

# **ChatGPT: Changing Education, One Prompt at a Time**

*A quantitative study of factors influencing students' usage of ChatGPT*

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## Abstract

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An AI tool that has gained massive media attention in the past months is the language model ChatGPT. The rapid adoption of the tool by students made the authors of this study curious about exploring the chatbot further, using technology adoption theory. This study aims to understand how the original constructs of UTAUT2 (Unified Theory of Acceptance and Use of Technology 2): *Performance Experienced*, *Effort Experienced*, *Hedonic Motivation*, *Social Influence & Facilitating Conditions*, influence students' usage of ChatGPT. To better fit the novel technology of ChatGPT, the authors have extended UTAUT2 with *Trust*, *Accessibility*, *Humanization*, *Data Privacy Risks & Creativity*. Ten hypotheses have been formulated based on the constructs presented above. To test the hypotheses, data on students at Stockholm School of Economics have been collected through an online questionnaire (N = 205). The data was analyzed through multiple regressions, with three different dependent variables of usage frequency (1) "How often do you use ChatGPT?" (2) "How many questions do you ask ChatGPT on average per week?" and (3) "When was the last time you used ChatGPT?". The author's extension of UTAUT2, adding additional constructs, resulted in a greater ability to explain the usage frequency of ChatGPT among students. Due to reliability and validity issues, the following constructs were removed from the multiple regressions: *Social Influence*, *Facilitating Conditions*, *Accessibility*, *Humanization* and *Data Privacy Risks*. Out of the remaining five constructs, *Performance Experienced*, *Creativity & Hedonic Motivation* influenced students' usage of ChatGPT. *Performance Experienced* was shown to be the strongest predictor of students' usage of ChatGPT, while *Effort Experienced* was non-significant and *Hedonic Motivation* had a significant negative effect. Regarding the contributing constructs, *Creativity* showed a significant positive effect on student's usage of ChatGPT and *Trust* showed a non-significance effect. This study contributes with its findings that *Creativity* is an important significant predictor of students' usage of ChatGPT and that *Performance Expectancy* can also be generalized to this context. Moreover, the dependent variable of usage has been studied, instead of the mediator of behavioral intention, which leads to more valid results and further contribution to the literature. Lastly, the findings indicate that UTAUT2 has limitations when predicting usage of ChatGPT and therefore new models and theories need to be explored. These can be built upon the findings of this study in order to provide a more comprehensive understanding of ChatGPT usage.

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**Keywords:** ChatGPT, Unified Theory of Acceptance and Use of Technology (UTAUT2), Trust, Creativity, Accessibility, Humanization, Data Privacy Risks

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## Glossary

Dependent variable	The dependent variable is usage frequency of ChatGPT
Independent variables	The independent variables consist of five original constructs and five contributing constructs. The five original constructs are <i>Performance Experienced</i> , <i>Effort Experienced</i> , <i>Social Influence</i> , <i>Facilitating Conditions</i> and <i>Hedonic Motivation</i> . The five contributing constructs are <i>Trust</i> , <i>Accessibility</i> , <i>Humanization</i> , <i>Creativity</i> and <i>Data Privacy Risks</i>
ChatGPT-3	ChatGPT-3 is a generative AI-tool provided by the company OpenAI. Generative AI comprises a group of artificial intelligence (AI) models, and one of these models is the large language model (LLM) which ChatGPT-3 falls under (OpenAI, 2023)
Performance Experienced	<i>“the degree to which an individual believes that using the system will help him or her to attain gains in job performance”</i> (Venkatesh et al., 2003, page 447)
Effort Experienced	<i>“the degree of ease associated with the use of the system”</i> (Venkatesh et al., 2003, page 450)
Social Influence	<i>“the degree to which an Individual perceives that important others believe he or she should use the new system”</i> (Venkatesh et al., 2003, page 451)
Facilitating Conditions	<i>“the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system”</i> (Venkatesh et al., 2003, page 453)
Hedonic Motivation	<i>“the fun or pleasure derived from using a technology”</i> (Venkatesh et al., 2012, page 161)
Trust	The authors define Trust as <i>“whether students’ trust the output generated by ChatGPT”</i>
Accessibility	The authors define Accessibility as <i>“the extent to which ChatGPT is available for its user to access”</i>
Humanization	The authors define Humanization as <i>“ChatGPT’s human-like characteristics such as humor and friendliness”</i>
Data Privacy Risks	The authors define Data Privacy Risks as <i>“concerns regarding data privacy as OpenAI stores data on users’ email address &amp; prompts”</i>
Creativity	The authors define Creativity as <i>“the extent to which ChatGPT enhances creativity through brainstorming, ideation etc”</i>
Usage of ChatGPT	Usage frequency
Prompt	A specific question, instruction, or task asked to ChatGPT.

Prompt-engineering	Prompt engineering refers to the skill of knowing “ <i>how to give clear and effective instructions to GPT-3</i> ” (Shieh, 2023, paragraph 1).
Item	Refers to the questions that are included in the questionnaire. An item is a synonym for a question.

## Abbreviations

<i>UTAUT2</i>	Unified Theory of Acceptance and Use of Technology 2
<i>US</i>	Usage Frequency
<i>PE</i>	Performance Experienced
<i>EE</i>	Effort Experienced
<i>SI</i>	Social Influence
<i>FC</i>	Facilitating Conditions
<i>HM</i>	Hedonic Motivation
<i>TR</i>	Trust
<i>AC</i>	Accessibility
<i>HU</i>	Humanization
<i>PC</i>	Data Privacy Risks
<i>CR</i>	Creativity
<i>LLM</i>	Large Language Model
<i>CA</i>	Cronbach Alpha
<i>CR</i>	Construct Reliability
<i>AVE</i>	Average Variance Extracted
<i>AIEd</i>	Artificial Intelligence in Education
<i>IS</i>	Information Systems
<i>SSE</i>	Stockholm School of Economics
<i>DIT</i>	Theory of Diffusion of Innovation
<i>TRA</i>	Theory of Reasoned Action
<i>TPB</i>	Theory of Planned Behavior
<i>TAM</i>	Technology Acceptance Model
<i>TTF</i>	Theory of Task-Technology Fit

## Table of Content.

<b>1. Background</b>	<b>9</b>
1.1 Introduction	9
1.2 Pre-study	11
1.3 Research Gap	11
1.4 Purpose & Research Question	12
1.5 Delimitations	12
1.6 Expected Contribution	12
1.7 Overview of Study	13
<b>2. Literature Review</b>	<b>14</b>
2.1 AI and Chatbots in Society	14
2.2 AI and Chatbots in Education	15
2.3 Technology Adoption Theories	16
2.3.1 Diffusion of Innovations (DIT)	17
2.3.2 Theory of Reasoned Action (TRA)	18
2.3.3 Theory of Planned Behaviour (TPB)	18
2.3.4 Technology Acceptance Model (TAM)	19
2.3.5 Task-Technology Fit (TTF)	20
2.3.6 Unified Theory of Acceptance and Use of Technology (UTAUT)	21
2.3.7 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)	22
<b>3. Theoretical Framework</b>	<b>24</b>
3.1 Adapted UTAUT2 Model	24
3.2 Modifications of Constructs	25
3.3 Intention-Usage Relationship	25
3.4 Original constructs	26
3.4.1 <i>Usage of ChatGPT</i>	26
3.4.2 <i>Performance Experienced (Ex Performance Expectancy)</i>	26
3.4.3 <i>Effort Experienced (Ex Effort Expectancy)</i>	27
3.4.4 <i>Social Influence</i>	28
3.4.5 <i>Facilitating Conditions</i>	28
3.4.6 <i>Hedonic Motivation</i>	29
3.4.7 <i>Price Value (Omitted)</i>	29
3.4.8 <i>Habit (Omitted)</i>	29
3.5 Contributing constructs	30
3.5.1 <i>Trust</i>	30
3.5.2 <i>Accessibility</i>	31
3.5.3 <i>Humanization</i>	33
3.5.4 <i>Data Privacy Risks</i>	34
3.5.5 <i>Creativity</i>	35
<b>4. Methodological Approach</b>	<b>37</b>
4.1 Our Roadmap	37
4.2 Research Design	38

4.3 Main study	40
4.3.1 Sampling	40
4.3.2 Questionnaire Design	40
4.3.3 Choosing Questions	43
4.3.4 Data Collection	43
4.3.5 Data Analysis	44
4.3.6 Validity	44
4.3.7 Replicability & Generalizability	44
4.4 Overview of the Main Study	45
4.5 Measurement Model: Data Quality	46
4.5.1 Reliability	49
4.5.1.1 Indicator Reliability	49
4.5.1.2 Construct Reliability	50
4.5.2 Validity	50
4.5.2.1 Convergent Validity	50
4.5.2.2 Discriminant Validity	51
4.5.3 Pre-requisites for Multiple Linear Regression	52
<b>5. Results</b>	<b>53</b>
5.1 Hypothesis Testing	53
5.2 Presentations of Findings	58
5.3 Overview of Hypothesis Testing	60
<b>6. Discussion</b>	<b>62</b>
6.1 Revised Conceptual Framework	62
6.2 Discussion of Results	62
6.2.1 Performance Experienced	62
6.2.2 Effort Experienced	63
6.2.3 Social Influence	63
6.2.4 Facilitating Conditions	63
6.2.5 Hedonic Motivation	64
6.2.6 Trust	65
6.2.7 Accessibility	66
6.2.8 Humanization	66
6.2.9 Data Privacy Risks	67
6.2.10 Creativity	67
6.3 Limitations of study	68
<b>7. Conclusion</b>	<b>70</b>
7.1 Main Results	70
7.2 Contribution to Literature	71
7.3 Implications	71
7.3.1 Implications for Students	71
7.3.2 Implications for Schools	72
7.3.3 Implications for Businesses	73
7.4 Future Research	74
<b>8. Bibliography</b>	<b>75</b>



<b>9. Appendix</b>	<b>99</b>
Background	99
Appendix 1: Pre-study	99
Theoretical Framework	100
Appendix 2: Overview of literature regarding contributing constructs	100
Appendix 3: ChatGPT generating false answers	103
Appendix 4: ChatGPT's training data	104
Appendix 5: The message displaying when ChatGPT is over capacity	104
Appendix 6: Example of a humanized conversation with ChatGPT	105
Appendix 7: Example of how the chatbot can help brainstorm ideas	106
Methodological Approach	107
Appendix 8: GDPR and Anonymization	107
Appendix 9: Questionnaire	108
Results	110
Appendix 10: Revised Rotated Component Matrix	110
Appendix 11: Overview of descriptive measures	111
Appendix 12: Multicollinearity	113
Appendix 13: Breusch-Pagan test	113
Appendix 14: Descriptive statistics for US_1, US_2 and US_3	114
Discussion and Conclusion	114
Appendix 15: Usage variety frequencies	114
Appendix 16: When did you start using ChatGPT?	115
Appendix 17: What do you use ChatGPT for in school	116
Appendix 18: How much would you be willing to pay per month for ChatGPT in SEK?	116

# 1. Background

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*The following chapter will explore the phenomena of ChatGPT and its significance as a subject to study. Additionally, a pre-study will be presented along with the research question, delimitations, expected contribution and research gap.*

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## 1.1 Introduction

In today's tech-savvy world, new technologies are introduced on a continuous basis. Artificial Intelligence (AI) is a rapidly advancing field that develops intelligent machines that can think, learn and adapt like humans. AI has been a topic of interest for the last decade but has recently gained renewed attention due to the emergence of chatbots, taking the world by storm.

In November 2022, OpenAI introduced the chatbot “ChatGPT-3” (hereafter referred to as ChatGPT) and it immediately became a hype around the globe. OpenAI achieved an impressive milestone of reaching 100 million users within only two months, which is significantly faster than TikTok (nine months) and Instagram (two years) (Hu, 2023). Microsoft initially invested 1 million dollars in OpenAI and has since decided to invest an additional 10 billion dollars in January 2023 (Forbes, 2023). Since the launch of ChatGPT in November last year, it has become a race between the big tech giants to launch their own chatbot. Windows launched “Bing” in February 2023 and Google launched “Bard” in March 2023 (Forbes, 2023b; Dastin, 2023). However, ChatGPT has by far achieved the most attention, especially from the younger generations on social media.

ChatGPT, short for Chat Generative Pre-trained Transformer, is a generative AI tool that enables users to generate text by providing it with prompts (Browne, 2023). Using the prompts it receives, ChatGPT can help with ideation and creative problem-solving (Mollick, 2022) as well as writing articles, essays, and poetry to name a few (Hu, 2023). It operates through a large language model (LLM) and employs deep learning techniques, allowing it to understand human language and generate responses using extensive datasets (Browne, 2023). ChatGPT is the largest and most powerful language processing AI-model up until now

(Browne, 2023). Something that sets ChatGPT apart from traditional search engines is its capacity to generate human-like responses and engage in two-way conversations (Haddad, 2023; Browne, 2023). ChatGPT-4, a more powerful successor to ChatGPT-3, was launched on March 14th 2023, with eight times the processing power of its predecessor. However, accessing ChatGPT-4 requires a monthly subscription fee of \$20 and limits users to 100 prompts per four hours (Haddad, 2023).

