.911	0.916	0.944	0.849
Habit	0.917	0.927	0.948	0.858
Performance impact	0.939	0.941	0.961	0.892
Self-efficacy	0.829	0.855	0.884	0.657
Task characteristics	0.754	0.778	0.857	0.667
Task-technology fit	0.904	0.904	0.94	0.839
Technology characteristics	0.84	0.843	0.904	0.758

Table 7 – Fornell-Larcker criterion

	1	2	3	4	5	6	7	8	9	10
1. Additional effort	0.858									
2. Effort expectancy	0.03	0.897								
3. Effort opportunism	-0.2	0.173	0.921							
4. Habit	0.172	0.443	0.294	0.926						
5. Performance impact	0.151	0.472	0.333	0.772	0.944					
6. Self-efficacy	0.136	0.443	0.169	0.427	0.501	0.811				
7. Task characteristics	0.091	0.283	0.163	0.436	0.512	0.352	0.817			
8. Task-technology fit	0.124	0.589	0.345	0.653	0.823	0.525	0.508	0.916		
9. Technology characteristics	0.047	0.5	0.258	0.62	0.726	0.464	0.598	0.686	0.87	
10. Use of an AI tool	0.043	0.419	0.294	0.771	0.805	0.413	0.47	0.686	0.624	1

Table 8 – Cross loadings

	Additional effort	Effort expectancy	Effort opportunism	Habit	Performance impact	Self-efficacy	Task characteristics	Task-technology fit	Technology characteristics	Use of an AI tool
AE_1	0.793	-0.019	-0.317	-0.007	0.038	0.053	0.027	0.035	-0.013	-0.039
AE_2	0.974	0.049	-0.113	0.236	0.184	0.165	0.092	0.149	0.077	0.075
AE_3	0.794	-0.02	-0.351	-0.016	0.045	0.02	0.099	0.037	-0.044	-0.035
EE_1	0.025	0.904	0.181	0.452	0.482	0.448	0.325	0.59	0.531	0.436
EE_2	0.033	0.872	0.108	0.323	0.369	0.333	0.182	0.485	0.382	0.318
EE_3	0.022	0.915	0.172	0.407	0.407	0.4	0.239	0.498	0.418	0.363
EO_1	-0.187	0.108	0.937	0.287	0.277	0.107	0.118	0.276	0.209	0.253
EO_2	-0.252	0.158	0.937	0.275	0.311	0.164	0.17	0.333	0.263	0.269
EO_3	-0.116	0.204	0.89	0.252	0.326	0.189	0.157	0.337	0.237	0.288
H_1	0.187	0.422	0.345	0.954	0.783	0.4	0.445	0.661	0.651	0.769
H_2	0.207	0.424	0.174	0.924	0.708	0.44	0.354	0.6	0.502	0.679
H_3	0.073	0.384	0.293	0.9	0.645	0.343	0.411	0.545	0.565	0.691
PI_1	0.141	0.477	0.304	0.72	0.954	0.484	0.515	0.813	0.699	0.779
PI_2	0.114	0.429	0.283	0.709	0.934	0.461	0.42	0.745	0.651	0.722
PI_3	0.172	0.429	0.354	0.758	0.945	0.473	0.51	0.77	0.704	0.777
SE_1	0.073	0.404	0.113	0.46	0.528	0.831	0.408	0.536	0.536	0.479
SE_2	0.218	0.316	0.172	0.366	0.428	0.845	0.23	0.415	0.311	0.273
SE_3	0.064	0.364	0.147	0.245	0.283	0.763	0.128	0.321	0.256	0.246
SE_4	0.085	0.345	0.129	0.254	0.321	0.801	0.312	0.378	0.329	0.282
TC_1	0.044	0.291	0.145	0.362	0.446	0.306	0.848	0.459	0.595	0.382
TC_2	0.169	0.19	0.143	0.382	0.45	0.326	0.846	0.452	0.446	0.432
TC_3	-0.016	0.208	0.106	0.319	0.343	0.212	0.752	0.307	0.406	0.327
TTF_1	0.146	0.487	0.273	0.592	0.789	0.452	0.451	0.887	0.623	0.629
TTF_2	0.089	0.561	0.328	0.59	0.752	0.471	0.489	0.942	0.636	0.641
TTF_3	0.106	0.569	0.347	0.612	0.719	0.52	0.456	0.918	0.626	0.615
TechC_1	0.089	0.393	0.191	0.652	0.664	0.375	0.478	0.618	0.846	0.616
TechC_2	0.037	0.49	0.273	0.527	0.665	0.446	0.536	0.62	0.903	0.555
TechC_3	-0.009	0.422	0.208	0.428	0.557	0.388	0.55	0.547	0.861	0.448
UAI_1	0.043	0.419	0.294	0.771	0.805	0.413	0.47	0.686	0.624	1

