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Exploring Student Adoption of Generative AI in Education

Kasper Schroll

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 In

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Universidade Nova de Lisboa

Exploring Student Adoption of Generative AI in Education

by
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Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Information Systems and Technologies Management.

Supervised by
Professor Manuela Aparicio, Ph.D., NOVA Information Management School

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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.

[Copenhagen, 31.01.2024]

ABSTRACT

This thesis explores the impact of generative AI, such as ChatGPT, on education. Specifically, it examines the factors influencing the adoption of generative AI and its potential impact on student engagement, performance, and upskilling. Recognizing the evolving nature of this field, there is a pressing need to explore its complexities further. As a result, the study not only identifies key variables that shape the adoption of generative AI in education but also addresses gaps in the existing literature. The thesis presents a theoretical model to explore the topic, utilizing a structural equation model (PLS-SEM) and employing empirical testing through a survey. The findings indicate that 46.5% of generative AI adoption can be explained by educational level, performance expectancy, social influence, and trust. Additionally, the model highlights the explanatory power of generative AI in influencing student engagement (25.4%), student performance (47.9%), and upskilling (28.8%). The research provides significant novel insights into the evolving role of generative AI in reshaping education, offering a nuanced perspective crucial for guiding future initiatives and policies in this dynamic field.

KEYWORDS

Generative AI; ChatGPT; Education; Structural equation modeling; AI Adoption.

Sustainable Development Goals (SDG): 4 – Quality Education

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

Adop	AI Adoption
AI	Artificial Intelligence
EfExp	Effort Expectancy
GPT	Generative Pre-trained Transformer (part of the acronym ChatGPT)
LLM	Large Language Model
PExp	Performance Expectancy
SEM	Structural Equation Model
SI	Social Influence
StEng	Student Engagement
StPerf	Student Performance
Upsk	Upskilling
UTAUT	Unified Theory of Acceptance and Use of Technology

1. INTRODUCTION

Generative AI, as exemplified by models such as ChatGPT, is reshaping multiple sectors, with one notable example being its transformative role in education (Zhai, 2023). Hence, this thesis aims to enlighten the dynamic evolution of generative AI, concentrating specifically on its current influence on education. The primary objective is to explore and emphasize the importance of generative AI by highlighting the factors that drive its adoption and the potential outcomes resulting from this adoption.

Furthermore, the impact of generative AI on education presents several interesting areas for further research. Firstly, Wang et al. (2023) emphasize the need to broaden the scope of AI adoption research by including more universities and students from varied backgrounds. Secondly, Chatterjee and Bhattacharjee (2020) highlight the unexplored potential in studying the factors that influence AI adoption in educational settings, pointing to numerous variables that require further investigation. Lastly, Foroughi et al. (2023) and Hasselqvist Haglund (2023) shed light on the significant role of AI system evolution in shaping user adoption decisions. Therefore, as generative AI progresses with new advanced updates, ongoing research becomes increasingly essential in understanding its influence, particularly as models continue to advance. Given these interesting research gaps, the paper will explore the following research question:

RQ: ***Determining the Impact of Generative AI in Educational Settings: Analyzing AI Adoption and Its Influence on Students Engagement, Performance and Upskilling.***

Research Objectives:

1. Identify variables explaining the impact of generative AI in education.
2. Develop and model adoption variables, explaining how they correlate with student engagement, performance, and upskilling.
3. Test the model in an empirical setting by collecting data through a survey.

Furthermore, in terms of methodology, the thesis consists of a literature review drawing from academic sources in both educational and technological research. It employs a natural science-based methodology, progressing from hypothesis formulation to theory development, all to uncover objective truths. It relies on quantitative research methods, primarily employing surveys for data collection. The thesis will mainly be build around theoretical structural equation modeling (PLS-SEM) (Hair et al., 2011). Here the model will undergo empirical testing, utilizing the survey dataset to validate its theoretical constructs (Henseler et al., 2009).

In terms of the results, the R^2 serves as an indicator of the model's explanatory power. Specifically, 46.5% of AI Adoption is accounted for by the independent variables of Educational Level, Performance Expectancy, Social Influence, and Trust. The model explains 25.4% of Student Engagement, 47.9% of Student Performance, and 28.8% of Upskilling.

The paper will follow a structured approach, beginning with Chapter 2, which provides a literature review covering different discourses on generative AI within an educational context. This section will delve into the advantages and disadvantages of generative AI, along with an exploration of the ethical perspective surrounding the topic. Moving to Chapter 3, the paper will introduce the structural equation model (PLS-SEM) and articulate the hypotheses, providing a detailed explanation for each construct within the model. Chapter 4 will be dedicated to the empirical study and model testing, involving detailed analysis and examination of the obtained results. Subsequently, Chapter 5 will delve into a comprehensive discussion, followed by the conclusion in Chapter 6.

2. STUDENT ADOPTION OF GENERATIVE AI: A LITERATURE REVIEW

The following section provides an introduction to the topic of generative AI in education, beginning with an informative explanation of generative AI. Additionally, there will be an overview of the ongoing discourse and debates surrounding generative AI while also touching upon other relevant subtopics. Following this, two additional sections will delve into the advantages and disadvantages of generative AI, along with the ethical perspective, given their relevance in the area.

2.1 GENERATIVE AI WITHIN THE EDUCATIONAL CONTEXT

Generative AI, a subset of artificial intelligence, leverages machine learning techniques to create new content encompassing text, images, music, etc. (Totlani, 2023). It accomplishes this by learning from established data patterns (Cornell University, 2023). Noteworthy instances of generative AI include Large Language Models (LLMs), such as ChatGPT, designed explicitly to generate text resembling human language. They achieve this by drawing upon extensive datasets of text (Su & Yang, 2023). These LLMs, equipped with comprehensive parameter configurations, excel in various tasks, including answering questions and summarizing materials. Furthermore, other prominent generative AI tools like Perplexity and Bard share similar characteristics, effectively producing text that closely resembles human-generated content (Infante et al., 2024). In contrast, other players in the natural language processing landscape, such as Grammarly and Quillbot, specialize in using AI to proofread and assist with paraphrasing (Churi et al., 2022).

The increasing use of generative AI by students underscores its central and prominent concern in education. Consequently, scholars and media have shown increased interest in the potential integration of generative AI in educational contexts. For instance, Sullivan et al. (2023) extensively analyzed a sample of (n = 100) articles to examine the prevailing discourse on generative AI. Their findings revealed that nearly half of the analyzed news articles delved into the topic of integrating generative AI, mainly focusing on the integration of ChatGPT (Sullivan et al., 2023). Thus, concepts like adaptive testing/assignments, personalized learning/feedback, the utilization of chat-bots, and brainstorming ideas represent some use cases in which scholars see significant potential for AI integration (Sullivan et al., 2023; Wang et al., 2023; Chen et al., 2020). Building on this discussion, Jeon and Lee's (2023) qualitative data, gathered through teacher interviews, underscore the necessity of establishing a consensus on how students can utilize these tools and fostering an environment that encourages open discourse about the information they acquire and use.

In this broader context of AI's potential applications, teachers' acceptance and perception of generative AI, as investigated by Iqbal et al. (2023) and Jeon and Lee (2023), reveal a nuanced perspective of opinions. Iqbal et al. (2023) found a prevailing negative attitude among teachers toward ChatGPT, citing concerns about potential student cheating and fostering laziness. However, amidst this skepticism, some participants acknowledged the utility of ChatGPT in specific contexts, such as providing automated feedback and freeing up teachers for other tasks. Jeon & Lee's (2023) study offers a more optimistic perspective, emphasizing the collaborative potential between teachers and AI. The study suggests that instead of being overly concerned about depending too heavily on AI, it's more important to recognize teachers' vital role in guiding students to use AI well and ethically. The study highlights three teacher roles—orchestrating resources, fostering student investigation, and promoting ethical awareness—underscoring the need for teacher-student interaction in shaping pedagogical decisions related to AI. Additionally, Kaplan-Rakowski et al. (2023) offer an interesting perspective, suggesting a correlation between AI exposure and the extent to which teachers integrate it into their teaching methods. This implies that as educators become more familiar with AI, they are more likely to include it in their teaching approach gradually. These contrasting views underscore the complex interplay between teachers and generative AI, requiring collaboration and a nuanced approach to leverage its potential while addressing relevant concerns effectively.

Having explored generative AI and its diverse applications, the subsequent sections will delve into two specific dimensions. Firstly, the upcoming section will focus on the advantages and disadvantages of generative AI, examining practical benefits and challenges. Subsequently, the following section will tackle the complex ethical considerations that emerge as this technology becomes more integrated into education. These discussions aim to provide a holistic understanding of the generative AI landscape within educational contexts.