Despite ChatGPT's widespread use and popularity, it has also faced criticisms. Some concerns regard its biases and at times untrustworthy answers. The field that perhaps has drawn the most attention is its influence on the educational system, due to its ability to generate text. It has been widely debated whether the tool should be seen as cheating or as an aid for students (Lukpat, 2023). Some argue for the former and have therefore banned ChatGPT, foremost public schools in the US (Rosenblatt, 2023). Some schools have changed the way they examine students, by for example transitioning from written papers to oral or offline exams (Bogost, 2022). Advocates of ChatGPT as a learning aid believe that its high potential as an educational tool outweighs its risks (Roose, 2023). ChatGPT can assist students in comprehending concepts, drawing connections and preparing for exams while professors can use it for preparing lectures and for grading, given the tools' ability to evaluate text.

AI as a research topic has been studied extensively, however not ChatGPT due to its novelty. When studying ChatGPT, it is important to consider its unique chatbot characteristics. Firstly, ChatGPT can be defined as a black box as it is difficult to assess its output and trustworthiness (Haenlein & Kaplan, 2019). Secondly, it requires consideration of data privacy risks, given that OpenAI stores your email and prompts. Thirdly, ChatGPT is unique from an accessibility point of view, as the tool is not always available for users due to occasional capacity overload. Fourthly, the creative use cases of ChatGPT, makes the chatbot unique. Fifth, ChatGPT becomes unique for its human-like writing style, making it feel like conversing with an actual person. These unique characteristics become highly relevant and interesting to study when determining what influences students' usage frequency of ChatGPT.

## 1.2 Pre-study

To better understand the phenomena of ChatGPT, a pre-study was conducted entailing conversations with students and a survey. Conversations with a handful of students were initiated to better reflect on what aspect of ChatGPT to further explore, along with how widespread the usage of the chatbot was. After these conversations, a survey was sent out on the 16th of February 2023 to the authors' cohort of master students studying Business and Management at Stockholm School of Economics (SSE), asking if (1) they had used ChatGPT, and (2) for what areas they have used it for: school, work, and/or other purposes. 43 respondents participated.

The results of the pre-study showed that 79% of the respondents had used ChatGPT (i.e. 34 students), and out of these 34 students everyone had used it for school-related work, many for private purposes and some for work (Appendix 1). Before conducting the pre-study the authors were unsure about the study's scope and whether to focus on students' intention to use ChatGPT or narrow it down to only focusing on students who have used ChatGPT. After analyzing the results of the pre-study, the authors could conclude that eight out of ten students had used ChatGPT, and all of them for school tasks. From a data collection point of view, this gave us a valuable indication that it was feasible to choose the second approach, namely to only focus on students who have confirmed their usage of ChatGPT.

## 1.3 Research Gap

An extensive review of previous literature and theory has resulted in clear research gaps. Limited studies have been conducted on chatbot usage in education among students. The few studies that have been conducted on chatbots in an educational setting are rather focusing on the perspective of professors than students (Eguaras et al., 2021; Smutny & Schreiberova, 2020). Additionally, the novelty of ChatGPT implies lacking empirical research. Furthermore, scholars of adoption theories emphasize the need to explore new technology and age groups within consumer technology adoption research (Venkatesh et al., 2012), which is what this study does. By conducting a study on the new technology *ChatGPT*, in an *educational setting* and from the perspective of *students*, this study fills these gaps, ultimately contributing with new valuable findings in a research context that currently lacks empirical studies.

## 1.4 Purpose & Research Question

This study aims to fill the research gap presented above, by providing a better understanding of factors influencing students' usage of ChatGPT. In order to do so, both traditional factors from technology adoption theories and additional factors unique for ChatGPT will be examined. Consequently leading to the following research question:

*What factors influence students' usage of ChatGPT?*

## 1.5 Delimitations

This study observes University students, and not students from other levels of education. The sample is limited to one business school in Sweden, Stockholm School of Economics. The time period of the study is January to May 2023, meaning there has been a time constraint. Since OpenAI keeps developing new versions of ChatGPT, the basis of this study is limited to ChatGPT-3, and has not incorporated the paid successor of ChatGPT-4.

## 1.6 Expected Contribution

This study aims to make several theoretical contributions by exploring the research question above. First of all, by adding more research and empirical evidence to the currently limited field of technology adoption theories in the context of chatbots and students. The study contributes to theory by examining new potential explanatory factors related to ChatGPT: *Trust, Accessibility, Humanization, Data Privacy Risks* and *Creativity*. Furthermore, the traditional factors of adoption theories: *Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions* and *Hedonic Motivation*, are tested in order to evaluate their generalizability. Additionally, the authors have chosen to study the direct relationships between the independent variables and usage, meaning that the variable of intention, which most often is used in this research field, is removed. Only a handful studies have been made on actual usage, according to Tamilmani et al. 's review (2018). By doing so, the study contributes to new reliable and significant relationships.

The rapid adoption of ChatGPT by students highlights the need to comprehend which factors that drive the usage, which are valuable implications for both students and schools. However, as the interest of chatbots is growing in other fields too (Gnewuch et al., 2018), the findings are also valuable for businesses and the general public.

## 1.7 Overview of Study

Theoretical Framework	Unified Theory of Acceptance and Use of Technology (UTAUT2) <i>Factors influencing usage</i>
Phenomenon	Usage of new technology <i>ChatGPT</i>
Empirical Context	Education <i>Students at Stockholm School of Economics</i>
Research Question	<i>What factors influence students' usage of ChatGPT?</i>

*Figure 2: Overview of Study*

## 2. Literature Review

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*This chapter explores and discusses the relevance of previous academic literature, to establish knowledge in the chosen field of chatbots and education. Furthermore, technology adoption models are discussed and evaluated, ultimately leading up to the choice of adopting UTAUT2 in this study.*

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### 2.1 AI and Chatbots in Society

AI is defined as the capacity of a system to comprehend external data, acquire knowledge from it and apply that knowledge to accomplish particular tasks and goals (Haenlein & Kaplan, 2019). Many of the emerging technologies that are currently being adopted in today's society are based on AI, such as smart speakers, self-driving cars and image recognition (Haenlein & Kaplan, 2019).

The development of AI can be traced back to the 1940s, but the term AI was first coined in 1956 (Haenlein & Kaplan, 2019). Currently, AI does not only affect people's personal lives through different AI devices but also how companies are making decisions and interacting with stakeholders (Haenlein & Kaplan, 2019). The benefits of incorporating AI in businesses are many, such as automating business processes, gaining valuable insights through data analysis, and engaging with customers and employees through chatbots (Davenport & Ronanki, 2018). From a consumer point of view, AI enables intelligent platforms, smart devices and tailored suggestions (Adner et al., 2019). However, one of the major drawbacks is its inscrutability and not being able to explain how it derives to its conclusions (Berente et al., 2021; Faraj et al., 2018). This issue is often referred to as the black box problem of AI (Brožek et al., 2023).

Chatbots are built on AI technology and the use of natural language processing (Davenport & Ronanki, 2018). Wollny et al. (2021) states that one central part of chatbots is their sense-making of human input data. Furthermore, chatbots stimulate human conversations, enabling individuals to engage with digital devices in a way that can resemble communicating with a real human (De Cicco et al., 2020). Today's preference for messaging

as the main channel for communication in combination with advances in natural language processing, has made chatbots prominent in society, especially in the retail industry (Gnewuch et al., 2018). Chatbots can also be speech-based agents such as Apple's Siri or Google's Alexa (Rizomyliotis et al., 2022). Chatbots' ability to have human-like dialog helps consumers by providing answers to their questions, whether it is about their online-purchase or favorite music.

## 2.2 AI and Chatbots in Education

AI in an educational setting was introduced almost three decades ago and is often referred to as AIEd (Ouyang & Jiao, 2021). AIEd includes practices such as teaching robots, learning analytics dashboards, adaptive learning systems and human-computer interactions (Chen et al., 2020). According to Ouyang & Jiao (2021), there are three paradigms of AI in education. The first paradigm is AI-directed (learner-as-recipient), the second is AI-supported (learner-as-collaborator) and the third is AI-empowered (learners-as-leaders). Since the introduction of AIEd, paradigm one and two have been the primary ones, implicating intelligent tutoring systems and dialogue-based tutoring systems. Moving forward, paradigm three is estimated to have a larger influence on AIEd, promoting human-computer cooperation and focusing on AI biases and the black box problem of not knowing how AI is making its decisions. Moreover, Ouyang & Jiao (2021) highlights that it is important for AIEd to not only focus on the pure implementation of AI technology but also the integration of various aspects, such as pedagogical, social, cultural and economic dimensions. Chatbot technology belongs to dialog systems, a computer system designed to converse with a human, which provides quick and customized services to everyone in the educational sector. This can be compared to AI technology in paradigm two (Pérez et al., 2020, Wollny et al., 2021; Ouyang & Jiao, 2021).

Wollny et al. (2021) makes a systematic literature review on chatbots in education and identifies three kinds of chatbots based on their pedagogical roles in education. These roles include (1) *learning* (chatbots used as a tool to teach content) (2) *assisting* (chatbots that simplify the student's life by doing parts of the student's tasks), and (3) *mentoring* (chatbots that support student's development). ChatGPT is considered to have all three roles. In another systematic review of chatbots in education done by Okonkwo & Ade-Ibijola (2021) the



authors conclude that the benefits of chatbots are their integration of content, quick access, motivation, engagement and immediate assistance.

## 2.3 Technology Adoption Theories

The following sections discuss the major existing technology adoption theories, arguing for their relevance, applicability, benefits and drawbacks. The figure below demonstrates a timeline and overview of these theories, which will be assessed one by one, ultimately leading to this study's model of UTAUT2.

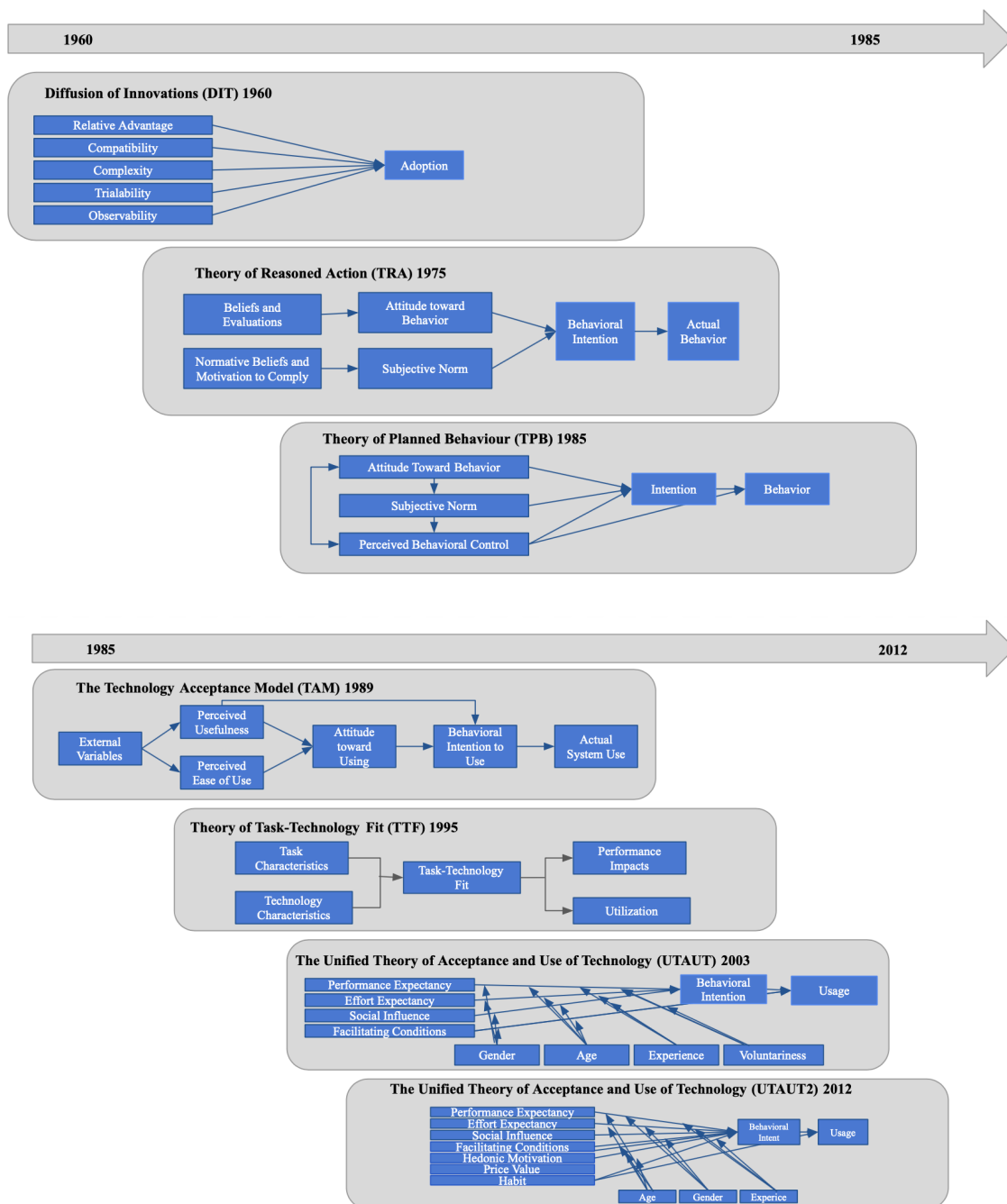


Figure 3: Overview of how the models within technology adoption have evolved over time

Constant technological improvements in our society calls for models that can help us understand why individuals adapt to new technology. There is a wide body of research on technology adoption models, stemming from the 1960s. Researchers keep exploring factors that can explain an individual's intention to use a technology, and how this predicts actual usage (Davis et al., 1989). Due to the dynamic growth of technologies, the models have extended over time, adding new factors to stay relevant. In the following section the authors will discuss how these theories on technology adoption have evolved over time, but at the same time reflect on which of the models is most applicable to the phenomena of ChatGPT in an educational setting.