Table 9 – Heterotrait-Monotrait Ratio of correlations (HTMT)

	1	2	3	4	5	6	7	8	9	10
1. Additional effort										
2. Effort expectancy	0.052									
3. Effort opportunism	0.332	0.187								
4. Habit	0.137	0.488	0.32							
5. Performance impact	0.113	0.513	0.357	0.828						
6. Self-efficacy	0.116	0.511	0.194	0.466	0.543					
7. Task characteristics	0.121	0.338	0.191	0.52	0.598	0.41				
8. Task-technology fit	0.097	0.655	0.377	0.714	0.892	0.586	0.601			
9. Technology characteristics	0.079	0.574	0.292	0.699	0.813	0.527	0.742	0.785		
10. Use of an AI tool	0.06	0.442	0.307	0.804	0.83	0.432	0.536	0.722	0.676	

5.2. STRUCTURAL MODEL EVALUATION

Once we confirmed the reliability of the measurement model, we could proceed with analyzing the relationships between the study’s constructs (the structural model). The figure 2 illustrates the results of this analysis. To assess these relationships, we examined various metrics, including the explained variance (R-squared) and the strength and significance (p-value) of the paths connecting the constructs (β).

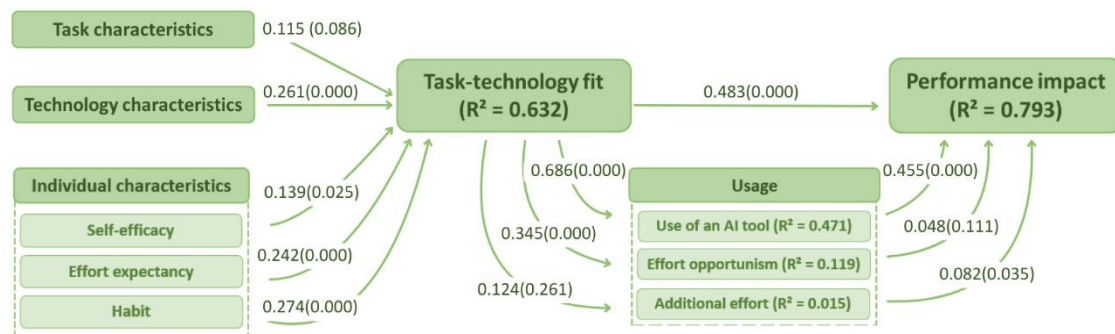


Figure 2 – Structural model. Note: The first value in each arrow represents the path coefficient and the second value, in parenthesis, the p-value.

By looking into the relationships between the study’s constructs, as shown in figure 2, to assess the strength and significance of these connections, a bootstrapping technique was employed with 5,000 resamples of the original data, this approach provides a more robust estimate of the standard error for each path coefficient, allowing us to determine if the

relationships are truly meaningful (statistically significant). Additionally, we evaluated the presence of multicollinearity, which can distort results. Since the variance inflation factor (VIF) indicated no such issue, it confirms the independence of this study's constructs.

Our findings suggest that the model variation in student performance is 79.3%. This is because the construct "Performance impact" exhibits a strong relationship and is statistically significant (p -value < 0.05) with task-technology fit ($\beta = 0.483$, p -value = 0.000) and use of an AI tool ($\beta = 0.455$, p -value = 0.000). Moreover, the data reveals that the construct task-technology fit has a positive relationship and is significantly influenced by technology characteristics ($\beta = 0.261$, p -value = 0.000), and by the students' individual characteristics being these self-efficacy ($\beta = 0.139$, p -value = 0.025), effort expectancy ($\beta = 0.242$, p -value = 0.000) and habit ($\beta = 0.274$, p -value = 0.000), supporting the hypotheses H2, H3a, H3b, H3c, H4a, H4b, H5, H6a and H6c.

On the other hand, it was not possible to demonstrate that performance impact was directly impacted by effort opportunism ($\beta = 0.048$, p -value = 0.111) and that task-technology fit was impacted with additional effort ($\beta = 0.124$, p -value = 0.261). In the same way, due to insufficient statistical evidence task-technology fit was not able to demonstrate its impact on task characteristics ($\beta = 0.115$, p -value = 0.086).