2.2 Negative and Positive Sides of Generative AI

This section serves as a general overview of some of the central viewpoints regarding the impact of generative AI on education. Researchers have extensively examined the advantages and disadvantages, still, there exists a notable separation of opinion within the research community regarding its overall impact, with arguments on whether AI's influence will be ultimately positive or negative.

A primary contention against the adoption of generative AI revolves around the potential for biased outcomes. For instance, Rasul et al. (2023) assert that "*ChatGPT-generated text may contain factual biases due to biased training data, which could perpetuate misconceptions held by learners"* (Rasul et al., 2023, p.48). Accordingly, other researchers emphasize the importance of ensuring that the information generated by ChatGPT is unbiased and generally delivers an objective standpoint (Su & Yang, 2023). Another closely related concern revolves around the possibility of inaccurate information. Thus, with more students directly relying on generative AI tools as their primary source of information, the potential danger of false information becomes specifically relevant (Limna et al., 2023). Therefore, it arguably becomes essential for students to recognize the importance of verifying information when relying on AI-generated content. Another interesting aspect is the potential impact on students' fundamental skill development. Researchers have raised concerns about how AI may adversely affect critical thinking, creativity, and the overall authenticity of students' writing skills (Cardon et al., 2023). However, since this technology is relatively new, predicting its long-term influence on students' future skill sets remains challenging.

Examining the positive aspects of generative AI unveils various interesting viewpoints, including the opportunity for students to access answers to questions outside of regular class hours (Cotton et al., 2023). Additionally, the convenience of accessing answers beyond traditional class schedules aligns with the evolving demands of modern education, offering students greater flexibility in their learning journey (Gill et al., 2023). Hence, in the future, it arguably becomes more important for educators to balance the needs of students in terms of AI supporting their independent learning while maintaining the integrity of in-class instruction, fostering a holistic educational experience. Another notable aspect of generative AI is its potential for personalization, where it can serve as a tailored learning assistant, catering to individual needs. Here, Zhai (2022) points to some specific scenarios, such as the "*use of AI to generate customized lesson plans, provide personalized feedback and support, and track student progress*" (Zhai, 2022, p.9). The changing level of personalization can, therefore, potentially have a great impact on students' learning outcomes, supporting an effective and tailored educational experience. An additional noteworthy outcome of generative AI integration is the potential for upgraded efficiency and improved idea generation in the students' writing process, which naturally can offer substantial benefits to a diverse range of students (Cardon et al., 2023). For example, Botchu et al. (2023) emphasize how generative AI can offer valuable support to individuals with dyslexia, while Wang et al. (2023) showcase how it might significantly enhance the educational experience for international students. Consequently, there are indeed noteworthy instances of AI proving to be a valuable tool for those facing various forms of disadvantages.

To sum up, the discourses surrounding the impact of generative AI on education remain unclear. On the one hand, concerns about biases, inaccuracies, and potential adverse effects on critical skills are raised, highlighting the need for caution and careful consideration in its implementation. On the other hand, the advantages, such as accessibility, flexibility, and personalization, hold promise for enhancing the educational experience. As educators and researchers continue to explore the role of generative AI in education, it becomes evident that a balanced approach, harnessing its benefits while addressing its challenges, will be crucial for shaping the future of education.

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2.3 ETHICAL ASPECTS OF GENERATIVE AI

The following section will address the ethical perspective surrounding generative AI in education. With AI tools becoming increasingly common among students, various ethical dilemmas have arisen. Hence, some major challenges vary from data privacy concerns to questions regarding equal access to these tools. Consequently, the ethical environment of AI in education remains complex and multidimensional.

One perspective mainly pointed out is the potential issue of data privacy. Hence, with students interacting and relying more on generative AI, the potential issue of sharing sensitive data arises (Zhai, 2022). Notably, a tool like ChatGPT has the capability to access and interact with sensitive information, such as age, personal identity, and academic history (Limna et al., 2023). Due to the abovementioned issues, researchers point to the importance of having policies in place. Specifically, Qadir (2023) argues that "*It's important for schools to have clear policies in place regarding the use of these tools and to ensure that student data is properly protected.*" (Qadir, 2023, p.4). Hence, as generative AI becomes more deeply integrated into education, there is an argument for establishing clear guidelines to govern students' interactions and data privacy with these tools.

Furthermore, another perspective is the lack of transparency when interacting with generative AI models. The lack of transparency can be linked with the concept of AI systems often being a “black box”, meaning operations or general function of the system cannot be understood by humans. As Petch et al. (2022) define, 'black box' refers to “*models that are sufficiently complex that they are not straightforwardly interpretable to humans*” (Petch et al., 2022, p.1). This concept is highlighted by Sun and Medaglia (2019) in their paper, stating, “*This lack of transparency is perceived as a major challenge; the AI technology represents as a 'black box,' and its users have no power to understand its mechanisms or modify them to tackle potential problems*” (Sun & Medaglia, 2019, p.31). Consequently, users encounter difficulties in comprehending the inner workings of the system and the techniques used to generate specific outcomes (Zhai, 2022). Thus, the inability to understand or modify the underlying mechanisms of AI systems may lead to accountability, bias, and fairness issues, raising important questions about the ethical use and impact of generative AI technologies.

Lastly, one ethical dilemma is the equality in having access to these specific tools. Thus, ensuring that everyone has the necessary training and access to these tools is essential, given their potential advantages (Chan, 2023). Here, Cotton et al. (2023) expressly point out that “*For example, if a student has access to GPT-3 and uses it to generate high-quality written assignments, they may have an unfair advantage over other students who do not have access to the model*"” (Cotton et al., 2023, p.3). There are, therefore, arguably opportunities for some students to have unfair advantages over others. This dilemma raises questions about whether teachers should ensure that every student ultimately has access to and training in using the tools. The mentioned issue gains greater prominence when one considers the potential for students to exploit specific generative AI tools for cheating. Consequently, some researchers highlight how these systems may threaten the fundamental goals of education (Cotton et al., 2023).

In summary, the ethical aspects of generative AI in education involve concerns related to data privacy, transparency, and equal access. Data privacy and transparency issues underscore the need for clear policies. At the same time, unequal access to AI tools can lead to unfair advantages among students and potentially compromise the fundamental goals of education.

These considerations emphasize the importance of ethical guidelines and thoughtful integration of generative AI in education.

2.4 COMPARISON AMONG MODELS

In this section, a comparison will be made among studies that have employed Structural Equation Models (SEM) to investigate the adoption factors of AI in an educational context. Utilizing a comparison table, the aim is to highlight independent variables, dependent variables, significant hypotheses, and insignificant hypotheses. Additionally, this comparative analysis aims to identify common trends and highlight divergent findings, shedding light on the nuanced nature of AI adoption within educational settings. Through synthesizing these insights, a deeper understanding of the multifaceted dynamics shaping the integration of generative AI in education will be contributed. Furthermore, the significance of SEM, particularly in relation to p-values as an analytical tool for describing complex relationships within the educational AI landscape, will be underscored. It's worth noting that a relationship is considered insignificant if its p-value is 0.05 or higher, aligning with hypothesis testing standards (Cohen, 1992).