### 2.3.1 Diffusion of Innovations (DIT)

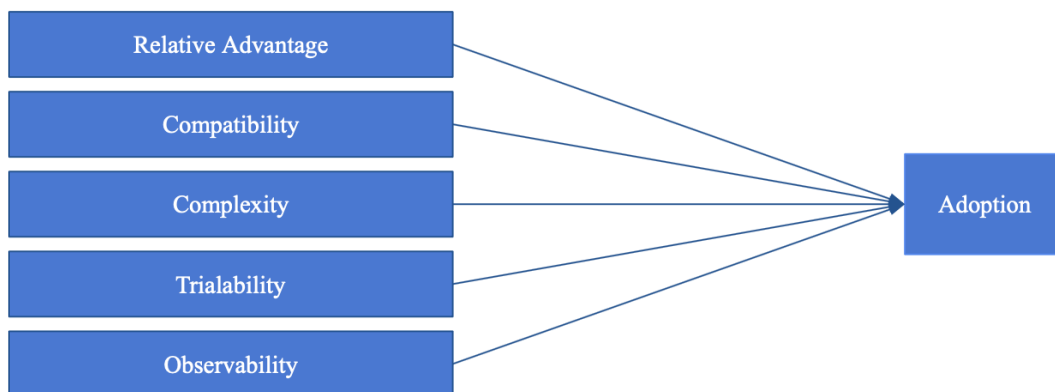


Figure 4: Diffusion of Innovations (Rogers, 1995)

One of the oldest models within technology adoption is Roger's theory of *Diffusion of Innovations (DIT)* developed in 1995 (Rogers, 2003). The theory explains how an innovative product spreads over time in a population. To predict the speed of adoption in a population, the model utilizes the attributes: "Relative Advantage", "Compatibility", "Complexity", "Trialability" and "Observability". Additional elements influencing the spread of innovations are: type of innovation design, communication channels, nature of the social system and extent of change agents' promotion efforts. Moreover, the rate of adoption is described as the relative speed at which an innovation is adopted, and is often illustrated by a curve. The curve shows the span of adoption time for a population and categorizes consumers into early adopters, early majority, late majority and laggards. (Rogers, 2003)

The model was developed for adoption of innovations within and across organizations. However, critique against the theory argues that the model is in fact more suitable for analyzing individuals rather than organizations (Lundblad, 2003). Despite this, the theory is not the best fit for this study as it does not take into account the social context, which can be argued as important when it comes to students. Rather the theory assumes a one-way flow of communication from innovators to adopters (Rogers, 2003).

### 2.3.2 Theory of Reasoned Action (TRA)

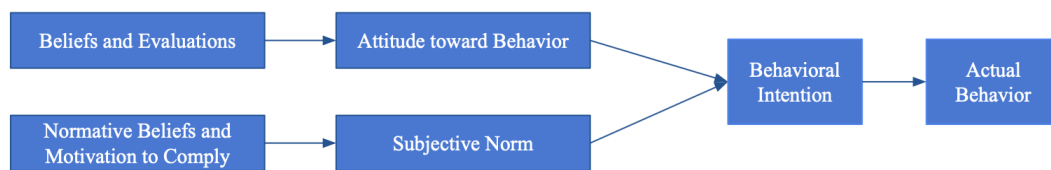


Figure 5: Theory of Reasoned Action (Fishbein & Ajzen, 1975)

*Theory of Reasoned Action (TRA)* is the second oldest model, constructed by the authors Fishbein & Ajzen. The authors study conscious intentional behavior, utilizing two main factors: “Attitude toward Behavior” which explains an individual’s evaluation of a behaviour, and “Subjective Norm” which describes an individual’s social pressure to perform or not perform a behavior (Fishbein & Ajzen, 1975; Fishbein & Ajzen, 2009). However, the theory has been criticized by scholars for not being reliable nor capable of predicting and comprehending human behavior (Server, 1983). Due to its highlighted criticism and focus on beliefs, the authors do not consider it a relevant theory to use in this study’s context.

### 2.3.3 Theory of Planned Behaviour (TPB)

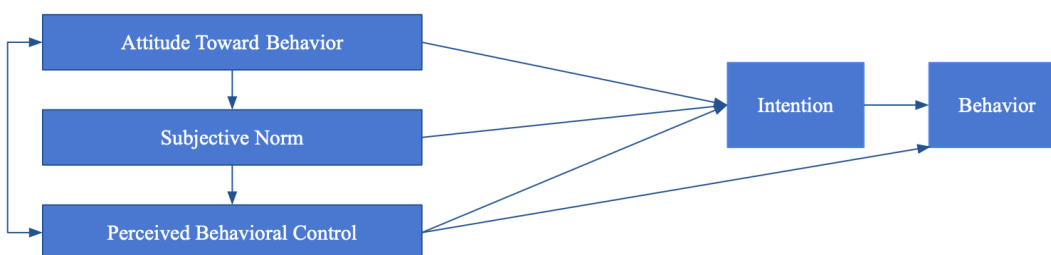


Figure 6: Theory of Planned Behavior (Ajzen, 1991)

*Theory of Planned Behavior (TPB)* developed by Ajzen (1991) is an extension of the above Theory of Reasoned Action (TRA) by adding the concept of “Perceived Behavioral Control”. “Perceived Behavioral Control” refers to the extent to which users believe that they have control over their actions and that there are no limiting factors hindering users from adopting a technology. The major drawback of this theory is the oversimplification of the influence of intention on behavior and how that is affecting the decision-making process (Sheppard, 1988). Moreover, the theory does not include specific factors that encourage or hinder behavior but rather only provides a general framework (Ajzen, 1991). This study wants to examine factors that are believed to influence and encourage students’ actual usage of ChatGPT, and therefore this theory becomes unsuitable.

### 2.3.4 Technology Acceptance Model (TAM)

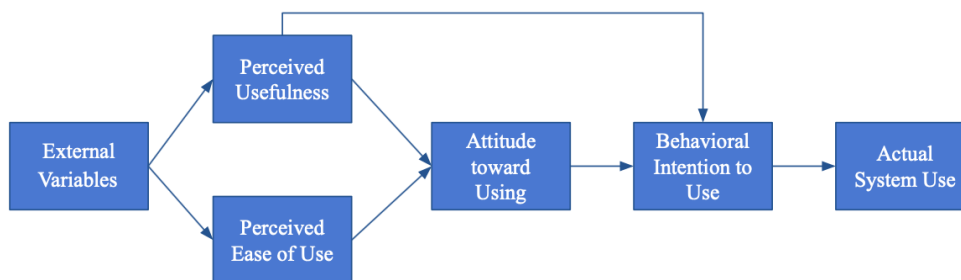


Figure 7: Technology Acceptance Model (Davis, 1986)

The *Technology Acceptance Model (TAM)*, developed by Davis (1986), is a highly influential framework within the field of technology acceptance and is frequently cited in research (Jaya et al., 2017). The article on TAM has a noteworthy number of 31 175 citations to date. The extensive body of research that has since emerged is impressive in both its scale and breadth (Lee et al., 2003). TAM is a theoretical framework used to explain an individual's acceptance of information systems (IS). According to TAM, an individual's acceptance of information systems is influenced by two primary factors: “Perceived Usefulness” and “Perceived Ease of Use” (Lee et al., 2003). TAM was originally presented by Davis in 1986 and is based on TRA. Many studies confirm that TAM has outperformed the previous theories of TRA and TPB regarding explained variance (Davis et al., 1989; Venkatesh et al., 2003). However, TAM has received criticism for being too simplified, as it is unrealistic to believe that only a few factors can explain decisions and behavior in all kinds of contexts (Bagozzi, 2007), and

therefore the authors of this study has chosen to not proceed with this theory. Due to ChatGPT's novelty, the authors believe a conceptual framework with more factors is advantageous.

### 2.3.5 Task-Technology Fit (TTF)

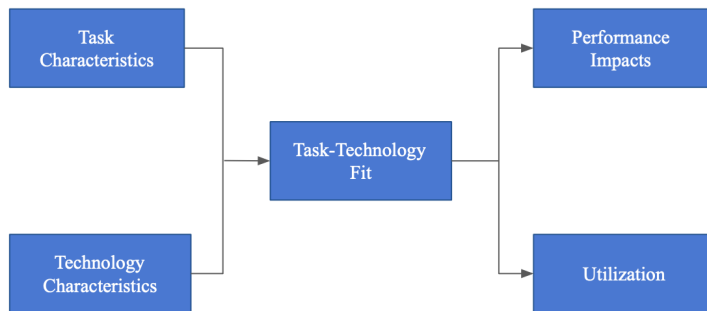


Figure: Task-Technology Fit (Goodhue & Thompson, 1995)

The *Task-Technology Fit (TTF)* theory, developed by Goodhue & Thompson (1995), incorporates the aspect of achieving a fit between the task that the user performs and the technology. Their findings showed that a great fit increases the technology's utilization and performance. TTF is stated to be a suitable theory for assessing already launched products. Spies et al. (2020), who have reviewed the application of the TTF theory, describe that it has been used in various settings, but mostly within healthcare and mobile technology. TTF has received criticism for not including the social context of adopting a technology. The social environment can be seen as an important factor influencing technology adoption, especially for a tool like ChatGPT, and therefore it is unfortunate that this factor is not included in the model (Rai & Selnes, 2019). As such, the authors did not proceed with this theory.

### 2.3.6 Unified Theory of Acceptance and Use of Technology (UTAUT)

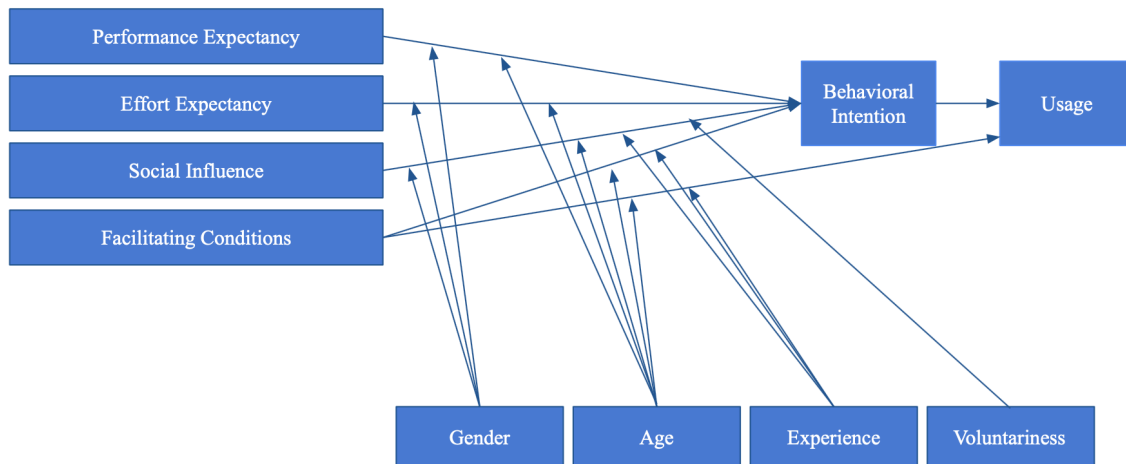


Figure 9: Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003)

Venkatesh et al. (2003) developed the *Unified Theory of Acceptance and Use of Technology (UTAUT)* theory, which is based on the eight (five of them described above) most prominent models in technology adoption. In order to decide which constructs to include in UTAUT, Venkatesh et al. (2003) compared and conceptualized the similarities in the eight competing models (Tan, 2013). The following four constructs were proven to have a significant role as determinants of user acceptance: *Performance Expectancy*, *Effort Expectancy*, *Social Influence* and *Facilitating Conditions* (Figure 9). In addition, *Gender*, *Age*, *Experience* and *Voluntariness* was described as key moderators, influencing the relationships in the model (Venkatesh et al., 2003). UTAUT is a widely used theoretical framework in organizational settings, applicable for various industries such as healthcare and banking (Hoque & Sorwar, 2017, Zhou et al., 2010). To this date it has been cited 20 852 times (Scopus Metric Details, n.d.).

However, the theory has been criticized for only focusing on acceptance in the implementation process. In other words when the organization already has made the decision to adopt the technology, and organizational members need to buy-in. It has been criticized for this approach as it treats implementation as a one-time event rather than a continuous process, which it typically is (Kuziemy et al., 2019). In addition, UTAUT has been criticized to have a narrow view on technology adoption as it focuses on the individual's intention to use. Still, the theory is one of the standard approaches in the information management field (Al-Mamary et al., 2016). Although its many benefits, making it highly suitable for this

study, its focus on organizations rather than on consumers adoption of technology, makes it not entirely convincing to adopt to the context of ChatGPT usage among students.