6. DISCUSSION

6.1. THEORETICAL IMPLICATIONS

Having established the results and findings from the questionnaires in the previous chapter, the discussion chapter analyzes the meaning and implications of the results data. With this, this study's goal is to evaluate the influence of ChatGPT, a well-known and accessible AI tool these days, in students' within an educational setting, using an adapted TTF model (Goodhue & Thompson, 1995). As the findings support most of the previous research on related constructs, we can conclude that 9 out of the 12 hypotheses are empirically supported.

Hypothesis 1 (H1) is supported by the relationship between task characteristics and task-technology fit ($\beta = 0.115$, $p\text{-value} = 0.086$) it doesn't suggest a statistically significant impact. This relationship indicates that the inherent characteristics of the tasks might play a role in determining how well the technology fits, but other factors could also be influencing this fit. These findings imply that task characteristics likely play a role in task-technology fit, meaning the cause of using ChatGPT for a task depends more on other factors like technology characteristics and individual characteristics than the nature of an educational task.

Looking into Hypothesis 2 (H2), the relationship between the technology characteristics and the task-technology fit is significant and positive ($\beta = 0.261$, $p\text{-value} = 0.000$), supporting the task-technology fit model (D'Ambra & Wilson, 2004; Goodhue & Thompson, 1995; Howard & Rose, 2019), meaning that the effectiveness of a technology, in this case ChatGPT in an educational setting is directly related to how well it meets the specific needs of the task that is intended to support, so the more the characteristics of the technology align with the needs of the task, the better the technology is in terms of usability and functionality, meaning a better fit overall.

As for the individual characteristics hypotheses of this model (H3a, H3b, H3c), which are self-efficacy ($\beta = 0.139$, $p\text{-value} = 0.025$), effort expectancy ($\beta = 0.242$, $p\text{-value} = 0.000$) and habit ($\beta = 0.274$, $p\text{-value} = 0.000$), they are all statistically significant and have a strong relationship with task-technology fit meaning that the more self-efficacy a student has, the more confidence in their ability to use ChatGPT they have, which significantly improves their perception of the ChatGPT fit for their tasks. This aligns with Bandura & Adams (1977) study on self-efficacy, which suggests that individuals who believe in their abilities are more likely to embrace and effectively use new technologies. It indicates that students' with high self-efficacy will perceive a better fit between their needs and ChatGPT, thereby increasing the likelihood of adopting and effectively using it, proving H3a. Effort expectancy also has a strong positive relationship to task-technology fit (H3b), indicating that when students' perceive the use of ChatGPT as easy and requiring minimal effort, they perceive a better alignment with their academic tasks, this aligns with Mitchell & Nebeker (1973) study. This finding means that reinforcing the perceived ease of use plays an important role in technology acceptance. It

implies that making ChatGPT more user-friendly and accessible will enhance its fit for educational tasks, thereby increasing its adoption and usage among students'. Lastly, the significant positive relationship between habit and task-technology fit demonstrates that students' who have established habits of using ChatGPT or other similar technologies will be more willing to perceive a good fit between ChatGPT and their tasks. Hypothesis (H3c) aligns with Fiorella (2020) study, which emphasizes that habitual behavior is a strong predictor of future usage. Therefore, students' accustomed to using AI tools in their studies will find it easier to integrate ChatGPT into their workflow, perceiving it as a suitable tool for their tasks.

In the model, the hypothesis that relates task-technology fit and use of an AI tool (H4a) is significant, indicating a strong relationship ($\beta = 0.686$, $p\text{-value} = 0.000$), meaning that the more frequently and effectively an AI tool is used, the better the fit between the technology and the students' tasks (Goodhue & Thompson, 1995; Howard & Rose, 2019), this relationship implies that the actual use of the AI tool reinforces the perception that the technology is well suited for the tasks it supports, this proves the hypothesis and concludes that practical experience and frequent use help students' understand and optimize the tool for their specific needs. H4b, shows the relationship between task-technology fit and effort opportunism ($\beta = 0.345$, $p\text{-value} = 0.000$) which is statistically significant, effort opportunism, refers to exploiting ChatGPT where less effort is needed to achieve a desired outcome, this has significant impact on the perceived fit of the technology with the students' tasks, suggesting that the fit between the technology and tasks relies on opportunistic attempts to minimize effort. H4c, illustrates the relationship between task-technology fit and additional effort ($\beta = 0.124$, $p\text{-value} = 0.261$) which is not statistically significant, indicating that additional effort, or the extra time invested beyond the typical to complete an educational task, does not significantly influence how well the technology aligns with the task requirements. This suggests that task-technology fit is more dependent on inherent technology-task alignment than on the extra effort students' put into making the AI tool work for their needs.