Table 1 - Comparisons Among AI Adoption Research Within Educational Settings

Study	Education AI context	Study objective	Independent variables	Dependent variables	Significant hypothesis (p < 0.05)	Insignificant hypothesis (p ≥ 0.05)
ChatGPT, a friend or a foe? (Yatoo & Habib, 2023)	Random selected, from five public universities	Factors Contributed to the Use of ChatGPT	- Perceived Usefulness (PU) - Perceived Ease of Use (PEU) - Social Influence (SI) - Facilitating Conditions (CF) - Perceived Interest (PJ)	- Behavior Intention (BI)	- PU --> BI | p = 0.004 - PEU --> BI | p = 0.000 - SI --> BI | p = 0.002 - CF --> BI | p = 0.003 - PJ --> BI | p = 0.002	-
Understanding the Dynamics of ChatGPT Adoption Among Undergraduate Students: Dataset from a Philippine State University (Himang et al., 2023)	Undergraduate Students	Finding ChatGPT adoption factors	- Performance expectancy (PE) - Effort expectancy (EE) - Social influence (SI) - Price value (PE) - Habit (HAB)	- Behavior Intention (BI)	- SI → BI | p < 0.001 - PV → BI | p < 0.001 - HAB → BI | p < 0.001 - PE → BI | p = 0.015	- EE → BI | p = 0.301
Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling (Chatterjee & Bhattacharjee, 2020)	Random Selection of Indian Higher Education Institutes	AI Adoption in Indian Higher Education	- Perceived Risk (PR) - Performance expectancy (PE) - Effort expectancy (EE) - Facilitation conditions (FC)	- Attitude (ATT) - Behavioral intention (BI)	- PR → ATT | p < 0.001 - FC → BI | p < 0.001 - EE → ATT | p < 0.05	- PE → ATT | p > 0.05
Navigating the Complexity of Generative AI Adoption in Software Engineering (Russo, 2023)	Software engineer	Adoption of Generative Artificial Intelligence tools within software engineering	- Personal and Environmental Factor (PEF) - Perceptions about Technology (PT) - Compatibility Factors (CF) - Social Factors (SF)	- Intention to use (IU)	- PEF → PT | p = 0.000 - PT → CF | p = 0.000 - PT → SF | p = 0.000 - CF → IU | p = 0.000	- PEF → IU | p = 0.949 - SF → IU | p = 0.170 - PT → IU | p = 0.204
What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT (Tiwari et al., 2023)	ChatGPT-savvy millennials	Identifying factors in students' attitude toward ChatGPT for education.	- Perceived usefulness (PU) - Perceived ease of use (PEU) - Perceived credibility (PC) - Perceived social presence (PSF) - Hedonic motivation (HM)	- Behavioral intention to use Chatgpt (IAC) - Attitude towards Chatgpt (AC)	- PU = AC | p = 0.000 - PC = AC | p = 0.000 - HM =AC | p = 0.000 - AC = IAC | p = 0.000	-PEU = AC | p = 0.078 - PSF = AC | p = 0.005
Use of ChatGPT in academia: Academic integrity hangs in the balance (Bin-Nashwan et al., 2023)	Respondents from Higher Academic Positions	Motivations that drive academics to adopt ChatGPT in academic settings.	- Time-saving feature (TSF) - E-word of mouth (e-WOM) - Peer influence (PI) - Self-esteem (SE) - Academic self-efficacy (ASE) - Perceived stress (PS)	- Use of ChatGPT in academia (ChatGPT)	- TSF --> ChatGPT | p = 0.000 - e-WOM --> ChatGPT | p = 0.000 - SE --> ChatGPT | p = 0.012 - ASE --> ChatGPT | p = 0.002 - PS --> ChatGPT | p = 0.000 - PI --> ChatGPT | p = 0.033	-
Determinants of Intention to Use ChatGPT for Educational Purposes: Findings from PLS-SEM and fsQCA (Foroughi et al., 2023)	Malaysian University Coursework Students	Investigating ChatGPT Usage Intention	- Performance Expectancy (PE) - Effort Expectancy (EE) - Social Influence (SI) - Facilitating Conditions (FC) - Hedonic Motivation (HM) - Learning value (LV) - Habit (HAB) - Personal Innovativeness (PI) - Information Accuracy (IA)	- Intention to Use (IU)	- PE --> IU | p = 0.000 - EE → IU | p = 0.048 - SI → IU | p = 0.0282 - FC —> IU | p = 0.019 - HM → IU | p = 0.019 - LV → IU | p = 0.024	- HAB → IU | p = 0.315
AI-Based Chatbots Adoption Model for Higher-Education Institutions: A Hybrid PLS-SEM-Neural Network Modelling Approach (Mohd Rahim et al., 2022)	Malaysian postgraduate students with prior chatbot application experience.	Chatbot Adoption in Higher Education Institutions.	- Performance Expectancy (PE) - Effort Expectancy (EE) - Social Influence (SI) - Facilitating Conditions (FC) - Hedonic Motivation (HM) - Habit (HT) - Interactivity (INT) - Design (DE) - Ethics (ET) - Perceived Trust (PT)	- Behavioural Intention (BI) - Use (USE)	- BI -> USE | P = 0.0000 - DE -> PT | P = 0.0012 - ET -> PT | P = 0.0000 - HT -> BI | P = 0.0000 - INT -> PT | P = 0.0278 - PE -> BI | P = 0.0479 - PT -> BI | P = 0.0000	- EE -> BI | P = 0.4722 - FC -> BI | P = 0.2953 - HM -> BI | P = 0.3320 - SI -> BI | P = 0.3310
To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology (Strzelecki, 2023)	Polish University Student	Examining predictors of ChatGPT adoption in higher education.	- Performance Expectancy (PE) - Effort Expectancy (EE) - Social Influence (SI) - Facilitating Conditions (FC) - Hedonic Motivation (HM) - Habit (HAB) - Personal Innovativeness (PI)	- Behavioral Intention (BI) - Use Behavior (UB)	- PE --> BI | p = 0.000 - SI --> BI | p = 0.002 - FC --> UB | p = 0.000 - HM --> BI | p = 0.000 - HAB --> BI | p = 0.000 - HAB --> UB | p = 0.000 - BI --> UB | p = 0.000 - EE --> BI | p = 0.028 - PI --> BI | p = 0.026	- FC --> BI | p = 0.906
Predicting Adoption Intention of Artificial Intelligence (Emon et al., 2023)	Professionals in Bangladesh using ChatGPT for research and practical applications	Investigate ChatGPT adoption among professionals	- Attitude Towards Artificial Intelligence (ATAI) - Performance Expectancy (PE) - Effort Expectancy (EE) - Social Influence (SI) - Facilitating Conditions (FC) - Hedonic Motivation (HM) - Trust (T)	- Behavioral Intention to Use (BIU) - Actual Use (AU)	- ATAI -> BIU | p = 0.03 - PE -> BIU | p = 0.00 - EE -> BIU | p = 0.01 - FC -> BIU | p = 0.00 - T -> BIU | p = 0.00	- SI -> BIU | p = 0.12 - HM -> BIU | p = 0.86

The table underscores the significance of critical factors such as performance expectancy, effort expectancy, and social influence. These variables are frequently encountered when studying technology adoption, also illustrated by their presence in the UTAUT framework (Venkatesh et al. 2003). The relevance of these variables underscores their critical role in shaping technology adoption, especially in educational AI contexts. Interestingly, there remains a noticeable variance in whether variables are deemed significant across different studies. For example, some studies emphasize social influence as a significant factor (Yatoo & Habib, 2023; Himang et al., 2023; Foroughi et al., 2023; Strzelecki, 2023), while others argue its insignificance (Russo, 2023; Mohd Rahim et al., 2022; Emon et al., 2023). Effort expectancy is categorized as significant by certain studies (Chatterjee & Bhattacharjee, 2020; Foroughi et al., 2023; Strzelecki, 2023; Emon et al., 2023), while others indicate its insignificance (Himang et al., 2023; Mohd Rahim et al., 2022). Performance expectancy is generally consistent, with most studies indicating its significance, except for Chatterjee & Bhattacharjee (2020). Studies incorporating trust consistently find it significant (Emon et al., 2023; Mohd Rahim et al., 2022). Considering the varied results, it's important to note that these studies are conducted in different countries, suggesting potential cultural influences. Additionally, it's essential to acknowledge that this research area is still very new and evolving, contributing to the lack of consistency in study results. This also underscores the necessity for further research. Given this ongoing evolution, there is still considerable scope for exploration in this field. Furthermore, it is worth noting that trust has not received sufficient attention, with only two studies incorporating it. This emphasizes the need for a more substantial focus on ethical dimensions in future educational AI research, ensuring a comprehensive understanding of technology adoption in this field. Lastly, another insight from the table is the high emphasis on adoption factors, with a noticeable absence of focus on the actual outcomes of this adoption. This further underscores the relevance of the thesis focus.

3. RESEARCH MODEL PROPOSAL

This section introduces a novel conceptual model that considers the dimensions affecting students' adoption of generative AI in education. These dimensions draw inspiration from prior research, as seen in Table 1, which has explored similar domains. Like previous studies, this model incorporates part of the theory of adoption, recognizing its importance in understanding technology adoption factors (Venkatesh et al. 2003). The model will incorporate education level, as Chung et al. (2016) emphasized, recognizing its relevance in education. Additionally, this model aims to examine the ethical dimensions, particularly the influence of trust, which is highly relevant, as demonstrated in the literature review (Choudhury & Shamszare, 2023). Lastly, the model's scope extends beyond the exclusive examination of adoption factors. It also strives to reveal the potential consequences of this adoption, drawing insights from the definitions provided by the following authors. Specifically, Kucuk and Richardson (2019) contribute to our understanding of student engagement, Tadese et al. (2022) provide insights into student performance, and Jaiswal et al. (2021) offer perspectives on upskilling. This approach provides an alternative perspective on the topic.