### 2.3.7 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

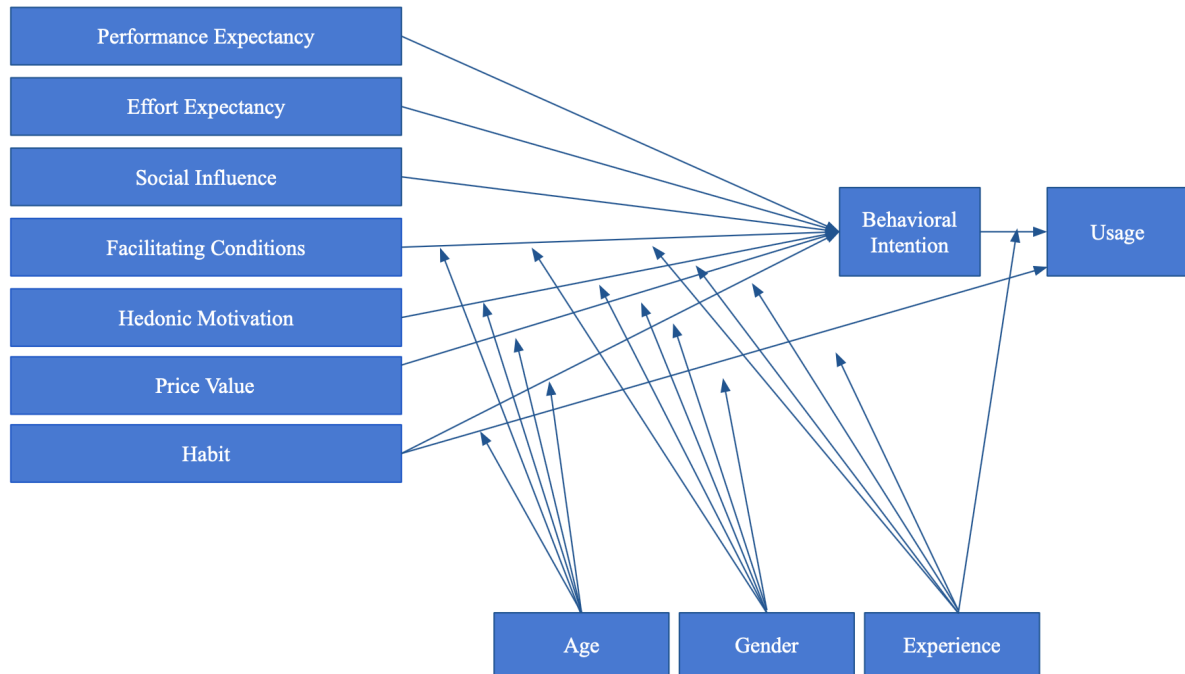


Figure 10: Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012)

UTAUT2 is the most widely used extension of UTAUT (Morosan & DeFranco, 2016). The model is developed to be applied in a consumer technology use-setting, instead of an organizational setting which UTAUT is developed for (Venkatesh et al., 2012). The growth of citations for UTAUT2 is proportionally higher than for UTAUT. To this date, the number of citations for UTAUT2 is 6227 (Scopus Metric Details, n.d.-b).

Three new crucial constructs are added in UTAUT2, to better capture what influences consumer's adoption of technology. These are (1) *Hedonic Motivation* which derives from motivation theory (Venkatesh et al., 2012; Vallerand, 1997) (2) *Price Value* which includes research about consumer behavior related to cost (Dodds et al., 1991; Venkatesh et al., 2012) and (3) *Habit* which challenges the role of behavioral intention as it has a direct effect on usage (Kim & Malhotra 2005; Kim et al., 2005; Venkatesh et al., 2012). Moreover, the moderators from UTAUT, *Age*, *Gender* and *Experience*, are kept while the moderator of *Voluntariness* is removed (Venkatesh et al., 2012). Since UTAUT2 is developed for a

consumer use-setting, voluntariness becomes irrelevant since the consumers have the freedom to decide for themselves whether they want to use a technology or not.

Since its publication date, *UTAUT2* has been modified by researchers with different constructs and moderators to better fit and explain technology adoption in various settings (Venkatesh et al., 2012; Aswani et al., 2018; El-Masri; Tarhini, 2017).

The theory's assumption of a direct relationship between behavioral intention and actual usage has been questioned, a criticism that most technology adoption theories share (Kuziemytsky et al., 2019). This is often referred to as the intention-behavior gap, as empirical evidence shows only a low-to-medium effect for this association (Bhattacharjee & Sanford, 2009; Bhattacharjee & Sanford, 2006). Jeyaraj (2021) adds that the link between intention and behavior should be rethought in future research. To meet this critique, Venkatesh et al. (2012) presented the variable of habit, a construct that affects both behavioral intention and usage (Slade et al., 2014). However, this might not be enough to rethink the intention-behavior gap. In section 3.3, the authors of this study explain how the intention-behavior gap is avoided in this study. Another limitation of *UTAUT2* is the model's predictive validity, replicability and generalisability, as there are much fewer studies done on *UTAUT2* compared to other technology adoption theories (Slade et al., 2014).

First of all, *UTAUT2* is a relevant model to adopt since this study examines students' (consumers) usage of ChatGPT rather than organizations, which *UTAUT* is developed for. Secondly, *UTAUT2* is considered a powerful framework as it can contribute to understanding important phenomena when adapted and extended with relevant constructs (Goodhue, 2007; Bagozzi, 2007). This makes *UTAUT2* a great fit for this study. Thirdly, the authors wanted to discover and test multiple factors since ChatGPT is novel and lacks prior research. As such, *UTAUT2* suited the purpose well, considering it takes into account a wide range of factors. If the authors were to study a more established technology, a more streamlined and simplified model would perhaps be more applicable.



### 3. Theoretical Framework

*In the following chapter, this study's theoretical framework and factors will be presented and conceptualized, based on the existing literature and research gap.*

#### 3.1 Adapted UTAUT2 Model

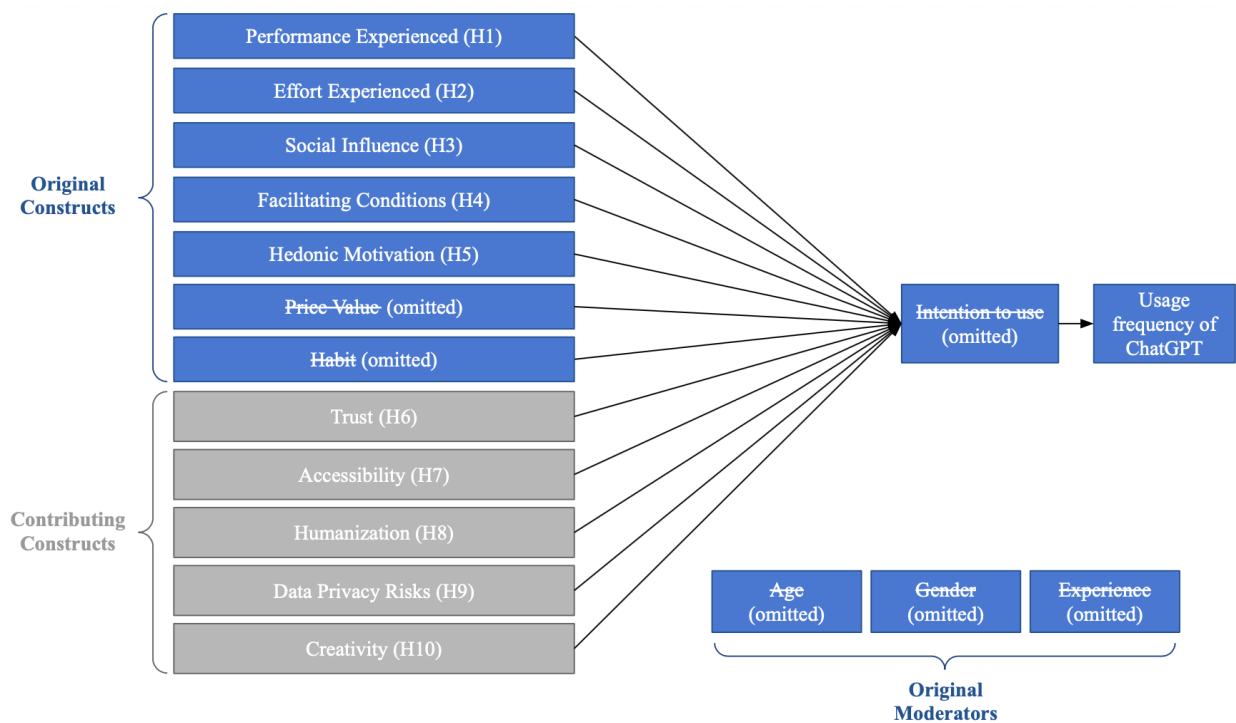


Figure 11: Adapted UTAUT2 model

In the adapted model, the original independent constructs *Performance Expectancy*, *Effort Expectancy*, *Social Influence*, *Facilitating Conditions* and *Hedonic Motivation* from UTAUT2 are utilized (Venkatesh et al., 2012) along with our contributing independent constructs *Trust*, *Accessibility*, *Humanization*, *Data Privacy Risks* and *Creativity*. The following factors have been omitted: *Price Value*, *Habit* and *Intention to use*, and will be further explained in the following sections.

Additionally, the three moderators of *Age*, *Gender* and *Experience* have also been omitted. Many studies which have extended the theory of UTAUT2 in the context of higher education have decided to drop the moderators due to the narrow range of students' age and similar

experiences (Moorthy et al., 2019; El-Masri & Tarhini., 2017). In addition, Terblanche et al's. (2022) results prove that gender and level of study do not have a significant moderating effect when it comes to students in higher education.

### 3.2 Modifications of Constructs

According to the authors of UTAUT2, future researchers should identify new critical constructs important to different contexts in order to make extensions to the model (Venkatesh et al., 2012). Tamilmani et al. (2017) conducted a systematic review of UTAUT2 citations, which revealed that researchers who applied the framework often introduced external constructs. It indicates that UTAUT2 cannot be utilized as a standalone theory to fully understand technology usage across all contexts. In order to properly apply this model, it has therefore been extended with additional constructs to fit this study's context of ChatGPT in education better. The authors followed a two-step approach when deciding which constructs to contribute with. Firstly, by identifying the main characteristics of ChatGPT. Thereafter, exploring how these have been studied in previous literature (Appendix 2). In the end, *Trust*, *Accessibility*, *Humanization*, *Data Privacy Risks* and *Creativity* was chosen due to their potential influence on student's usage of ChatGPT.

### 3.3 Intention-Usage Relationship

The authors of this study chose the dependent variable of *usage* instead of *intention* for several reasons. According to best practices within UTAUT2, the dependent variable should match the life cycle of the technology. When studying a novel technology, scholars typically have *intention* as their dependent variable, as the product has not yet gained traction and a large user base. When studying a mature technology however, *usage* is more suitable, (Tamilmani et al., 2018). Normally a technology launched only half a year ago (November 2022) would be defined as novel, as it is still in the introduction stage of its life cycle (Tamilmani et al., 2018). However, due to the rapid growth and adoption of ChatGPT in society, ChatGPT can be argued to be already mature. This is also backed-up by the pre-study which demonstrated that over 70% of students use ChatGPT (figure 1). As such, *usage* can be argued for and is proceeded with as the dependent variable in this study.

Having *usage* as the dependent variable instead of *intention*, gives the authors of this study an opportunity to break free from the many intention studies represented in UTAUT2 research, as most technology adoption studies examine *intention* rather than actual *usage* behavior (Venkatesh et al., 2012; Alalwan et al., 2017). Differentiating from these studies does not only enable the authors to deliver a contribution, but also more valid findings as relationships proven significant for usage are more reliable than significant relationships for intention. The reasoning is that it is much easier to say that you intend to do something than actually doing it (Bhattacharjee & Sanford, 2009; Bhattacharjee & Sanford, 2006). To conclude, the authors bypass this critiqued intention-behavior issue by adopting *usage*.

### **3.4 Original constructs**

In the section below, the original independent constructs from UTAUT2: *Performance Expectancy*, *Effort Expectancy*, *Social Influence*, *Facilitating Conditions*, *Hedonic Motivation*, *Price Value* & *Habit* are described and adapted to the context of this thesis. The dependent variable of usage is also further explained and adopted.

#### **3.4.1 Usage of ChatGPT**

Usage is defined as a formative construct that consists of both the variety of use and the frequency of use (Venkatesh et al., 2012). In this study however, usage will only be defined by usage frequency. The decision to measure “how much” students use ChatGPT, as opposed to “why” they use it, is because it is more tangible and quantifiable to measure. In this study, the following questions were used to measure usage frequency: US\_1 (“How often do you use ChatGPT?”), US\_2 (“How many questions do you ask ChatGPT on average per week?”) and US\_3 (“When was the last time you used ChatGPT?”). Henceforth, the term “usage” refers to usage frequency, for the sake of simplicity.

#### **3.4.2 Performance Experienced (Ex Performance Expectancy)**

Performance Expectancy describes the extent to which a consumer perceives that utilizing a new technology will provide benefits and facilitate the ability to achieve job-related activities (Venkatesh et al., 2003). According to Venkatesh et al. (2003), Performance Expectancy is the strongest predictor of the dependent variable. In this study, the construct is renamed from Performance Expectancy to Performance Experienced since the variable intention has been

removed. Consequently, students have to reflect on their experienced performance rather than expected performance of using ChatGPT.