As for the hypothesis that lead to this study's outcome, performance impact, which illustrates the overall productivity of students', the relationship between this variable and task-technology fit (H5), use of an AI tool (H6a) and additional effort (H6c) are statistically significant, ($\beta = 0.483$, $p\text{-value} = 0.000$), ($\beta = 0.455$, $p\text{-value} = 0.000$) and ($\beta = 0.082$, $p\text{-value} = 0.035$), respectively. This means that when the technology is well matched to the tasks it supports, there is a positive effect on performance outcomes, ensuring that when the technology aligns with the requirements of the tasks leads to a better fit which improves performance and also the more an AI tool is used, the greater the positive impact on performance (Aljukhadar et al., 2014; Goodhue & Thompson, 1995), suggesting that students' who frequently and effectively use AI tools experience improvements in performance, due to the AI tool's ability to enhance productivity. Despite additional effort having a weaker effect it is still statistically significant, suggesting that students' tend to do a minimal effort in

achieving higher grades than the ones ChatGPT can give them even though the extra effort has a slight positive impact on their tasks performance.

On the other hand, H6b, is the hypothesis between performance impact and effort opportunism ($\beta = 0.048$, $p\text{-value} = 0.111$), leads us to conclude despite not being statistically significant, that minimizing the effort of doing a task through opportunistic strategies does not directly impact performance in a meaningful way, indicating that finding ways to minimize effort does not necessarily translate into significant performance improvements.

Finally, the first research question (RQ1): "How does students' opportunistic use of ChatGPT affect their performance on academic tasks?" is directly addressed by the significant positive relationship between task-technology fit and effort opportunism which illustrates that students' by taking advantage of ChatGPT where less effort is needed significantly perceive a better fit of the technology with their tasks. This opportunism, where students' use ChatGPT to minimize effort, significantly influences how they engage with their academic tasks, suggesting that while it may enhance task completion efficiency, it does not necessarily translate to improvements in deeper learning outcomes, as indicated by the non-significant impact on overall performance (H6b). This implies that finding shortcuts through technology does not reflect on better performance, raising questions about the depth of learning and understanding.

As for the second research question (RQ2): "How does the additional effort performed by students' to improve their grades influence their performance on academic tasks when using ChatGPT?". The non-significant relationship between task-technology fit and additional effort indicates that the extra time students' invest beyond the typical to complete an educational task does not significantly influence how well the technology aligns with task requirements. However, despite its weak effect, H6c shows that even with a small increase in effort, performance is still positively impacted statistically. This implies that more work improves performance without significantly changing the perceived fit of technology, emphasizing the importance of cautiousness on over relying too much on AI tools.

Overall this study can be justified with the following theories, the theory of planned behavior and the cognitive theory, which together provide a comprehensive framework for understanding the dynamics of using educational tools like ChatGPT.

The theory of planned behavior helps explain the behavioral intentions behind using ChatGPT. It suggests that students' decisions to use ChatGPT are influenced by their behavioral beliefs (perceptions of the outcomes of using ChatGPT), normative beliefs (social pressures and expectations regarding the use of ChatGPT), and control beliefs (perceived ease or difficulty of using ChatGPT). Collectively, these beliefs shape students' intentions to adopt behaviors they perceive as beneficial for enhancing their learning experiences with ChatGPT (Bosnjak et al., 2020).

The cognitive load theory explains how educational tools like ChatGPT can optimize cognitive processing. This theory is concerned with the management of working memory capacity during learning tasks. It suggests that effective educational tools can help reduce unnecessary cognitive load, thereby freeing up cognitive resources for higher-order thinking. However, the theory also challenges the assumption that a high load is invariably beneficial. It points out that learning can occur even without additional demands on working memory, indicating that the integration and automation of knowledge can happen efficiently with well-designed educational interventions (Schnitz & Kürschner, 2007).

These theories collectively point out the complexity of integrating technology like ChatGPT in educational settings, emphasizing the need for tools that are both easy to use and effective in reducing cognitive overload, while still promoting robust learning and retention.

6.2. PRACTICAL IMPLICATIONS

The findings suggest that while additional effort can be beneficial, students' generally do not tend to invest in it. Instead, they often take a more opportunistic approach, relying on AI tools like ChatGPT to complete their tasks to achieve a satisfactory grade rather than attempt for the best possible outcome, the lack of significant impact of additional effort indicates that students' rely on what ChatGPT provides, and they're typically content with those results, not showing a strong tendency to do extra work to maximize their grades, encouraging students' to engage deeply with their coursework beyond using AI tools for quick answers can be a good solution for this, since this can be done by designing assignments that require critical thinking and personal input, pushing students' to apply their understanding more fully.