Each dimension within this model will be paired with a hypothesis to test, contributing to a comprehensive investigation of the adoption and impact of generative AI in educational contexts.

Table 2 – Construct definition

Contruct	Definition	Reference
Education level	*"Education level, defined as the highest level of formal education completed as of the interview date"*	(Chung et al., 2016, p.2)
Effort expectancy	*"Effort expextancy is defined as the degree of ease associated with the use of the system"*	(Venkatesh et al., 2003, p.450)
Performance expectancy	*"Performance expectancy is defined as the degree to which an individual believes that using the sys- tem will help him or her to attain gains in job performance."*	(Venkatesh et al., 2003. p.447)
Social influence	*"Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the new system."*	(Venkatesh et al., 2003, p.451)
Trust	*"We define Trust in ChatGPT as a user's willingness to take chances based on the recommendations made by this technology."*	(Choudhury & Shamszare, 2023, p.3)
AI Adoptation	*"The present study defines AI adoption intention as the degree of willing to adopt AI's production"*	(Cheng et al., 2023, p.6)
Student engagement	*"Engagement refers to active involvement in course activities with continuous efforts to attain desired learning outcomes"*	(Kucuk & Richardson, 2019, p.199)

Student performance	*"Academic performance/ achievement is the extent to which a student, teacher, or institution has attained their short or long-term educational goals and is measured either by continuous assessment or cumulative grade point average (CGPA)"*	(Tadese et al., 2022, p.2)
Upskilling	*"In this study, we operationalize upskilling as learning new skills to sharpen employee's abilities to understand and utilize AI-based systems"*	(Jaiswal et al., 2021, p.1180)

3.1 MODEL AND HYPOTHESIS

Education level, indicating the highest degree of formal education completed as of the interview date, will be a key parameter measured in this study (Chung et al., 2016). Specifically, the educational level will be assessed based on the highest qualification completed by participants at the time of survey participation. This metric serves not only as a demographic descriptor to characterize the sample data but is likewise relevant to the measurement model due to its potential importance. Previous research has emphasized the significant role of education in understanding individuals' adaptability to AI, establishing a correlation between the level of education and attitudes toward AI (Yigitcanlar et al., 2022). This is exemplified by the findings of Hong (2022), indicating that individuals with higher education levels are more likely to receive advice about using AI technology. Consequently, educated individuals may have greater exposure to information and recommendations concerning AI. Given the prior research and the specific focus of this study on students' adoption of generative AI, the variable of educational level becomes particularly interesting. The study will, therefore, aim to test the following hypothesis.

Hypothesis 1*: Educational level positively influences the adoption of generative AI in educational settings.*

Effort Effort expectancy refers to the perception of the level of ease or difficulty associated with using generative AI technology (Venkatesh et al., 2003). It represents the extent to which an individual perceives that using generative AI is a straightforward and user-friendly process. In an educational context, this dimension reflects students' beliefs about how easy or challenging it is to utilize generative AI for their learning. Despite effort expectancies being extensively discussed in the literature, there is disagreement among studies regarding its significance in the adoption of generative AI in education. Hence, Himang et al. (2023) argue that the variable is insignificant in adoption, while other studies highlight it has a significant impact (Chatterjee & Bhattacharjee, 2020; Foroughi et al., 2023; Strzelecki, 2023).

Investigating effort expectancy is critical, as it may significantly shape students' attitudes and intentions regarding the adoption of generative AI. The perceived ease of use could potentially impact students' decisions regarding the adoption of generative AI, and this study aims to understand the extent of this influence. In particular, this section seeks to examine the proposed hypothesis.

Hypothesis 2*: Effort expectancy positively influences the adoption of generative AI in educational settings.*

As described by Venkatesh et al. (2003), performance expectancy refers to an individual's belief that using a technology or system will improve their chances of achieving better outcomes. In the context of education, Diep et al. (2016) build upon this concept by combining performance expectancy with perceived learning benefits, emphasizing its impact on improving overall learning performance. Hence, in an educational context, this dimension signifies how students perceive that integrating generative AI into their learning processes will improve their academic performance. Exploring performance expectancy is essential, as evidenced by its consistent presence in the literature review, and is identified as the most influential predictor of intention (Venkatesh et al., 2003). By investigating this dimension, the study aims to understand the role of performance expectancy in students' decisions to adopt generative AI and its potential impact on their educational outcomes. Specifically, this section aims to investigate the presented hypothesis.

Hypothesis 3: *Performance expectancy positively influences the adoption of generative AI in educational settings.*

Social influence is the extent to which an individual's adoption of a new technology is influenced by the perceived expectations and behaviors of others (Venkatesh et al., 2003). Expanding on this concept, Taylor and Todd (1995) emphasize the influence of peers and superiors within the context of social influence. In the context of this thesis and within the educational setting, social influence involves fellow students, professors, and other influential figures. Understanding the dynamics of social influence is essential as it may play a crucial role in shaping students' attitudes and intentions regarding the adoption of generative AI. This study aims to explore the extent of its impact and its influence on students' decision-making processes. Consequently, the section serves to explore the following hypothesis.

Hypothesis 4*: Social influence positively influences the adoption of generative AI in educational settings.*

Defining trust is a complex task given its broad scope. However, drawing inspiration from the work of Choudhury and Shamszare (2023), trust is described as the user's willingness to take chances based on the recommendations made by the technology. This definition underscores the user's confidence in the technology's ability to provide reliable recommendations, forming the basis for the study's exploration of trust in generative AI, which includes dimensions such as reliability, transparency, and privacy. According to Niu and Mvondo (2023), establishing trust in tools like ChatGPT is crucial for fostering user retention and loyalty. This emphasizes the need to investigate the trust factor, which could significantly influence students' decisions regarding incorporating generative AI into their educational journey. Thus, this study aims to comprehensively explore the impact of trust, specifically by testing the hypothesis outlined below.

Hypothesis 5*: Trust positively influences the adoption of generative AI in educational settings.*

In the realm of AI adoption, Cheng et al. (2023) assert a crucial perspective, defining AI adoption as the extent of willingness to embrace AI. This viewpoint aligns with Agrawal et al. (2022), who emphasize the significance of the individual level in understanding how people engage with and integrate AI technologies into their specific situations. This emphasis on individual adoption becomes particularly noteworthy when examining how students incorporate AI into their academic journey. Whether seeking inspiration for writing, ensuring grammatical correctness, or enhancing idea generation, this purposeful adoption extends beyond influencing the broader academic landscape—it profoundly shapes the unique educational journey of each student.

The literature has presented various definitions of student engagement. Schindler et al. (2017) outline two primary perspectives: one centered on students' feelings and thoughts towards learning, and the other emphasizing students' behavioral involvement in activities (Schindler et al., 2017). The latter definition, aligning with Kucuk and Richardson (2019), underscores that "*engagement refers to active involvement in course activities with continuous efforts to attain desired learning outcomes*," a perspective adopted in this paper (Kucuk & Richardson, 2019, p.199). Acknowledging the significance of student engagement in the learning process and its relevance, exploring its dynamics becomes crucial. This investigation becomes particularly intriguing when considering the potential impact of generative AI adoption on this variable. In particular, this section aims to investigate the hypothesis outlined below.

Hypothesis 6a*: The adoption of generative AI positively affects student engagement.*

Student performance is commonly linked to academic achievements, often measured by indicators such as Grade Point Average (Godwin et al., 2015). However, in the context of this study, the concept of student performance extends beyond traditional metrics to encompass a broader understanding, emphasizing academic accomplishments, skill acquisition, and overall student success (Hazzam & Wilkins, 2023). Thus, this perspective also aims to evaluate crucial factors like learning experience and efficiency in learning time. Exploring how the integration of generative AI precisely influences student performance is of considerable interest. The literature review has already examined the debate surrounding whether this development has a positive impact or not, making this an essential aspect to investigate further. As technology continues to shape educational landscapes, understanding its effects on student performance becomes increasingly essential for effective education. With this context, the goal is to investigate the following hypothesis.

Hypothesis 6b*: The adoption of generative AI positively affects student performance*.

Upskilling is another interesting perspective that the usage of generative AI might influence. While commonly associated with enhancing new skills for employees, drawing inspiration from Jaiswal et al. (2021) definition, upskilling is understood as the process of learning new skills. Furthermore, it is arguably important for students to consistently enhance their skills, enabling them to adapt to changes and stay relevant in the dynamic job market (Kilag et al., 2023; Piala et al., 2024). Hence, Li (2022) emphasizes that critical future skills revolve around analytical thinking, innovation, and problem-solving. Consequently, this study will specifically target skill development within these domains. Given this understanding, the study seeks to delve into the impact of generative AI on upskilling. Hence, the investigation aims to explore whether the utilization of generative AI tools positively enhances essential future skills. Therefore, this section aims to examine the following hypotheses.