Performance Expectancy originates from similar constructs found in the following theories: “Perceived Usefulness” from TAM, TAM2, combined TAM & TPB (Davis, 1989; Davis et al., 1989), “Extrinsic Motivation” from the Motivational Model (Davis et al., 1992), “Job-fit” from Model of PC Utilization (Thompson et al., 1991), “Relative Advantage” from Innovation Diffusion Theory (Moore & Benbasat 1991) and “Outcome Expectancy” from the Social Cognitive Theory (Compeau & Higgins 1995; Compeau et al., 1999).

In the context of this study, Performance Experienced concerns the productivity and usefulness that students experience when using the chatbot in their school work. Since ChatGPT can be used for a variety of tasks in school, Performance Experienced becomes a relevant construct to study.

**H1:** *The higher Performance Experienced, the more students use ChatGPT*

### **3.4.3 Effort Experienced (Ex Effort Expectancy)**

Effort Expectancy can be defined as the consumer’s ease of using a new technology (Venkatesh et al., 2012). Also in this case the construct has been renamed from Effort Expectancy to Effort Experienced, due to the same reasons mentioned above.

The construct of Effort Expectancy has its heritage from the following constructs and theories: “Perceived Ease of Use” from TAM & TAM2 (Davis, 1989; Davis et al., 1989), “Complexity” from MPCU (Thompson et al., 1991) and “Ease of Use” from Innovation Diffusion Theory (Moore & Benbasat 1991).

When applying Effort Experienced to this study, it can be described as the degree of ease students associate with using ChatGPT. In other words, how simple students perceive the tool to be when using it for their school tasks. Although the tool is basic in nature, students can have different perceptions of how easy it is to comprehend and engage with. As such it is of relevance to test this construct.

**H2:** *The less Effort Experienced, the more students use ChatGPT*

### ***3.4.4 Social Influence***

Social Influence can be described as the degree to which consumers believe that family and friends or other important people in their lives, support them in the use of a specific technology (Venkatesh et al., 2012).

The following theories lay the foundation for the construct of Social Influence: “Subjective Norm” from TRA, TAM2, TPB, Decomposed Theory of Planned Behavior and Combined TAM & TPB (Ajzen, 1991; Davis et al., 1989; Fishbein & Azjen, 1975; Mathieson, 1991; Taylor & Todd 1995a, 1995b), “Social Factors” from MPCU (Thompson et al., 1991) and “Image” from Innovation Diffusion Theory (Moore & Benbasat, 1991).

In this context, students' usage of ChatGPT for school work is most likely influenced by family, friends and classmates and their respective attitude towards the chatbot. When launched in November 2022, ChatGPT became a hype among students and the tool triggered different reactions, some being more enthusiastic and others more cautious. In addition, some students were more inclined to be affected by others' opinions, and therefore social influence is a relevant construct in this study.

**H3:** *The more Social Influence, the more students use ChatGPT*

### ***3.4.5 Facilitating Conditions***

Facilitating Conditions refers to consumers' perception regarding the available resources and necessary assistance to use a new technology (Venkatesh et al., 2012).

Facilitating Conditions are built on: “Perceived Behavioral Control” from TPB, DTPB, C-TAM-TPB (Ajzen, 1991; Taylor & Todd 1995a, 1995b), “Facilitating Conditions” from MPCU (Thompson et al., 1991) and “Compatibility” from Innovation of diffusion theory (Moore & Benbasat, 1991).

The Facilitating Conditions in the context of ChatGPT imply a computer or a smartphone, wifi and a user profile at OpenAI. Having a friend or classmate to ask for help when experiencing difficulties with ChatGPT is also considered Facilitating Conditions. The

Facilitating Conditions in this context can be considered rather straightforward, however it is still of interest to further understand its effect on student's usage.

**H4:** *The more Facilitating Conditions, the more students use ChatGPT*

### **3.4.6 Hedonic Motivation**

Hedonic Motivation is described by Venkatesh et al. (2012) as the pleasure a consumer experiences when using a technology. Originally, the construct of Hedonic Motivation derived from Van der Heijden's (2004) article, which found that perceived enjoyment was a strong determinant of the intention-to-use variable when it came to information systems.

In this study, students' perceived enjoyment of using ChatGPT is therefore measured as Hedonic Motivation. Given the fact that ChatGPT is enjoyable and has fun features, it is interesting to further examine how this influences student's usage.

**H5:** *The more Hedonic Motivation, the more students use ChatGPT*

### **3.4.7 Price Value (Omitted)**

Price Value is described as the perceived benefits of using a technology minus the cost of the technology (Venkatesh et al., 2012). In consumer contexts users are paying for a technology, leading to the price being an important construct affecting the adoption of a specific technology in UTAUT2. Therefore, the construct of price was added, which originates from Brown & Venketesh (2005), Chan et al. (2008), Coulter & Coulter (2007) and Dodds et al. (1991).

In the context of ChatGPT, Price Value can not be applied because the chatbot is free of charge for everyone (*OpenAI API*, n.d; Thorp, 2023). The construct of Price Value is therefore omitted.

### **3.4.8 Habit (Omitted)**

Habit refers to the extent to which a consumer perceives a certain behavior as automatic and ingrained (Venkatesh et al., 2012). Furthermore, Habit is a learned outcome that after

extended practice overrides other behavioral patterns (Lustig et al., 2004). The construct and definition originates from Limayem et al.'s (2007) findings.

In this study however, usage and Habit become overlapping concepts. The novelty of ChatGPT implies that similar tools have not been available for students to form habits around. The habits that students form around ChatGPT are therefore the first ones in this category, making measuring usage the same as measuring a student's habit of ChatGPT. Habit as a construct has therefore been omitted.

### **3.5 Contributing constructs**

In the following section, the contributing independent constructs: *Trust, Accessibility, Humanization, Data Privacy Risks & Creativity* are further explained.

#### **3.5.1 Trust**

Trust is a construct that several studies have added when applying UTAUT2, and the literature including this variable show how trust significantly affects behavioral intention when adopting emerging technology (Alalwan et al., 2017; El-Masri & Tarhini, 2017). Trust is therefore also viewed as an impactful factor in the adoption of AI (Hengstler et al., 2016; Tussyadiah et al., 2017) as it can be seen as an underlying mechanism that influences the usage of AI-tools (Lee et al., 2021).

Students can use ChatGPT for written assignments, advanced search engine for recommending reading material, interactive learning experience and reference assistance to name a few (Yorio, 2023). However, using ChatGPT for such tasks does not come without complications, as the chatbot has its limitations. ChatGPT can give incorrect answers, have a difficult time to straighten out ambiguous facts and generate misleading results (Gordijn & Have, 2023; O'Connor, 2023). Mollick (2023a) describes generative-AI's caveats with: "*AI lies continuously and well*" (paragraph 4). See Appendix 3 for an example of when ChatGPT generates speculative answers, by suggesting articles which are made up by ChatGPT. Thus, implicating a severe trust issue and a need for users to adopt critical thinking when using it.

Another drawback of AI tools is the low interpretability of knowing how it reaches its decisions (Brynjolfsson & McAfee, 2017). In the case of ChatGPT, the chatbot declares that

its answers are based on the information it was trained on, which includes texts from books, articles and websites. It also states that the answers provided might not always be perfect but that it strives to provide reliable information (Appendix 4). This means that any biases in the input data used to train the system will be persistent and might even be amplified (Haenlein & Kaplan, 2019). Social biases are one of many biases present in language models. A social bias can be described as a stereotype, usually linked to sociodemographic factors such as age, gender and/or geography (Sánchez-Junquera et al., 2021; Diaz et al., 2018). When the training data includes social biases, the model internalizes them and could for example become biased towards a specific gender (Huang et al., 2020). Lastly, the tool is prone to hurtful misuses such as spreading disinformation, fake news and propaganda, which ultimately can lead to chaos and confusion in society (Hsu & Thompson, 2023).

Ferrario et al. (2020) discusses trust and trustworthiness in human-AI interactions and concludes that the challenge with AI-powered solutions is its dynamic nature, which makes it difficult for users to trust it. A user can get different outcomes depending on what time during the day the outcome is generated, since the model continuously learns.

Trust in this setting refers to whether students trust the output generated by ChatGPT. As such, the authors are interested to explore how this affects usage of ChatGPT.

**H6:** *The more Trust towards ChatGPT, the more students use ChatGPT*

### ***3.5.2 Accessibility***

One of the major drawbacks of ChatGPT is the accessibility problem that users often face when using the tool (Eliçik, 2023). ChatGPT's extremely large user base (Gordijn & Have, 2023) and high demand leads to their servers sometimes running at capacity. Consequently, it makes ChatGPT periodically not accessible for its users (Appendix 5). One factor influencing the volatile capacity is the different time zones of users, leading to Europeans having a hard time accessing the chatbot when American users are awake. In the paragraphs below, accessibility issues will be compared to delay issues in other studies, as they create the same type of frustration among users.



Limited accessibility to ChatGPT can be experienced as frustrating. Frustration connected to technology use can be harmful to consumers. Strebel et al. (2004) highlights that high consumer frustration can delay committing to a technology. Skjuve et al. (2019) highlights the importance of chatbot responsiveness and conversation flow in creating positive user experiences. One of the users in their study stated: *"The conversation speed was so slow, which affected the flow"* (Skjuve et al., 2019, page 44).

Additionally, Zhou, Li, et al. (2010) agrees that insufficient technology can affect users' perception and thus the degree of use. In their study, the authors examine the effect of flow experience on mobile internet users's loyalty. Instead of using the term "accessibility" that we use, they use the term "flow experience", which they define as *"a seamless sequence of responses facilitated by machine interactivity"* (Zhou, Li, et al., 2010, page 932). The authors added it as a new construct to their model due to its significant influence on user behavior, shown in a study by Novak et al. (2000). Zhou, Li, et al. (2010) findings concluded that users formed negative perceptions of the mobile network provider if it was too slow and/or if it did not provide timely information. As a consequence, it negatively affected the reliability of the platform leading to users rejecting it. Although mobile platforms are different from ChatGPT, the study shows the importance of incorporating an accessibility factor when studying online user behavior, as it affects whether users enjoy and adopt a technology or not (Zhou, Li, et al., 2010).

When it comes to students, Galletta et al. (2004) has studied how tolerant students are to website delays. Their findings showed that if a web page takes over four seconds to browse the user's performance and behavioral intentions decrease. If the delay is over eight seconds attitudes towards that web page start to become negative as well. Students were more accepting towards a higher waiting time if the school task performed was more complex (Galletta et al., 2004). Since ChatGPT is reached through a website, the same relations should be applied in this context.

To conclude, there are many synonyms for accessibility such as flow experience, system flow and conversation speed, to name a few from the above sources. Many articles argue for its negative effect on usage. As accessibility issues is rather unique to ChatGPT, it becomes an interesting factor to explore.

**H7:** *The more limited Accessibility to ChatGPT, the less students use ChatGPT*

### **3.5.3 Humanization**

A dominant trend in consumer AI is the growing emphasis on technology with human-like qualities (Ramadan et al., 2021; Ki et al., 2020). Humanization of chatbots implies humanlike responses indicating emotional intelligence, humor, social presence and friendliness (Hermann, 2021; Schanke et al., 2021; Skjuve et al., 2019). AI applications with human-like characteristics have the potential to foster consumer attachment and increase the usage of AI (Hermann, 2021; Qiu & Benbasat, 2009). In addition, Rizomyliotis et al.'s (2022) study found that customized interactions and humanized chatbots increase positive user experiences. In terms of ChatGPT, the user can experience that chatting with the bot can be compared to conversing with a human. The user of ChatGPT is able to get nuanced answers as it can have a conversation back and forth with the chatbot, for example by writing “thank you for the text, but can you write it more academically?” or “can you also translate this to Swedish?”.

Chatbots can further reduce anxiety and stress among individuals by being able to discuss emotions and give guidance (Dhanasekar et al., 2021). A chatbot can also be seen as a friend due to its personality traits such as being non-judgmental, caring and being a listener (Dosovitsky & Bunge, 2021). Moreover, ChatGPT has been identified to have the following humanized characteristics: 1) *humor* (by for example announcing its capacity limitations with a rap) 2) *intentional conversational delays* (by not providing the full answer right away but rather typing it as a human, sentence by sentence) and 3) *friendliness* (by giving tips and showing compassion) (Chatterjee & Dethlefs, 2023; Appendix 6). According to Pérez et al. (2020), chatbots are more successful when they have personality traits.

On the other spectrum of humanization of chatbots is the phenomenon of uncanny valley. The more human-like a robot is perceived to be, the more empathy users feel towards it, but only to a certain level. Users may experience a drastic drop in empathy towards a robot once it becomes too humanlike. This dramatic shift can be described as uncanny valley (Mori et al., 2012). In a study done by Ciechanowski et al. (2019), a text chatbot (similar to ChatGPT) is compared to an animated avatar chatbot. The findings showed that users were experiencing

more uncanny effects with the avatar chatbot than with the text chatbot. These findings are positive results for ChatGPT.