The research findings also offer several practical implications for educational settings to integrate AI tools. Task characteristics play a significant role in technology fit, but it's equally important to consider the technology's features and individual student characteristics, educational settings should prioritize AI tools that align with educational tasks, emphasizing usability, functionality, and features that directly address student needs, this focus will ensure a good fit and maximize the AI tools potential.

Developing programs to enhance student self-efficacy and confidence in using AI tools significantly improves perceived task-technology fit, institutions must provide user-friendly interfaces and clear instructions to promote a positive student experience and encourage its adoption, training programs that build students' confidence through workshops, hands on activities, and mentorships will likely improve AI tools adoption, effectiveness and productivity.

Regular use of AI tools helps students' develop habits and build familiarity, leading to a better perceived fit. Students' with experience using similar technologies will find integrating tools

like ChatGPT easier, leveraging existing student expertise will facilitate a smoother transition, allowing students' to personalize their use of the tool and optimize it for specific tasks, ultimately leading to more effective learning.

Aligning technology with tasks and encouraging frequent, effective AI tool use positively impacts student performance, the emphasis should be on empowering students' to use AI tools strategically to enhance their performance and learning outcomes.

7. CONCLUSIONS

This dissertation aimed to study the impact of modern AI tools, particularly ChatGPT, in education. As these technologies are rapidly evolving, it's important to understand their influence. The findings of this study point to the important role of task-technology fit in students educational performance and technology adoption.

The study reveals that while students' task characteristics modestly affect task-technology fit, and variables such as technology characteristics, self-efficacy, effort expectancy and habits, have a greater influence. These variables contribute to a perception of a strong alignment between ChatGPT and educational tasks, facilitating ease of use and habitual integration. Significantly, the frequent use of AI tools like ChatGPT optimizes their efficacy for students specific needs, although additional effort does not significantly enhance task-technology fit, emphasizing a tendency towards opportunistic behavior rather than striving for higher academic achievements.

This suggests a tendency for students to prioritize minimal effort strategies using ChatGPT to achieve satisfactory grades, even though deeper engagement could lead to better learning outcomes. Educational approaches that encourage critical thinking and personal engagement with course materials, beyond simply relying on AI for quick answers, can be a valuable solution to promote deeper learning and motivate students to strive for excellence.

Thus, this research offers important insights into how AI tools like ChatGPT impact education, and important insights for the need to promote effective technology usage methods that enhance students' performance, maximize their learning outcomes and incentive the want for an in-depth knowledge absorption.

8. LIMITATIONS AND FUTURE WORK

This study acknowledges several limitations. Firstly, one of the limitations this study had was the short number of samples and time we had to collect them. This data was collected from various universities, degrees and levels of study of students' above 18, it would be interesting if this study's findings were applied for example in students' with different nationalities, cultures and traditions.

Secondly, this questionnaire was created to be answered anonymously and in an honest way but this method can also introduce bias, as students' might not accurately reflect their use and perception of AI tools. So further work to improve this would be by employing mixed-method approaches, like interviews or direct observation, this way more deeper insights could be provided into how students' actually use AI tools like ChatGPT beyond their questionnaires answers.

Furthermore, focusing only on ChatGPT might limit the understanding of how the rest of the AI tools that aid students' in their educational tasks, impact students' performance within their opportunistic behaviors and will to do extra work to get better grades. Thus, comparative studies on multiple AI tools could give interesting findings not only on students' opportunism but also evaluating if these tools are in fact more effective than problematic in educational settings.

Lastly, this study may not deeply analyze underlying psychological or behavioral reasons for students' overreliance on AI tools. So for future work incorporating psychological models could be beneficial for understanding what drives students' to use AI tools.