Hypothesis 6c*: The adoption of generative AI positively affects upskilling.*

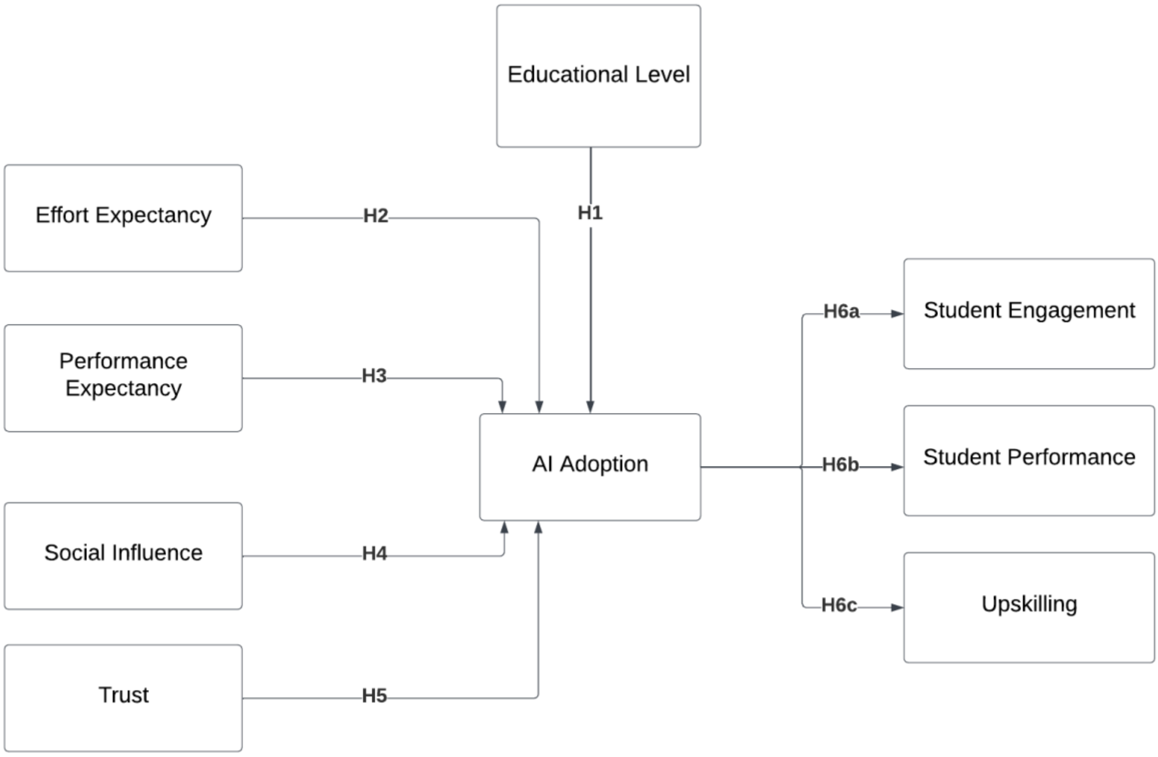

Figure 1 – Proposed Conceptual Model: Generative AI Adoption & Student Outcome Model

4. EMPIRICAL STUDY AND MODEL TESTING

4.1 CONSTRUCTING QUESTIONNAIRE

The questionnaire, detailed in Appendix A, is drawn from previous studies, ensuring their effectiveness through prior testing. Multiple authors have contributed to diverse constructs. Effort Expectancy, as an independent variable, is derived from the research of Chatterjee and Bhattacharjee (2020), Himang et al. (2023), and Strzelecki (2023). Social Influence is constructed based on the works of Strzelecki (2023) and Russo (2023). Performance Expectancy is shaped by the contributions of Strzelecki (2023) and Himang et al. (2023). Trust is built upon the research of Jo (2023) and Choudhury and Shamszare (2023). The construct of AI adoption is developed from the findings of Roy et al. (2023). The dependent variable, Student Engagement, is informed by the work of Al-Abdullatif and Gameil (2021), while Student Performance incorporates insights from Hazzam and Wilkins (2023) and Boubker (2023). Lastly, Upskilling drew inspiration from the study by Ebrahimi Mehrabani and Azmi Mohamad (2015). The specific questions were disseminated via the Qualtrics platform, and screenshots of these questions are available in Appendix B.

4.2 SAMPLE CHARACTERISTICS AND DISTRIBUTION

To ensure the survey's success, it was primarily shared across various social media platforms, especially Facebook and LinkedIn, targeting individuals currently undergoing some form of education. Using my personal network helped gather more participants quickly, as I encouraged my connections to share the survey within their networks. This approach efficiently led to reaching the targeted number of participants.

Out of the total 258 respondents, 207 provided complete and valid answers, as shown in Table 3. To filter out participants who did not meet the criteria, the survey included an initial screening question: "Are you currently enrolled as a student in any educational institution?". Additionally, measures were taken to exclude incomplete responses or instances where answers remained consistent throughout the survey. Upon reviewing the sample, it is evident that participants were mainly from Denmark, Portugal, and Germany— the three largest contributing countries. Furthermore, most respondents fell within younger age groups and had predominantly obtained a bachelor's degree. Additionally, from Figures 2 and 3, the usage frequency and level of interest can be observed. It is evident that most participants use generative AI often and have a high level of interest in it.

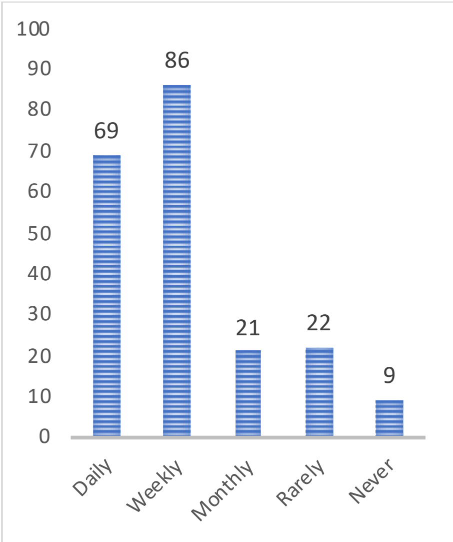

Figure 2 – Generative AI Usage Frequency

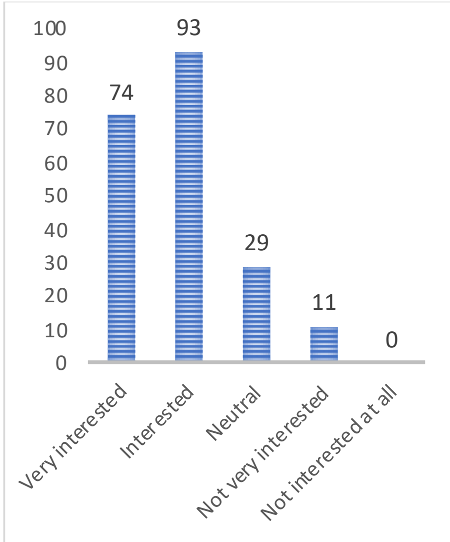

Figure 3 – Level of Interest in Generative AI

In terms of participants' familiarity with generative AI tools, they were asked about their recognition of specific tools (Seen in Figure 4). ChatGPT was the most widely recognized, followed by Bing Chat and DALL-E. The participants also had the option to mention additional tools not listed.