Based on all the findings above, the unique humanized characteristics of ChatGPT, makes us assume that Humanization of ChatGPT has an overall positive effect on students' usage of ChatGPT.

**H8:** *The more Humanization of ChatGPT, the more students use ChatGPT*

### **3.5.4 Data Privacy Risks**

With the increasing digitization of personal data, concerns around data privacy have become more prevalent in recent years. The fear of getting personal information disclosed without the user's permission summarizes what Data Privacy Risks imply (Featherman & Pavlou, 2003). Oftentimes users agree on giving out data in order to use a certain technology, however consumers are not always keen on doing it (Sharma et al., 2022). According to Shaw & Sergueeva (2019) user data has grown extensively. Companies are today able to request both personal information but also retrieve information on where the user is located and their previous activities. The large amount of data being analyzed and aggregated increases the vulnerability of the users (Shaw & Sergueeva, 2019).

In the case of ChatGPT, the user faces two data privacy concerns: 1) having to share an email-address in order to sign up 2) knowing that all you write to the chatbot is saved and can be used by OpenAI (*OpenAI Help Center*, n.d.). These are barriers that can concern and discourage users from using ChatGPT. However, the benefit is being able to use an effective text-generating tool, which for some outweighs the concerns for data privacy risks. Although significant research has been conducted on Data Privacy Risks (Lim, 2018; Prokofieva & Miah, 2019; Wahlstrom et al., 2020), its importance has differed depending on industry and context (Okazaki et al., 2020). Therefore, it is relevant to discover within the context of ChatGPT. Studying Data Privacy Risks within UTATU is however not new. Sharma et al. (2022) have for example used this construct to examine AI-based autonomous shopping systems. As there are major differences between a chatbot and a shopping system, it is interesting to also study in this context for ChatGPT (Sharma et al., 2022).

**H9:** *The higher perceived Data Privacy Risks, the less students use ChatGPT*

### 3.5.5 Creativity

In Swedish higher education, creativity is an ability that is both encouraged and highly valued in students. At Stockholm School of Economics, the vision is expressed as “*students who graduate from SSE must have an entrepreneurial and creative approach to the world*” (Mission & Vision, n.d.). SSE also offers elective courses from the Royal College of Music in Stockholm and Konstfack University of Arts, Crafts and Design, two of Sweden’s most prestigious creative Universities (MSc in Business & Management Program Description, n.d.). Creativity is also an ability that frequently shows up in course syllabuses, where creative and original thinking is rewarded (Brands and Comm Course syllabus.pdf, n.d.).

There is a distinct connection between AI and creativity, as AI has the potential to serve as a catalyst for human creativity (Kirkpatrick, 2023). When discussing creativity in art, writing and music the author states that AI can be both good starters and finishers of an art piece. Moreover, creativity in the context of AI can be described in terms of novelty and value (Lee, 2022). According to Boden (1998), novelty can be explained as new connections being made between either familiar ideas, the development of already existing ideas or the transformation of existing ideas. Tying back to ChatGPT, students can use the chatbot to find novel connections between concepts and theories in a specific context (Appendix 7).

In addition, a study by Wieland et al. (2022) shows how participants produced more ideas with more diversity when brainstorming with chatbots rather than with a human partner. Unlike humans, machines can process loads of information and combine disparate elements, making them less prone to mental fixedness in idea generation (Lanzolla, 2022). AI algorithms have been proven to enhance human imagination and help provide a wider range of creative suggestions to consider (Campbell, 2021). However, important to remember is the fact that humans still remain the crucial factor in the creative process (Campbell, 2021). As Brynjolfsson & McAfee (2017) states “*Computers are devices for answering questions, not for posing them*” (paragraph 39). The author intends to convey that AI tools work great for answering questions, but humans are the ones remaining essential, as they are the entrepreneurs knowing what to ask for (Brynjolfsson & McAfee, 2017). Lastly, human-algorithm decision systems, combining human and algorithms, have shown to perform better than both lone human and lone algorithm decision makers (Burton et al., 2020). Chatbots and specifically ChatGPT can therefore be used effectively by students for

brainstorming, imagination and coming up with creative ideas in their school work. Based on these findings, it is hypothesized that:

**H10:** *The higher perceived Creativity of ChatGPT, the more students use ChatGPT*

## 4. Methodological Approach

*This chapter explains the critical choices that have been made, along with why a quantitative approach has been pursued. In addition, an in-depth description of how the questionnaire has been designed is provided. Lastly, acknowledgments on validity, replicability and generalization are highlighted.*

### 4.1 Our Roadmap

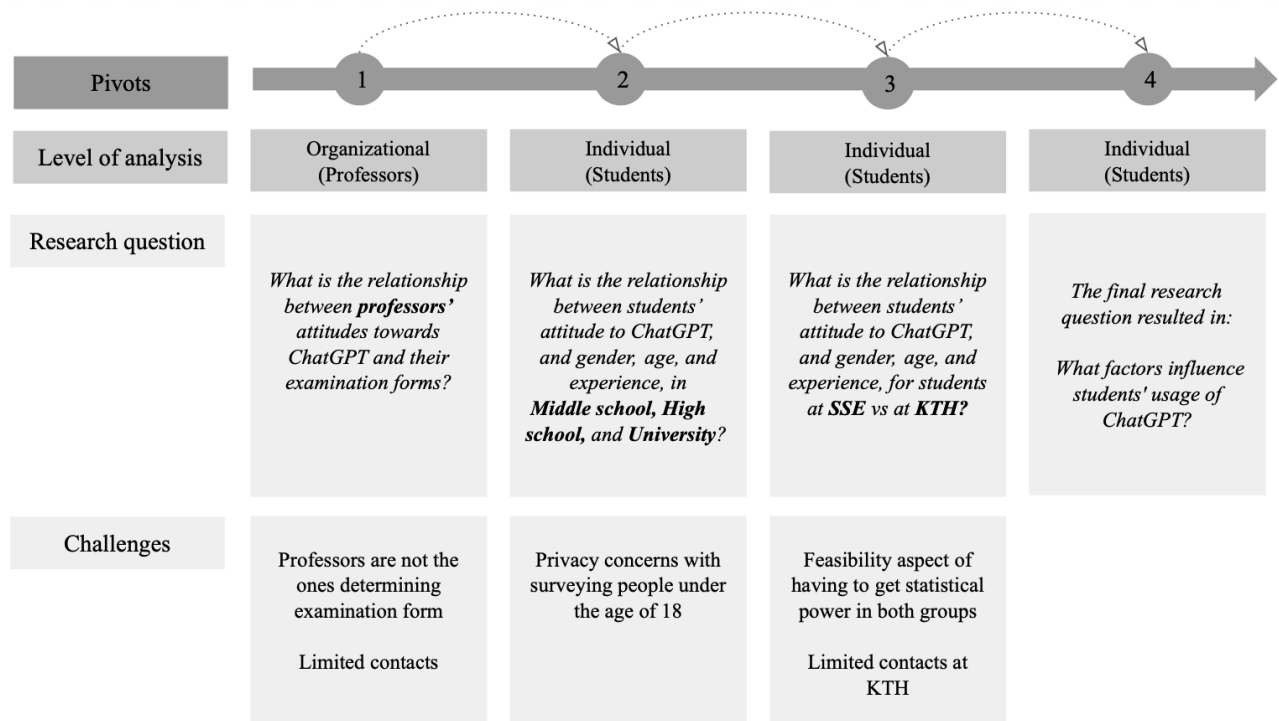


Figure 12: Roadmap of the writing process leading up to the final research question

Having tried ChatGPT ourselves, we quickly realized that this remarkable tool has endless opportunities for creating value. Consequently, we started to investigate different theories involving value as the dependent variable. However, we soon realized that theories concerning perceived value often also emphasize cost and since ChatGPT is free of charge, these theories become difficult to apply. The dependent variable of usage therefore became a more suitable variable to explore.

As the hype in media exploded at the time, we understood how revolutionizing the chatbot is in an educational setting. Initially, we therefore, wanted to observe how usage and attitude of ChatGPT differed between Universities in Sweden. By surveying professors, the authors wanted to determine if measures had been taken, such as examination changes. However, we encountered feasibility challenges of having limited contacts among professors and that these decisions are taken on a centralized level and not by each professor. This led to a shift in focus towards students instead, a segment that we had a network in and knew was using ChatGPT.

Our next choice of path was to decide which students to focus on. Since UTAUT2 includes the moderator “age”, the authors were interested in comparing the usage of ChatGPT between the three levels of education: Middle School, High School and University students. We were curious to understand if the usage pattern would differ among those groups, considering the older students probably possess more experience in AI. Increased knowledge of AI implies awareness of its many opportunities and use cases, but also cautiousness about its downsides, such as ethics and biases. Thereby making it interesting to study. However, we unfortunately encountered feasibility setbacks as surveying underaged students was problematic, which made us pivot once again.

Since High School students and University students are close in age, other variables than age could be interesting, such as educational background. Therefore we pivoted not to compare high schoolers with University students but instead to compare SSE students with KTH students (The Royal Institute of Technology). We wanted to see if a more technical background could have an effect on the usage of ChatGPT. However, after a while, we pivoted and eliminated this direction since it implied a much larger sample. Moreover, there were other more exciting variables to study. Thereby we chose to study SSE students solely.

## **4.2 Research Design**

The study was conducted as a quantitative approach, given the aim to explore the relationships between several constructs and usage. A quantitative approach was chosen for a number of reasons. Firstly, given the background and purpose of the study, a quantitative approach is considered appropriate. Secondly, the maturity state of this field is intermediate due to the state of prior research and study design (Edmondson & McManus 2007). There is

published literature about consumer technology adoption theories, including UTAUT2, but constructs and relationships within these theories still need further exploration. In accordance with intermediate theory research, this study combines distinct literature from previous work to suggest new constructs and theoretical relationships while at the same time maintaining old constructs. Further, Edmondson & McManus (2007) suggest that the methodological fit for an intermediate field is a mix of a quantitative and qualitative approach. However, our study will be solely quantitative (Edmondson & McManus 2007). The value of adding a qualitative side to an intermediate research field is argued by Edmondson & McManus (2007) to support the quantitative tests, better explain the relationships between the variables, and provide a deep understanding of a new construct. In this study, however, the “behavioral intention” variable has been removed from the model, making the relationships between the variables less complicated to comprehend. The argumentation for the contributed variables is backed up by previous literature and, to some extent, also empirical evidence, explaining the rationale of their addition. Thirdly, conducting a solely quantitative study by collecting data through a questionnaire corresponds with the methodology of the vast majority of earlier research within the field of technology adoption.

According to Bryman & Bell (2015), a quantitative research approach is often associated with a deductive strategy, which is also the case in this study. The study process is deductive as it follows a linear process, with its starting point in reviewing theory before developing hypotheses (Bryman & Bell, 2015). In total, ten hypotheses were developed based on our adopted model of UTAUT2. To test these hypotheses, data collected from our questionnaire have been analyzed to reject or confirm the hypothesis and, ultimately, revise the theory based on the findings.



### 4.3 Main study

The questionnaire aims to answer the Research Question presented in section 1.3. The questionnaire has been designed with consideration for the respondents and analysis techniques.

#### 4.3.1 Sampling

The authors of this study are enrolled at Stockholm School of Economics, and therefore students at this business school were targeted when collecting data due to their accessibility. According to Bell et al. (2018) this can be defined as a convenience sampling, which is a type of non-probability sampling.

To reach the targeted sample, we sent out the questionnaire in two different Facebook groups with students at SSE, to get a broad reach. As a second step, we carried out the old-fashioned approach of walking around tables at SSE, asking personally if people were interested in participating in our questionnaire. The authors have incorporated several measures to increase the chances of receiving a high response rate. As a hygiene factor, the questionnaire includes anonymity and GDPR consent information, to assure compliance (Appendix 8). Furthermore, a lottery draw in terms of a gift card was initiated to attract more participants. Respondents wishing to be part of the competition had the opportunity to email us afterward, to remain anonymous. Having an exciting topic and non-sensitive answers has enabled us to more efficiently collect data. In addition, we made sure to state that the questionnaire only is for students who have tried or used ChatGPT. However, as we can't guarantee that everyone reads the instructions carefully, we included a control question at the beginning, asking if the student had used ChatGPT before, yes/no.

#### 4.3.2 Questionnaire Design

**Relevance and accuracy.** We have spent a significant amount of time on formulating and revising the questionnaire in order to avoid vague questions that are difficult for the respondent to interpret. Warwick and Lininger (1975) emphasize the importance of putting enough time into the questions, as errors in questions are larger than errors in sampling, which many tend to forget. The authors further emphasizes that crafting a good question requires a focus on both *relevance* and *accuracy*. *Relevance* can be achieved when the objective of the questions and the information gathered is appropriate for the study. *Accuracy*

can be achieved by appropriate wording, style, type and sequence of questions. Conjointly by having interesting and motivating questions for the respondent to answer (Warwick & Lininger, 1975). Trying the questionnaire out on a test group and revising it accordingly has also helped us achieve higher accuracy.

***Adopting design to the audience.*** Moser and Kalton (2017) recommends putting yourself in the shoes of the typical and least educated respondent when designing the questionnaire. As we collected questionnaire answers solely from SSE students, we knew when writing the questions that the respondents' lowest level of education is a High School degree. Furthermore, we decided to have the questionnaire in English, as SSE is an international business school with English as its official language. This choice was reasonable from a reliability point of view, to avoid faulty interpretations.