BIBLIOGRAPHICAL REFERENCES

- Akkoyunlu, B., & Soyly, M. Y. (2008). International Forum of Educational Technology & Society A Study of Student's Perceptions in a Blended Learning Environment Based on Different Learning Styles. Source: *Journal of Educational Technology & Society*, 11(1), 183–193. <https://doi.org/10.2307/jeductechsoci.11.1.183>
- Aljukhadar, M., Senecal, S., & Nantel, J. (2014). Is more always better? Investigating the task-technology fit theory in an online user context. *Information and Management*, 51(4), 391–397. <https://doi.org/10.1016/j.im.2013.10.003>
- Alonso, F., López, G., Manrique, D., & Viñes, J. M. (2005). An instructional model for web-based e-learning education with a blended learning process approach. *British Journal of Educational Technology*, 36(2), 217–235. <https://doi.org/10.1111/j.1467-8535.2005.00454.x>
- Al-Rahmi, W. M., Al-Adwan, A. S., Al-Maatouk, Q., Othman, M. S., Alsaud, A. R., Almogren, A. S., & Al-Rahmi, A. M. (2023). Integrating Communication and Task–Technology Fit Theories: The Adoption of Digital Media in Learning. *Sustainability (Switzerland)*, 15(10). <https://doi.org/10.3390/su15108144>
- Baartman, L. K. J., & De Bruijn, E. (2011). Integrating knowledge, skills and attitudes: Conceptualising learning processes towards vocational competence. In *Educational Research Review* (Vol. 6, Issue 2, pp. 125–134). <https://doi.org/10.1016/j.edurev.2011.03.001>
- Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. In *Journal of AI* (Vol. 52, Issue 7). <https://doi.org/10.61969/jai.1337500>
- Bandura, A., & Adams, N. E. (1977). Analysis of Self-Efficacy Theory of Behavioral Change'. In *Cognitive Therapy and Research* (Vol. 1, Issue 4). <https://doi.org/10.1007/BF01663995>
- Basbeth, F., Manajemen, P., Asrul, M., & Ibrahim, H. (2018). Four Hours Basic PLS-SEM A Step by Step Guide With Video Clips For Student and Scholar. <https://www.researchgate.net/publication/344954763>
- Bhattacharjee, A., & Lin, C. P. (2015). A unified model of IT continuance: Three complementary perspectives and crossover effects. In *European Journal of Information Systems* (Vol. 24, Issue 4, pp. 364–373). Palgrave Macmillan Ltd. <https://doi.org/10.1057/ejis.2013.36>
- Bilad, M. R., Yaqin, L. N., & Zubaidah, S. (2023). Recent Progress in the Use of Artificial Intelligence Tools in Education. *Jurnal Penelitian Dan Pengkajian Ilmu Pendidikan: E-Saintika*, 7(3), 279–315. <https://doi.org/10.36312/esaintika.v7i3.1377>

- Bosnjak, M., Ajzen, I., & Schmidt, P. (2020). The theory of planned behavior: Selected recent advances and applications. In *Europe's Journal of Psychology* (Vol. 16, Issue 3, pp. 352–356). PsychOpen. <https://doi.org/10.5964/ejop.v16i3.3107>
- Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., ... Amodei, D. (2020). Language Models are Few-Shot Learners. <https://commoncrawl.org/the-data/>
- Castronova, J. A. (2002). Discovery Learning for the 21 st Century: What is it and how does it compare to traditional learning in effectiveness in the 21 st Century? https://www.academia.edu/10871733/Discovery_Learning_for_the_21st_Century_What_is_it_and_how_does_it_compare_to_traditional_learning_in_effectiveness_in_the_21st_Century
- Chen, J., Liu, Z., & Hu, R. (2022). Research on the Influence of Tolerance of Opportunistic Behaviors of Channel Boundaries on the Choice of Response Strategies. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.823416>
- D'Ambra, J., & Wilson, C. S. (2004). Use of the world wide web for international travel: Integrating the construct of uncertainty in information seeking and the Task-Technology Fit (TTF) model. *Journal of the American Society for Information Science and Technology*, 55(8), 731–742. <https://doi.org/10.1002/asi.20017>
- Drnovšek, M., Wincent, J., & Cardon, M. S. (2010). Entrepreneurial self-efficacy and business start-up: Developing a multi-dimensional definition. *International Journal of Entrepreneurial Behaviour and Research*, 16(4), 329–348. <https://doi.org/10.1108/13552551011054516>
- Dunn L. (2002). LEARNING AND TEACHING BRIEFING PAPERS SERIES Oxford Centre for Staff and Learning Development. www.brookes.ac.uk/services/ocsltd/resources/briefing_papers
- Dutta, S., & Chakraborty, T. (2023). Thus Spake ChatGPT. *Communications of the ACM*, 66(12), 16–19. <https://doi.org/10.1145/3616863>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>