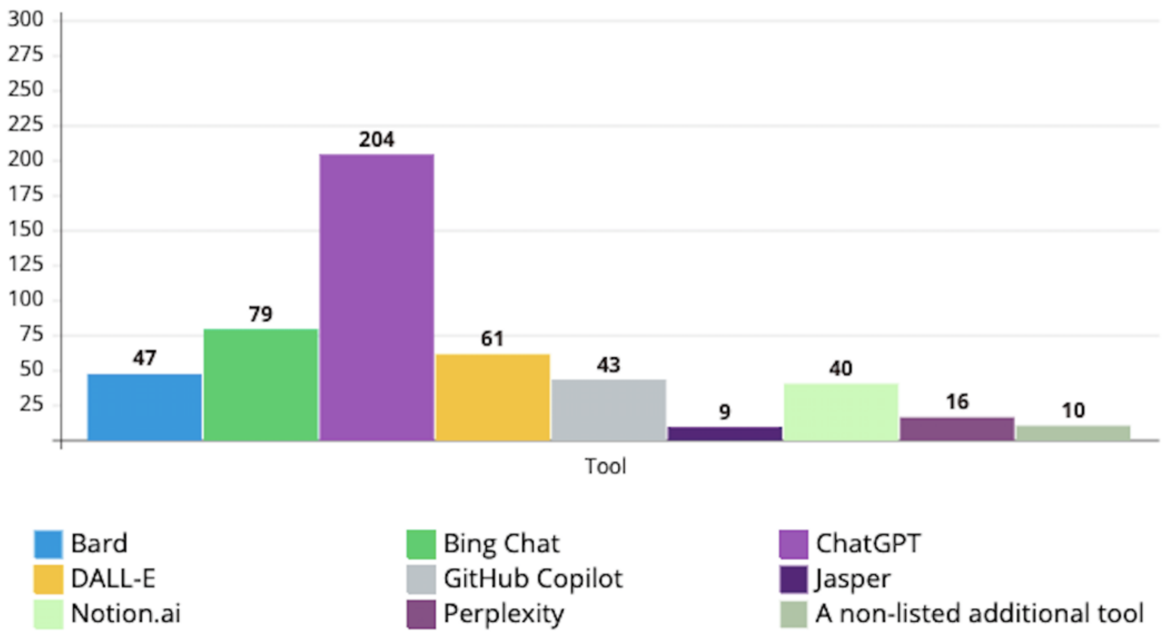

Figure 4 – Recognized Generative AI Tools

Table 3 - Sample Characteristics

Sample Characteristics	%	n = 207
Gender		
Female	46,4	96
Male	52,2	108
Non-binary	1,0	2
Prefer not to say	0,5	1
Age		
18 - 24	52,2	108
25 - 34	43,0	89
35 - 44	3,4	7
45 - 54	0,5	1
55 - 64	-	-
65+	-	-
Educational level completed		
High School Diploma or Equivelent	26,6	55
Bachelor's Degree	58,5	121
Master's Degree	14,0	29
Doctorate (Ph.D. or equivalent)	0,5	1
Current country of residence		
Austria	1,0	2
Belgium	0,5	1
Colombia	0,5	1
Denmark	46,4	96
France	2,9	6
Germany	16,4	34
India	0,5	1
Latvia	0,5	1
Luxembourg	1,0	2
Portugal	23,2	48
Spain	1,0	2
Sweden	1,4	3
Switzerland	1,0	2
United Kingdom of Great Britain and Northern Ireland	0,5	1

4.3 MEASUREMENT MODEL RESULTS

Analysis of the cross-loading table reveals a positive outcome, wherein each variable exhibits stronger loadings with its designated construct compared to any other construct (Appendix B). This robust pattern of loadings signifies that the model demonstrates strong convergent validity (Hair et al., 2011). The consistently higher loadings between observed variables and their respective latent constructs affirm the effectiveness of the measurement model in accurately capturing the intended dimensions (Henseler et al., 2009).

Table 4 provides a detailed overview of the reliability measures for each construct, utilizing key metrics such as Cronbach's alpha, composite reliability (rho_a and rho_c), and Average Variance Extracted (AVE) (Hair et al., 2021). Notably, all constructs demonstrate strong internal consistency, with Cronbach's alpha values surpassing the accepted value of 0.7 (Shrestha, 2021). Additionally, both composite reliability coefficients, rho_a and rho_c, exhibit high levels of reliability, surpassing the recommended benchmark of 0.7 (Hair et al., 2021). A critical observation is that each construct's Average Variance Extracted (AVE) exceeds 0.5, indicating strong convergent validity (Shrestha, 2021). Note trust is not included; its value is one due to being a single item. In summary, these findings emphasize the reliability and convergent validity of the measurement model.

Table 4 - Internal Consistency Reliability and Convergent Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Effort Expectancy	0.716	0.722	0.84	0.637
Performance Expectancy	0.803	0.816	0.91	0.835
Social Influence	0.688	0.723	0.823	0.608
Student Engament	0.85	0.85	0.91	0.77
Student Performance	0.896	0.902	0.935	0.828
Upskilling	0.821	0.824	0.893	0.736
AI Adoption	0.808	0.832	0.912	0.838

The following table 5 aligns with the Fornell-Larcker criterion for discriminant validity. Each construct's diagonal value (square root of AVE) exceeds its highest squared correlation with any other construct, confirming the clear distinction between latent variables (Fornell & Larcker, 1981).

Table 5 - Discriminant Validity Assessment: Fornell-Larcker Criterion

	EducLevel	Effort Expectancy	Performance Expectancy	Social Influence	Student Engament	Student Performance	Trust	Upskilling	AI Adoption
EducLevel	**1**								
Effort Expectancy	0.215	**0.798**							
Performance Expectancy	0.028	0.263	**0.914**						
Social Influence	0.162	0.308	0.541	**0.78**					
Student Engament	0.201	0.289	0.505	0.483	**0.878**				
Student Performance	0.168	0.399	0.715	0.573	0.741	**0.91**			
Trust	-0.117	0.132	0.182	0.069	0.17	0.201	**1**		
Upskilling	0.18	0.377	0.58	0.513	0.656	0.751	0.168	**0.858**	
AI Adoptation	-0.227	-0.342	-0.628	-0.457	-0.504	-0.692	-0.125	-0.536	**0.915**

As seen from table 6, all HTMT ratios, consistently below 0.90, affirm strong discriminant validity, ensuring distinctiveness among constructs in the analysis (Henseler et al., 2015).

Table 6 - HTMT Ratios

	EducLevel	Effort Expectancy	Performance Expectancy	Social Influence	Student Engament	Student Performance	Trust	Upskilling	AI Adoption
EducLevel									
Effort Expectancy	0.254								
Performance Expectancy	0.032	0.348							
Social Influence	0.194	0.435	0.716						
Student Engament	0.218	0.368	0.611	0.625					
Student Performance	0.176	0.498	0.846	0.713	0.845				
Trust	0.117	0.155	0.208	0.071	0.183	0.214			
Upskilling	0.2	0.482	0.71	0.677	0.785	0.872	0.185		
AI Adoptation	0.252	0.446	0.769	0.577	0.603	0.803	0.141	0.649	

Examining the VIF table (table 7), where values above five may indicate collinearity issues, it's notable that all values in the study are below 5. This suggests that the predictor variablesare not highly correlated, reducing the risk of collinearity (Hair et al., 2011).

Table 7 - Variance Inflation Factor (VIF)

Variables	VIF value
EducLevel -> AI Adoption	1.091
Effort Expectancy -> AI Adoption	1.18
Performance Expectancy -> AI Adoption	1.48
Social Influence -> AI Adoption	1.505
Student Engament -> Student Performance	1.86
Trust -> AI Adoption	1.067
Upskilling -> Student Performance	1.949
AI Adoption -> Student Engament	1
AI Adoption -> Student Performance	1.488
AI Adoption -> Upskilling	1

In summary, these consistent and positive outcomes across multiple validation measures underscore the measurement model's reliability, validity, and overall robustness, affirming its suitability for capturing and assessing the intended dimensions of the study.

4.4 STRUCTURAL MODEL EVALUATION

Table 8 and Figure 3 provide an overview of the model's results. Notably, there is a high significance level for hypotheses H1, H2, and H3, underlining the influential role of educational level, effort expectancy, and performance expectancy in generative AI adoption. These factors, supported by low p-values, emphasize their importance in shaping the integration of generative AI in education. Moreover, the coefficients presented in the analysis indicate the direction of relationships between predictor variables and the outcome variable (generative AI adoption). A negative coefficient suggests a negative association, implying that an increase in the predictor variable is associated with a decrease in generative AI adoption. In contrast, a positive coefficient indicates a positive association. Specifically for the significant relationships, H1 (EducLevel -> AI Adoption), a negative coefficient of -0.17, suggests that a higher educational level is associated with a decrease in generative AI adoption. Hence, H1's negative correlation between educational level and AI adoption suggests a nuanced perspective. Individuals with higher education may approach AI adoption more critically. This might indicate that the higher the educational qualifications, the less they use AI tools, possibly because those with higher education levels perceive the tool's limitations better. Thus, this discovery is particularly interesting as it offers an alternative perspective on the relationship. Next, in the case of H2 (Effort Expectancy -> AI Adoption), a negative coefficient of -0.132 indicates that an increase in effort expectancy is linked to a decrease in generative AI adoption. Moving on to H3 (Performance Expectancy -> AI Adoption), the substantial negative coefficient of -0.53 suggests that higher performance expectancy is strongly associated with a decrease in generative AI adoption. This discovery is important because it shows that the relationship between expectations and adoption isn't straightforward, challenging established understanding. Hence, it might mean that students don't see using these tools as a lot of work but rather as something easy to use to complete their tasks. Moreover, the analysis reveals that trust and social influence (H4 and H5) exhibit non-significant impacts on generative AI adoption, with p-values suggesting that these variables do not substantially affect adoption decisions. This finding is particularly noteworthy, emphasizing that trust is not significant in adoption, challenging common assumptions. Furthermore, the model discloses a significant relationship between AI adoption and its impact on student outcomes. Thus, the strong connections found between adopting AI and the outcomes of student engagement, performance, and upskilling (H6, H7, and H8) highlight the meaningful impact of generative AI in education. A possible explanation for the rather high negative result could stem from a potential mismatch between expectations. Students' expectations of generative AI may not align with their actual experiences. While AI tools promise personalized learning pathways, data-driven insights, and adaptive feedback, students' encounters with these technologies may fall short of their expectations. This mismatch between expectation and reality could result in negative perceptions of AI adoption in the survey responses, despite the potential benefits identified in the research literature.