***Hidden questions.*** Furthermore, we have worked on shortening our questions, as Presser and Zhao (1992) stress that shorter and less complex questions decrease the risk of being misread. Moreover, Presser and Zhao (1992) taught us to avoid hidden questions, which we initially had. Hidden questions refers to asking two questions in one, where one is dependent on the other, ultimately making the data less reliable.

***Objectivity and scales.*** Moreover, questions should be objective and not lead the respondent to a certain answer. One should avoid leading the respondent in a positive or negative direction by the way the question is framed, but also avoid only offering certain answer alternatives (Warwick & Lininger, 1975). Our questionnaire has the same answer alternatives for each question (1. Strongly disagree, 2. Disagree, 3. Neutral, 4. Agree, 5. Strongly agree) with an evenly distributed scale (likert scale). By having this scale we minimize the risk of leading the respondent to choose an overly positive or negative answer (Iarossi, 2006).

***Leading and sensitive questions.*** Due to the extensive media coverage of ChatGPT and the criticism it has received for being perceived as a cheating tool for students, we made a conscious effort to avoid phrasing questions in a way that would lead respondents to believe we were attempting to catch them cheating. The importance of this study is not to examine whether ChatGPT is seen as cheating or not, but rather to understand what factors affect their usage. Therefore we were careful with including sensitive and misleading phrasing such as “generate text for your exam” or “cheating”.

**Consistency.** Moreover, the authors have tried to stay consistent when designing the questions by starting most questions with “I”. Consistency across questions helps respondents to answer more accurately. Furthermore, the authors have been clear about asking questions about present behavior, not future behavior, as respondents can not forecast future behavior. (Iarossi, 2006)

**Questionnaire length.** As we had to collect data on ten constructs with approximately three questions respectively, our questionnaire risked being too long. Iarossi (2006) raises this concern and argues that too long questionnaires can result in higher response errors, as respondents just tick any answer to get done as fast as possible. By including attention checks in our questionnaire, we mitigated that problem. However, we are aware that our still relatively long questionnaire is a limitation, as it can decrease the number of students willing to participate. Therefore the lottery draw was introduced as an incentive to increase the response rate. This could potentially be a limitation as some might respond carelessly just because wanting to win the competition (Shaw & Sergueeva, 2019). Having attention checks mitigate those risks, however, they can not alleviate the risk fully.

**Questions per construct.** From a statistical point of view, it is aspirational to have between three to four questions per construct in case any of them receives weak results after collecting the data. Having several questions per construct is a common questionnaire method, thus relevant for UTAUT2 studies. However, when the authors tried including four questions per construct, the questionnaire became too long, taking ten minutes or longer to complete, our test-group reported. Therefore we decided to make a strategic decision to stick with three questions per construct, reducing the time to about six minutes, thus increasing our chances of receiving a higher response rate. Moreover, the original article on UTAUT2 measures several of their constructs with only three questions (Venkatesh et al., 2012).

**Randomized order.** The questionnaire respondents received most questions in a randomized order to prevent biased responses. Iarossi (2006), however, argues that the sequence of the questions should be in a good and logical flow, to help the respondent understand the context. However, as we have three questions per construct, we risk that respondents answer the same on all of them if showcased after each other. As the questions are similar, they would also appear repetitive if showcased in sequence.

### 4.3.3 Choosing Questions

**Original independent and dependent constructs.** The majority of the questions used in the questionnaire are best practices from previous research. Questions concerning the original independent constructs: *Performance Experienced*, *Effort Experienced*, *Social Influence*, *Facilitating Conditions*, *Hedonic Motivation* are adopted from Venkatesh et al. (2012). The adopted questions have been used as a base but modified to the specific context of ChatGPT and students.

In contrast to how the original dependent construct of usage frequency is measured by Venkatesh et al. (2012) by time measured in minutes, on the technology, this has been changed to how often you use ChatGPT, how many questions you ask and when was the last time you used it. The three usage questions are: US\_1 (“How often do you use ChatGPT?”) US\_2 (“How *many questions* do you ask ChatGPT on average per week?”) and US\_3 (“When was the last time you used ChatGPT?”) (Appendix 9). This is because time spent on ChatGPT is harder to estimate than for other technologies.

**Contributing independent constructs.** Regarding the contributing independent constructs, there are extended studies of UTAUT2 that have incorporated Trust and Data Privacy Risks as new constructs (Choe et al., 2021; Dinev & Hart, 2006; Marikyan et al., 2022; Chao, 2019). The questions about Trust and Data Privacy Risks have therefore been adopted from previous literature in order to secure the question’s reliability. When it comes to the other contributing independent constructs, no best practice questions exist. Key characteristics for the constructs of Humanization, Accessibility and Creativity have therefore laid the foundation for these questions. In regards to Humanization, *humor*, *dialogue* and *human presence* were identified as the main factors and therefore the questions were formulated around these (Appendix 9). For Accessibility, the questions were built on *capacity limit*. Regarding Creativity, *outside-of-the-box thinking* and *innovative solutions* were in focus for the questions (Appendix 9).

### 4.3.4 Data Collection

The data was collected between the 16th and 27th of March 2023 in the online questionnaire software Qualtrics. Online questionnaires are advantageous over physical questionnaires due to their graphical appeal and user-friendly design, making them more convenient for

respondents to answer. For the authors, it eliminates coding time and reduces the risk of errors that may arise from manually transferring answers (Bell et al., 2018).

#### **4.3.5 Data Analysis**

SPSS has helped us code our questionnaire questions according to the likert scale, making strongly agree equal to 5, and strongly disagree equal to 1. The authors used SPSS to conduct the reliability, validity and regression tests.

#### **4.3.6 Validity**

Two important validity measures to consider in our questionnaire are content validity and face validity. It was important to us that our specific questions ask what the variable should contain conceptually, thus, it became relevant for us to conduct this qualitative validity check (Bryman & Bell, 2015). Rossiter (2002) defines Content Validity as “*a priori evidence that the items are a good representation of the construct*” (page 311). Content validity has been established by letting a professor at SSE review the questions corresponding to each construct. Also, a test panel of students tried the questionnaire and gave feedback. The feedback was then incorporated and the questionnaire was revised, thereafter tried on a new test panel. This was to ensure that the questions were easy to understand and captured the essence of our constructs, as well as that the scale of the measurement was reasonable. One recurring feedback was that many of the questions felt similar, which is understandable, as we have three questions per construct. However, that is not something we can change as multiple questions per construct are recommended, to be able to draw conclusions in the end. Lastly, in accordance with what Rossiter (2002) calls face validity, the authors demonstrate content validity retroactively, by going through the items post hoc the data collection. To do so, the authors reviewed the constructs thoroughly, by systematically defining keywords for each construct as a basis for the questionnaire. The authors found all questions correct, and hence did not remove any items post hoc.

#### **4.3.7 Replicability & Generalizability**

The detailed description of how the questionnaire was designed, and the in-depth reasoning about the methodological decisions, make it possible for other researchers to adopt our model and reach similar results. Another factor that increases this study’s replicability, is that the questions are general in their nature. Thus, the study can be replicated on other students at

different Universities. This leads to a high level of replicability, something which Bell et al. (2018) highlight as an important quality of quantitative research.

Moreover, this study aims to be highly generalizable. As our adopted model is developed for the technology of chatbots, the model can be used for such technology but in different contexts, not only in an educational setting. This is due to our contributing factors of Trust, Accessibility, Humanization, Data Privacy Risks and Creativity being general constructs in the context of chatbots. However, the findings in this specific study are only generalizable to students at SSE (Bell et al., 2018).

#### 4.4 Overview of the Main Study

Category	Value	Number of students	Percentage
Gender	Female	113	55.12 %
	Male	90	43.90 %
	Prefer not to say	2	0.98 %
Age	19-21	54	26.34 %
	22-24	88	42.92 %
	25-27	51	24.87 %
	28-30	9	0.0439 %
	Over 30	3	0.0146 %
Educational level	Bachelor	83	40.49 %
	Master	122	59.51 %
Total		N=205	100% per category

*Table 1: Overview of the respondent's demographics*

The authors have collected responses from 249 SSE students. This implies that we collected 12,5% of SSE's population, as the total sample size of SSE students is approximately 2000 students. After cleaning our data, our sample was reduced to 205 respondents. The cleaning included removing respondents who had: 1) not completed the questionnaire 2) not passed the two attention checks and 3) not used ChatGPT before. A rule of thumb when making regression analyses is to have at least ten observations per variable. As this study has ten

variables, a sample size of 100 is the minimum requirement, which this study fulfills by having 205 observations after cleaning the data. However, larger samples are always advantageous.

The demographics of our sample shows a good distribution between gender, with approximately 55% female and 43% male respondents. Most of our respondents are in the age group 19-27, which is reasonable as we examine bachelor and master students.

For two of the items in Data Privacy Risks (PC\_1 and PC\_2), the authors had to re-code the scale (from 1-5 to 5-1) to ensure all scales corresponded, as the two questions were asked with a negation unlike the other questions. The dependent variable of US\_1, which only consists of one item, was also re-coded in the same way to correspond with the other variables' scales.

#### 4.5 Measurement Model: Data Quality

To begin with, a Rotated Component Matrix was conducted to understand if the items explain the construct it aims to explain. The initial Rotated Component Matrix results can be viewed below in Table 2.

Items	Component								
	1	2	3	4	5	6	7	8	9
PE_1		.769							
PE_2		.760							
PE_3		.765							
EE_1			.783						
EE_2			.725						
EE_3			.705						
SI_1						.764			
SI_2						.781			
SI_3									.797
FC_1									.482
FC_2		.345	.316						
FC_3									.688
HM_1	.718								

HM_2	.785								
HM_3	.757								
TR_1				.719					
TR_2				.800					
TR_3				.763					
AC_1								.830	
AC_2								.634	
AC_3								.647	
HU_1	.527								
HU_2	.612								
HU_3						.550			
CR_1					.724				
CR_2					.687				
CR_3					.786				
PC_1.2*							.685		
PC_2							.674		
PC_3.2							.799		

*Table 2: First Rotated Component Matrix*

*Extraction Method: Principal Component Analysis.*

*Rotation Method: Varimax with Kaiser Normalization.*

*Rotation converged in 7 iterations.*

*\* Disclaimer: the reasoning behind the abbreviation for Data Privacy Risks being PC, is due to the authors initially naming the construct Privacy Concerns*

Most of the items got placed in the correct component (construct), meaning it explains the expected construct. However, the construct of Humanization had three high cross-loadings, two on Hedonic Motivation and one on Social Influence, meaning that Humanization did not explain the expected construct. Thus the construct of Humanization was removed.

Furthermore, the item of FC\_2 had cross-loadings on Performance Experienced and Effort Experienced and was therefore removed as it did not explain the correct construct either. SI\_3 had cross-loadings on Facilitating Conditions, and due to the removal of FC\_2, SI\_3 was moved to explain Facilitating Condition instead.

Based on the above modifications of items, a new Rotated Component Matrix was made. The revised Rotated Component Matrix showed no cross-loadings and supported internal consistency (Appendix 10). The factor loadings in the revised Rotated Component Matrix lays the foundation for the values presented in Table 3 below.



Construct	Items	Factor loading	CA	CR	AVE
Performance Experienced	PE_1	0.781	0.819	0.821	0.605
	PE_2	0.768			
	PE_3	0.784			
Effort Experienced	EE_1	0.769	0.702	0.799	0.570
	EE_2	0.746			
	EE_3	0.750			
Social Influence	SI_1	0.792	0.713	0.612	0.441
	SI_2	0.835			
Facilitating Condition	FC_1	0.495	0.552	0.710	0.459
	FC_2	Omitted*			
	FC_3	0.668			
	SI_3	0.829			
Hedonic Motivation	HM_1	0.730	0.797	0.843	0.643
	HM_2	0.844			
	HM_3	0.826			
Trust	TR_1	0.740	0.762	0.825	0.612
	TR_2	0.791			
	TR_3	0.814			
Accessibility	AC_1	0.833	0.582	0.750	0.504
	AC_2	0.640			
	AC_3	0.639			
Humanised	HU_1	Omitted*	-	-	-
	HU_2	Omitted*			
	HU_3	Omitted*			
Creativity	CR_1	0.769	0.769	0.796	0.566
	CR_2	0.683			
	CR_3	0.800			
Data Privacy Risks	PC_1	0.664	0.634	0.771	0.530
	PC_2	0.698			
	PC_3	0.814			

*Table 3: Overview of items, constructs and measures*

*\*Omitted as it explained another construct, according to findings in the Rotated Component Matrix*

The table above summarizes the main measures used to explain the items' and constructs' reliability and validity. Descriptive statistics about the items' means and standard deviation can be found in Appendix 11. The item's normality was tested using Skewness & Kurtosis, which showed that all items except for EE\_1, and EE\_2, passed the test, as they were in the correct range of -2 and 2 (George & Mallery, 2010; Appendix 11).