- Elias, R. Z. (2013). THE IMPACT OF MACHIAVELLIANISM AND OPPORTUNISM ON BUSINESS STUDENTS' LOVE OF MONEY. *Southwestern Business Administration Journal (SBAJ)*, 13(1), 1–22. <https://www.tsu.edu/academics/colleges-and-schools/jesse-h-jones-school-of-business/pdf/sbaj/sbaj-volume-13-no1and2-paper1.pdf>
- Esplugas, M. (2023). The use of artificial intelligence (AI) to enhance academic communication, education and research: a balanced approach. *Journal of Hand Surgery: European Volume*. <https://doi.org/10.1177/17531934231185746>
- Farhi, F., Jeljeli, R., Aburezeq, I., Dweikat, F. F., Al-shami, S. A., & Slamene, R. (2023). Analyzing the students' views, concerns, and perceived ethics about chat GPT usage. In *Computers and Education: Artificial Intelligence (Vol. 5)*. Elsevier B.V. <https://doi.org/10.1016/j.caeai.2023.100180>
- Fiorella, L. (2020). The Science of Habit and Its Implications for Student Learning and Well-being. In *Educational Psychology Review (Vol. 32, Issue 3, pp. 603–625)*. Springer. <https://doi.org/10.1007/s10648-020-09525-1>
- Fuchs, K. (2023). Exploring the opportunities and challenges of NLP models in higher education: is Chat GPT a blessing or a curse? In *Frontiers in Education (Vol. 8)*. <https://doi.org/10.3389/feduc.2023.1166682>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance Task-Technology Fit and Individual Performance Minneapolis, MN 55455. In *Source: MIS Quarterly (Vol. 19, Issue 2)*. <https://doi.org/10.2307/249689>
- Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2023). Assessing student-perceived impact of using artificial intelligence tools: Construction of a synthetic index of application in higher education. *Cogent Education*, 11(1). <https://doi.org/10.1080/2331186X.2023.2287917>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. In *European Business Review (Vol. 31, Issue 1, pp. 2–24)*. Emerald Group Publishing Ltd. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hatami, S. (2013). Learning styles. In *ELT Journal (Vol. 67, Issue 4, pp. 488–490)*. Oxford University Press. <https://doi.org/10.1093/elt/ccs083>
- Hoehle, H., & Huff, S. (2012). 6. Advancing Task-Technology Fit Theory: A formative measurement approach to determining task-channel fit for electronic banking channels. <https://library.oapen.org/bitstream/handle/20.500.12657/33571/459876.pdf?sequence=1#page=147>

- Howard, M. C., & Rose, J. C. (2019). Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. *Information and Management*, 56(6). <https://doi.org/10.1016/j.im.2018.12.002>
- Hu, P. J. H., & Hui, W. (2012). Examining the role of learning engagement in technology-mediated learning and its effects on learning effectiveness and satisfaction. *Decision Support Systems*, 53(4), 782–792. <https://doi.org/10.1016/j.dss.2012.05.014>
- Kember, D., Biggs, J., & Leung, D. Y. P. (2004). Examining the multidimensionality of approaches to learning through the development of a revised version of the Learning Process Questionnaire. *British Journal of Educational Psychology*, 74(2), 261–279. <https://doi.org/10.1348/000709904773839879>
- Kooli, C. (2023). Chatbots in Education and Research: A Critical Examination of Ethical Implications and Solutions. *Sustainability (Switzerland)*, 15(7). <https://doi.org/10.3390/su15075614>
- Kositanurit, B., Ngwenyama, O., & Osei-Bryson, K. M. (2006). An exploration of factors that impact individual performance in an ERP environment: An analysis using multiple analytical techniques. *European Journal of Information Systems*, 15(6), 556–568. <https://doi.org/10.1057/palgrave.ejis.3000654>
- Lo, C. K. (2023). What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature. In *Education Sciences* (Vol. 13, Issue 4). MDPI. <https://doi.org/10.3390/educsci13040410>
- Mitchell, T. R., & Nebeker, D. M. (1973). EXPECTANCY THEORY PREDICTIONS OF ACADEMIC EFFORT AND PERFORMANCE 1. In *Journal of Applied Psychology* (Vol. 57, Issue 1). <https://doi.org/10.1037/h0034181>
- Moussa, N. M. (2014). The Importance of Learning Styles in Education. <https://www.auburn.edu/academic/cla/ilsrj//Journal%20Volumes/Fall%202014%20Vol%201%20PDFs/Learning%20Styles%20Nahla%20Moussa.pdf>
- Nagin, D. S., Rebitzer, J. B., Sanders, S., & Taylor, L. J. (2002). American Economic Association Monitoring, Motivation, and Management: The Determinants of Opportunistic Behavior in a. In *Source: The American Economic Review* (Vol. 92, Issue 4). <https://doi.org/10.1257/00028280260344498>
- Osamor, A., Ifelebuegu, Kulume, P., & Cherukut, P. (2023). Chatbots and AI in Education (AIEd) tools: The good, the bad, and the ugly. *Journal of Applied Learning and Teaching*, 6(2), 332–345. <https://doi.org/10.37074/jalt.2023.6.2.29>
- Parthasarathy, M., & Bhattacharjee, A. (1998). Understanding Post-Adoption Behavior in the Context of Online Services. *Information Systems Research*, 9(4), 362–379. <https://doi.org/10.1287/isre.9.4.362>