Table 8 - Path coefficients hypothesis results

	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Significance
H1	EducLevel -> AI Adoption	-0.17	-0.167	0.06	2.845	0.004	**
H2	Effort Expectancy -> AI Adoption	-0.132	-0.133	0.055	2.396	0.017	*
H3	Performance Expectancy -> AI Adoption	-0.53	-0.529	0.073	7.23	0	***
H4	Social Influence -> AI Adoption	-0.1	-0.104	0.067	1.491	0.136	NS
H5	Trust -> AI Adoption	-0.024	-0.021	0.05	0.473	0.636	NS
H6	AI Adoption -> Student Engament	-0.504	-0.505	0.054	9.344	0	***
H7	AI Adoption -> Student Performance	-0.692	-0.692	0.038	18.137	0	***
H8	AI Adoption -> Upskilling	-0.536	-0.539	0.055	9.823	0	***

Note: NS = not significant; * significant at p < 0.05; ** significant at p < 0.01; *** significant at p < 0.001 (Cohen, 1992).

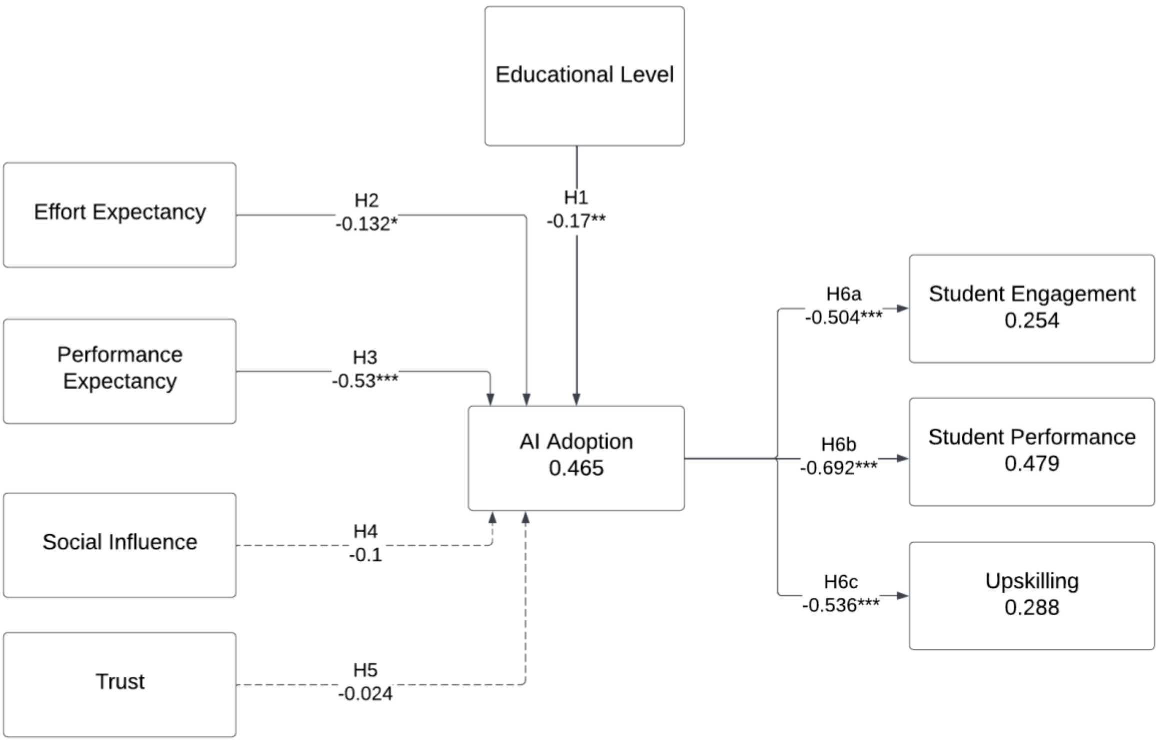

Figure 5 – Structural Model Results

5. DISCUSSION

From the eight hypotheses tested, six showed significant results. Notably, educational level emerged as a significant factor, contrary to the findings of Emon et al. (2023), who argued against its significance in adoption. The results align with Yigitcanlar et al. (2022), supporting the role of educational level in adoption. However, given the results of this paper, it appears that a higher level of education is associated with a negative impact on the adoption of AI. One possible explanation for this could be that individuals with advanced education tend to approach their adoption decisions with a more critical mindset. In the realm of effort expectancy, performance expectancy, and social influence, conflicting results were observed across different studies, as seen in the literature review. Effort expectancy exhibited significance, consistent with prior research (Chatterjee & Bhattacharjee, 2020; Foroughi et al., 2023; Strzelecki, 2023), while Himang et al. (2023) found no significant impact in this domain. Performance expectancy showed a highly significant level, aligning with the findings of (Himang et al. 2023; Foroughi et al., 2023; and Strzelecki, 2023). However, social influence was not significant, in line with Russo's study (2023) but conflicting with (Yatoo & Habib, 2023; Foroughi et al., 2023; Strzelecki, 2023). Interestingly, trust did not exert a significant effect on generative AI adoption, contradicting Emon et al.'s (2023) findings. This result is interesting, considering that trust is measured with critical factors such as privacy, transparency, and reliability. Arguably, in an ideal scenario, trust would be expected to play an essential role in adoption, especially given the novelty of generative AI. Including factors like privacy, transparency, and reliability in assessing trust levels makes the non-significant impact of trust on adoption a noteworthy outcome. Consequently, the study suggests that the primary influencers for generative AI adoption are educational level, effort expectancy, and performance expectancy.

Moreover, the outcomes of AI adoption among students were consistently found to be highly significant. These results align with Li's (2023) study, which investigated the impact of AI-based systems on learning interest and also reported significant findings. Moreover, student performance was determined to be significantly influenced, as supported by prior research from García-Martínez et al. (2023). Their work suggests that educational AI can notably affect student performance, particularly in quantity and willingness to learn. Upskilling, too, was found to be a significant outcome. Previous studies extensively discuss this domain, with some raising concerns about the potential adverse effects on critical and creative thinking (Cardon et al., 2023). On the contrary, others argue that AI can challenge students' ways of thinking, thereby fostering critical thinking (Guo & Lee, 2023).

6. CONCLUSIONS AND FUTURE WORKS

The thesis aimed to investigate the factors motivating students to adopt generative AI. Given the current relevance of the topic, the study specifically focused on understanding the impact of this adoption on areas such as performance, engagement, and upskilling. To accomplish this, the study began by examining the main discourses within the field to gain insights into the fundamentals of the topic and the existing body of knowledge. Following this, a conceptual model was developed and tested using quantitative data obtained from a survey focused solely on students.

The study's findings reveal significant theoretical implications, particularly in three key areas. Firstly, the limited impact of trust challenges prevailing assumptions, suggesting that factors such as privacy, transparency, and reliability may not exert as much influence on the adoption of generative AI as anticipated by existing academic literature. Secondly, the notable impact of generative AI adoption on student outcomes—including engagement, performance, and upskilling—underscores its transformative potential in education. This emphasizes the importance of considering not only the adoption process but also the broader implications of this adoption for students' outcomes. Thirdly, the study indicates that educational level influences the adoption of generative AI in educational settings, challenging existing assumptions and suggesting that individuals with higher educational levels may approach technology adoption differently, possibly being more critical in their decision-making.