- Piccoli, G., Ahmad, R., & Ives, B. (2001). Web-Based Virtual Learning Environments: A Research Framework and a Preliminary Assessment of Effectiveness in Basic IT Skills Training (Vol. 25, Issue 4). <https://doi.org/10.2307/3250989>
- Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, 12(1). <https://doi.org/10.1186/s41039-017-0062-8>
- Salloum, S. A., Qasim Mohammad Alhamad, A., Al-Emran, M., Abdel Monem, A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access*, 7, 128445–128462. <https://doi.org/10.1109/ACCESS.2019.2939467>
- Sarker, S., & Valacich, J. S. (2010). An Alternative to Methodological Individualism: A Non-Reductionist Approach to Studying Technology Adoption by Groups (Vol. 34, Issue 4). <https://doi.org/10.2307/25750705>
- Schnotz, W., & Kürschner, C. (2007). A reconsideration of cognitive load theory. *Educational Psychology Review*, 19(4), 469–508. <https://doi.org/10.1007/s10648-007-9053-4>
- Shabiralyani, G., Shahzad Hasan, K., Hamad, N., Iqbal, N., University Faisalabad, G., Pakistan, P., & Ghazi Khan, D. (2015). *Journal of Education and Practice* www.iiste.org ISSN (Vol. 6, Issue 19). Online. www.iiste.org
- Shaw, M. J., & Gribbins, M. (2005). Towards a Specific Theory of Task-Technology Fit for Mobile Information Systems. <https://www.researchgate.net/publication/4893126>
- Sun, H., Fang, Y., & Zou, H. M. (2016). Choosing a fit technology: Understanding mindfulness in technology adoption and continuance. *Journal of the Association for Information Systems*, 17(6), 377–412. <https://doi.org/10.17705/1jais.00431>
- Tsai, M. L., Ong, C. W., & Chen, C. L. (2023). Exploring the use of large language models (LLMs) in chemical engineering education: Building core course problem models with Chat-GPT. *Education for Chemical Engineers*, 44, 71–95. <https://doi.org/10.1016/j.ece.2023.05.001>
- Tynjälä P. (1997). Developing education students' conceptions of the learning process in different learning environments. [https://doi.org/10.1016/S0959-4752\(96\)00029-1](https://doi.org/10.1016/S0959-4752(96)00029-1)
- Venkatesh, V., Thong, J. Y. L., Xu, X., & Walton, S. M. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology Quarterly Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology1. In Source: *MIS Quarterly* (Vol. 36, Issue 1). <https://doi.org/10.2307/41410412>

- Vermunt, J. D. (1998). The regulation of constructive learning processes. *British Journal of Educational Psychology*, 68(2), 149–171. <https://doi.org/10.1111/j.2044-8279.1998.tb01281.x>
- Wixom, B. H., & Todd, P. A. (2005). A Theoretical Integration of User Satisfaction and Technology Acceptance. *Information Systems Research*, 16(1), 85–102. <https://doi.org/10.1287/isre.1050.0042>
- Woltering, V., Herrler, A., Spitzer, K., & Spreckelsen, C. (2009). Blended learning positively affects students' satisfaction and the role of the tutor in the problem-based learning process: Results of a mixed-method evaluation. *Advances in Health Sciences Education*, 14(5), 725–738. <https://doi.org/10.1007/s10459-009-9154-6>
- Xiao, B., & Song, G. (2022). Association between Self-Efficacy and Learning Conformity among Chinese University Students: Differences by Gender. *Sustainability (Switzerland)*, 14(14). <https://doi.org/10.3390/su14148725>
- Yang, H. D., Kang, S., Oh, W., & Kim, M. S. (2013). Are all fits created equal? a nonlinear perspective on task-technology fit. *Journal of the Association for Information Systems*, 14(12), 694–721. <https://doi.org/10.17705/1jais.00349>

APPENDIX A – NOVA IMS ETHICS COMMITTEE APPROVAL



This is to certify that

Project No.: **INFSYS2024-3-142288**

Project Title: **The Influence of ChatGPT on Student Conformity and Self-Efficacy**

Principal Researcher: **Beatriz Grilo**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 3/14/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of

- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 3/14/2024

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