Regarding practical implications, educational institutions must prioritize teaching students about transparency, privacy, and reliability, considering the potential future inclusion of generative AI in education. Hence, the study's finding that trust had a limited impact suggests a need for practical measures, including targeted educational modules, thereby ensuring that students are aware of the critical aspects of these tools.

The study faced notable limitations. The sample was primarily drawn from three specific countries, limiting the generalizability of findings. Future research should aim for a more diverse and representative participant pool. Additionally, relying solely on survey data may overlook nuanced perspectives. Therefore, future work could enhance insights using qualitative methods such as interviews or focus groups. Lastly, the study's temporal scope may limit its relevance over time as generative AI models evolve rapidly. Therefore, regular monitoring and updates are crucial to capture trends and changes.

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APPENDIX A

Measuring items used for the survey: Survey questions and references

Category	Codification	Measuring items	Reference
Effort expectancy	EfExp	*Generative AI is easy to learn*	(Chatterjee & Bhattacharjee, 2020)
Effort expectancy	EfExp	*Using generative AI can be done without extensive training or assistance*	(Himang et al., 2023)
Effort expectancy	EfExp	*It is easy for me to become skillful at using generative AI*	(Strzelecki, 2023)
Social influence	SI	*People who influence my behavior believe that I should use generative AI*	(Strzelecki, 2023)
Social influence	SI	*The number of fellow students who use generative AI technology influences my decision to use it*	(Russo, 2023)
Social influence	SI	*Fellow students who use generative AI technologies have an advantage over those who do not*	(Russo, 2023)
Performance expectancy	PExp	*I believe that generative AI is useful in my studies*	(Strzelecki, 2023)
Performance expectancy	Pexp	*Using generative AI helped me understand complex educational concepts*	(Himang et al., 2023)
Performance expectancy	PExp	*Generative AI helped me complete my assignments faster than if I didn't use it*	(Himang et al., 2023)
Trust	Trust	*When interacting with generative AI, I believe that my personal information is protected*	(Jo, 2023)
Trust	Trust	*Generative AI is reliable in providing consistent and trustworthy information*	(Choudhury & Shamszare, 2023)
Trust	Trust	*Generative AI is transparent in the sense that it openly communicates its processes and how it generates responses, enabling users to understand the logic behind its output and the sources of information it relies on*	(Choudhury & Shamszare, 2023)
AI Adoption	Adop	*How frequently do you use generative AI?*	(Roy et al., 2023)
AI Adoption	Adop	*How would you describe your level of interest in generative AI?*	(Roy et al., 2023)
Student Engagement	StEng	*Generative AI makes me put more effort into learning*	(Al-Abdullatif & Gameil, 2021)
Student Engagement	StEng	*Generative AI motivates me to invest additional effort in understanding and learning from my mistakes when faced with challenges*	(Al-Abdullatif & Gameil, 2021)
Student Engagement	StEng	*Generative AI adds excitement when I am working on my projects*	(Al-Abdullatif & Gameil, 2021)
Student Performance	StPerf	*Generative AI has enhanced my overall learning experience*	(Hazzam & Wilkins, 2023)
Student Performance	StPerf	*I believe generative AI tools contribute to improving my grades*	(Boubker, 2023)
Student Performance	StPerf	*Generative AI has made my learning more eficiente*	(Hazzam & Wilkins, 2023)
Upskilling	Upsk	*Generative AI has improved how I generate new ideas to problems by providing fresh perspectives and inspiration*	(Ebrahimi Mehrabani & Azmi Mohamad, 2015)
Upskilling	Upsk	*Generative AI is improving my problem-solving skills*	(Ebrahimi Mehrabani & Azmi Mohamad, 2015)
Upskilling	Upsk	*Generative AI is making it easier for me to find different solutions to problems*	(Ebrahimi Mehrabani & Azmi Mohamad, 2015)

APPENDIX B

Survey Questions: Qualtrics

Effort expectancy

Generative AI is easy to learn

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Using generative AI can be done without extensive training or assistance

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

It is easy for me to become skillful at using generative AI

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Social influence

People who influence my behavior believe that I should use generative AI

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

The number of fellow students who use generative AI influences my decision to use it

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Fellow students who use generative AI have an advantage over those who do not

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Performance expectancy	**I believe that generative AI is useful in my studies** [1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree] 1 2 3 4 5 6 7 **Using generative AI helped me understand complex educational concepts** [1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree] 1 2 3 4 5 6 7 **Generative AI helped me complete my assignments faster than if I didn't use it** [1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree] 1 2 3 4 5 6 7
Trust	**When interacting with generative AI, I believe that my personal information is protected** [1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree] 1 2 3 4 5 6 7 **Generative AI is reliable in providing consistent and trustworthy information** [1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree] 1 2 3 4 5 6 7 **Generative AI is transparent in the sense that it openly communicates its processes and how it generates responses, enabling users to understand the logic behind its output and the sources of information it relies on** [1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree] 1 2 3 4 5 6 7

Student Engagement

Generative AI makes me put more effort into learning

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Generative AI motivates me to invest additional effort in understanding and learning from my mistakes when faced with challenges

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Generative AI adds excitement when I am working on my projects

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Student Performance

Generative AI has enhanced my overall learning experience

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

I believe generative AI tools contribute to improving my grades

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Generative AI has made my learning more efficient

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7

Upskilling

Generative AI has improved how I generate new ideas to problems by providing fresh perspectives and inspiration

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

1 2 3 4 5 6 7

Generative AI is improving my problem-solving skills

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

1 2 3 4 5 6 7

Generative AI is making it easier for me to find different solutions to problems

[1 - Strongly Disagree; 2 - Disagree; 3 - Somewhat Disagree; 4 - Neutral; 5 - Somewhat Agree; 6 - Agree; 7 - Strongly Agree]

1 2 3 4 5 6 7

APPENDIX C

Cross-Loading table

	EducLevel	Effort Expectancy	Performance Expectancy	Social Influence	Student Engament	Student Performance	Trust	AI Adoption	Upskilling
EducLevel	**1**	0.215	0.028	0.162	0.201	0.168	-0.117	-0.227	0.18
EfExp1	0.2	**0.824**	0.153	0.187	0.233	0.282	0.147	-0.291	0.306
EfExp2	0.173	**0.76**	0.234	0.272	0.195	0.311	0.095	-0.24	0.229
EfExp3	0.142	**0.808**	0.25	0.287	0.259	0.364	0.072	-0.283	0.359
PExp1	0.018	0.27	**0.927**	0.475	0.456	0.638	0.124	-0.614	0.525
PExp3	0.035	0.206	**0.9**	0.518	0.468	0.673	0.216	-0.529	0.537
SI1	0.113	0.239	0.392	**0.73**	0.383	0.429	0.026	-0.301	0.453
SI2	0.133	0.205	0.385	**0.777**	0.341	0.369	0.014	-0.281	0.342
SI3	0.133	0.268	0.472	**0.83**	0.401	0.516	0.099	-0.447	0.407
StEng1	0.204	0.233	0.367	0.355	**0.892**	0.653	0.173	-0.452	0.574
StEng2	0.206	0.289	0.402	0.432	**0.912**	0.639	0.09	-0.434	0.56
StEng3	0.118	0.238	0.559	0.483	**0.827**	0.657	0.181	-0.439	0.591
StPerf1	0.181	0.389	0.653	0.543	0.749	**0.934**	0.176	-0.664	0.704
StPerf2	0.109	0.329	0.645	0.553	0.594	**0.878**	0.224	-0.576	0.654
StPerf3	0.164	0.368	0.656	0.472	0.672	**0.917**	0.152	-0.644	0.69
Trust2	-0.117	0.132	0.182	0.069	0.17	0.201	**1**	-0.125	0.168
Adop1	-0.203	-0.296	-0.52	-0.351	-0.422	-0.556	-0.132	**0.898**	-0.425
Adop2	-0.211	-0.328	-0.621	-0.474	-0.494	-0.699	-0.1	**0.933**	-0.546
Upsk1	0.172	0.254	0.425	0.395	0.54	0.589	0.118	-0.434	**0.844**
Upsk2	0.171	0.318	0.468	0.463	0.637	0.654	0.157	-0.45	**0.872**
Upsk3	0.124	0.389	0.588	0.457	0.513	0.684	0.156	-0.493	**0.858**

APPENDIX D

NOVA IMS | Ethical Committee Statement – Approved

NOVA IMS Information Management School

This is to certify that
Project No.: **INFSYS2023-11-236758**
Project Title: **Master Thesis: Exploring the Impact of Generative AI on Students**
Principal Researcher: **Kasper Schroll**

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 11/24/2023.

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, 11/24/2023

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

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

Universidade Nova de Lisboa