#### **4.5.1 Reliability**

Rossiter (2002) explains that many scholars, by default, use multiple questions to explain a construct. However, Rossiter criticizes that and points out that depending on the situation, a single-measurement approach could be more suitable. When studying complex variables, several measurements are beneficial, as it is hard to grasp and cover a diffuse concept with only one question. However, for more concrete variables, it is recommended to use a single item. Using multiple items for a concrete variable can in fact be damaging, as additional synonyms for the same attribute can lower the content validity of the construct (Rossiter, 2002). The authors of this study have chosen to include several items (three items) for the independent variables, as those constructs are more complex, in accordance with Rossiter (2002). To explain the dependent variable usage, only a single-item is necessary, as the dependent variable is concrete and easy for students to determine.

Furthermore, what is unique in this study is the adoption of the single-item approach to measure three dependent variables (Table 5). This enables a more in-depth understanding of usage frequency since it provides a more comprehensive analysis, strengthens the generalizability and validity of the findings, and provides a more nuanced understanding of students' usage of ChatGPT. As earlier presented, these are the three items: US\_1 ("How often do you use ChatGPT?") US\_2 ("How many questions do you ask ChatGPT on average per week?") and US\_3 ("When was the last time you used ChatGPT?"). These items are also the dependent variables and are used in the regressions below.

##### **4.5.1.1 Indicator Reliability**

According to Henseler et al. (2009), factor loadings is a measurement to ensure indicator reliability. Henseler et al (2009) argue that the factor loading should pass a threshold of 0.7

and if lower than 0.4 it should be removed. In our case, no factor loadings are lower than 0.4. Most loadings are above 0.7 and therefore excellent according to Tabachnick and Fidell (2007), except for FC\_1, FC\_3, AC\_2, AC\_3, CR\_2, PC\_1, PC\_2, which were slightly below 0.7 and therefore considered only very good according to their scale.

#### ***4.5.1.2 Construct Reliability***

To test the internal reliability, Cronbach's Alpha (CA) is used. Cronbach Alpha is necessary for questionnaire studies where you have several questions describing a construct. In this study, there are three questions per construct. Using Cronbach Alpha can help determine if the items can compile the construct or not.

The computed alpha coefficient varies between 1 and 0, where the value of 1 is considered perfect internal reliability. Researchers have discussed the acceptable level of internal reliability and 0.7 is typically viewed as the rule of thumb (Bell et al., 2018). In our study, one original independent construct (Facilitating Conditions) was below 0.7, and regarding the contributing independent constructs, two were below 0.7 (Data Privacy Risks & Accessibility). Therefore the constructs of Facilitating Conditions, Data Privacy Risks and Accessibility are dropped.

#### ***4.5.2 Validity***

The purpose of validity is to make sure that the construct captures the phenomena it is intended to capture (Bryman & Bell, 2015). It is about understanding if the construct actually measures what it is supposed to measure. Both convergent and discriminant validity should be considered, which will be discussed below. What can be noted is that validity should come sequentially after reliability, because if a construct consists of items that are not reliable, it can not provide a valid measure of the construct (Bryman & Bell, 2015).

##### ***4.5.2.1 Convergent Validity***

A confirmatory factor analysis was conducted with the measures of Average Variance Extracted (AVE) and Composite Reliability (CR) in order to test the constructs' convergent validity. To be able to calculate AVE and CR, the factor loadings for each item were used. Regarding CR, the acceptable level is to be above 0.7 (Hair et al. 2016) which all items passed, except for Social Influence which had a value of 0.612 (Table 3).

AVE was computed to evaluate the explanatory power of individual items. AVE is a measure of convergence adequacy, indicating that the construct's variance accounts for more variation than the error variance. Hair et al. (2016) state that the AVE should be above 0.5 as a threshold. All our AVE values were above 0.5, except for Social Influence and Facilitating Conditions, which had AVE values of 0.441 and 0.464 respectively (Table 3). Since Social Influence does not meet the required levels of validity, the construct is dropped. Note that Facilitating Conditions have already been dropped, as previously discussed.

#### 4.5.2.2 Discriminant Validity

To test the discriminant validity, the Pearson Correlation Matrix was used. Discriminant validity evaluates whether a construct, which in theory should not be related to another construct, is truly uncorrelated (Bell et al., 2018).

Construct	PE	EE	HM	TR	CR	US_1	US_2	US_3
PE	<b>0.78</b>							
EE	.286**	<b>0.75</b>						
HM	.294**	.356**	<b>0.80</b>					
TR	.345**	.218**	.243**	<b>0.78</b>				
CR	.437**	.198**	.314**	.205**	<b>0.75</b>			
US_1	.447**	.124	.062	.069	.441**	NA		
US_2	.302**	.057	.007	.054	.232**	.647**	NA	
US_3	.385**	.031	.061	.011	.259**	.668**	.397**	NA

Table 4:

*Pearson Correlation Matrix; Discriminant Validity*

*The bold values in diagonal are square roots of AVE*

*\*\*.* Correlation is significant at the 0.01 level (2-tailed).

The results from the Pearson Correlation Matrix indicate that all relationships are positive. Moreover, the correlation between the independent variables are weak to moderate (varying between 0.198-0.437), indicating that the constructs measure different characteristics. Regarding Performance Experienced and Creativity, the results in Table 4 show that they significantly correlate with the dependent variables (US\_1, US\_2 & US\_3).

Moreover, the bold numbers in diagonal represent the square root of AVE and in order to decide on the discriminant validity, these numbers should be larger than the correlation coefficient between any pairs of independent variables (Moutinho & Huarng, 2015). For example, the square root of AVE for Performance Experienced is 0.78 and that is larger than all of the correlation coefficients of the other independent variables (0.286, 0.294, 0.193, 0.345 and 0.437) and therefore discriminant validity is proven. In total, discriminant validity was established for all the independent variables. In addition, the patterns of loadings in the revised Rotated Component Matrix (Appendix 10) also support the discriminant validity.

After evaluating the constructs based on reliability and validity measures, we will proceed with the following: Performance Experienced, Effort Experienced, Hedonic Motivation, Trust and Creativity. The other constructs: Social Influence, Facilitating Conditions, Accessibility, Humanization and Data Privacy Risks have been dropped due to their lack of either reliability or validity. These constructs are therefore removed from the regression analysis to ensure reliable and accurate estimates of the relationships between the independent variables and usage.

#### ***4.5.3 Pre-requisites for Multiple Linear Regression***

Before proceeding with multiple linear regressions, the data must meet some assumptions (Tabachnick & Fidell, 2013). These include that the independent variables 1) should not have any multicollinearity, 2) that the data is homoscedastic and 3) that no outliers exist.

When the independent variables are highly correlated with each other, multicollinearity exists. In order to test the data and ensure that the independent variables do not have multicollinearity, a collinearity diagnostic was performed in SPSS. Appendix 12 shows the values of Tolerance and VIF and suggests that the independent variables should not have Tolerance value less than 0.10, or a VIF value above 5 (Pallant, 2016; Venkatesh et al., 2012). In our case, all independent variables met this requirement and therefore multicollinearity was not an issue.

Moreover, the data was tested for homoscedasticity by doing the Breusch-Pagan test. Homoscedasticity exists when the distribution of the residuals is the same across all values of

the independent variables, indicating that the distribution of the residuals is consistent (Pallant, 2016). When conducting the Breusch-Pagan test, a regression model is tested, and if the p-value is significant and below 0.05, there is evidence of heteroscedasticity in the model. In our case, the p-value was 0.353 (Appendix 13), therefore, the data is considered homoscedastic.

Another important assumption to check before continuing with regressions is to examine outliers in the data (Pallant, 2016). In order to check for outliers, the Mahalanobis distance was used. For each datapoint, a Mahalanobis distance value is computed. These values are then compared with a critical number which is based on the number of independent variables in the model. Tabachnick and Fidell (2013) have developed an overview of these critical numbers and in our case, this number was 27.88. The Mahalanobis distance values showed that two values (28.81 and 28.14) were above the critical value of 27.88 and, therefore, can be considered outliers. According to Pallant (2016), a value exceeding the critical value by much should be considered to be removed. However, in this case, the outliers are not much higher and therefore kept in the dataset.

The three tests above validates that the data meet the critical assumptions, and that multiple regressions now can be executed.

## 5. Results

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*In this chapter, the constructs that met the requirements were incorporated in the regressions. A findings overview is presented, showing which hypothesis that was supported and rejected.*

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### 5.1 Hypothesis Testing

In order to test if the contributing independent constructs have an effect on usage, multiple linear regressions will be executed. For each dependent variable, two models will be created. One model including the original independent constructs (PE, EE, HM), and one including both original and contributing independent constructs (PE, EE, HM & CR, TR). Since we have three dependent variables (frequency, questions asked per week, and last time used), six multiple regressions will be carried out and compared in total. The three dependent variables are as previously mentioned: US\_1 (“How often do you use ChatGPT?”), US\_2 (“How many questions do you ask ChatGPT on average per week?”) and US\_3 (“When was the last time you used ChatGPT?”).

Model	Dependent variable	Independent variables	R	R <sup>2</sup>	Adjusted R <sup>2</sup>	Std. Error of Estimate	Sig. variables
Model 1	US_1; Usage Frequency	PE, EE, HM	0.454	0.206	0.194	2.05381	PE <.001
Model 2	US_1; Usage Frequency	PE, EE, HM & CR, TR	0.549	0.302	0.284	1.93579	PE <.001 HM .042 CR <.001
Model 3	US_2; Questions asked	PE, EE, HM	0.314	0.098	0.085	52.03193	PE <.001
Model 4	US_2; Questions asked	PE, EE, HM & CR, TR	0.342	0.118	0.095	51.72341	PE <.001 CR .046
Model 5	US_3; Last time used	PE, EE, HM	0.395	0.156	0.143	0.68881	PE <.001

Model 6	US_3; Last time Used	PE, EE, HM & CR, TR	0.429	0.184	0.163	0.68063	PE <.001
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*Table 5: Model summary*

In Table 5, six different models are presented as a result of six regressions. Model 1, 3 and 5 contains only original independent constructs from UTAUT2 (PE, EE, HM) while model 2, 4 and 6 contain both the original and the contributing independent constructs (PE, EE, HM & TR, CR). The results of the models' Adjusted R<sup>2</sup> show that model 2 (Dependent variable: Usage Frequency; Independent variables: PE, EE, HM & CR, TR) explain more than model 1 (Dependent variable: Usage Frequency; Independent variables: PE, EE, HM), model 4 (Dependent variable: Questions asked; Independent variables: PE, EE, HM & CR, TR) explain more than model 3 (Dependent variable: Questions asked; Independent variables: PE, EE, HM) and model 6 (Dependent variable: Last time Used; Independent variables: PE, EE, HM & CR, TR) explain more than model 5 (Dependent variable: Last time Used; Independent variables: PE, EE, HM) (Pallant, 2016). This indicates that the models with the contributing independent constructs combined with the original independent constructs better explain students' usage of ChatGPT. PE is significant in all six models, while CR is significant in model 2 & 4 and HM is significant in model 2. Moreover, model 1 explains 19.4% of the variance compared to model 2, which explains 28.4% of the variance. Model 3 and model 4 explain 8.5% and 9.5% of the variance, respectively and models 5 and 6 explain 14.3% and 16.3% of the variance.

Furthermore, the Std Error of Estimate is a measure that assesses the quality of the regression model. For model 3 & 4, which has "questions asked" as the dependent variable, the Std Error is considerably larger than in the other models. In general, a smaller error is preferred as this implies that the model fits the data. However, for models 3 & 4, a larger St Error of Estimate was expected for several reasons. Since the respondents themselves wrote the number of questions they ask ChatGPT per week in free-text rather than in a Likert scale, it led to many different values and scattered data points. The minimum value was 0, while the maximum value was 300, indicating a large variability of the data (Appendix 14). These factors influence the models' Std Error of Estimate and could explain why model 3 & 4 has larger errors than the other models.



In the following section, all six regression models are presented, along with the coefficients for each construct.

***Model 1 (US\_1: Usage Frequency)***

<b>Variables</b>	<b>Unstandardized Coefficients Beta</b>	<b>Coefficients Std. Error</b>	<b>Standardized Coefficients Beta</b>	<b>t</b>	<b>Sig.</b>
<i>Constant</i>	1.292	1.290		1.001	.318
Performance Experienced	1.352	.195	.466	6.937	<.001
Effort Experienced	.084	.281	.021	.299	.766
Hedonic Motivation	-.271	.226	-.082	-1.197	.233

*Table 6: Coefficients for Model 1*

*Dependent variable: Usage Frequency; Independent variables: PE, EE, HM*

***Model 2 (US\_1: Usage Frequency)***

<b>Variables</b>	<b>Unstandardized Coefficients Beta</b>	<b>Coefficients Std. Error</b>	<b>Standardized Coefficients Beta</b>	<b>t</b>	<b>Sig.</b>
<i>Constant</i>	.881	1.222		.721	.472
Performance Experienced	1.064	.204	.367	5.219	<.001
Effort Experienced	.090	.266	.022	.340	.734
Hedonic Motivation	-.449	.219	-.137	-2.047	.042
Creativity	.879	.175	.340	5.033	<.001
Trust	-.255	.167	-.098	-1.532	.127

*Table 7: Coefficients for Model 2*

*Dependent variable: Usage Frequency; Independent variables: PE, EE, HM & CR, TR*

**Model 3 (US\_2: Questions asked)**

Variables	Unstandardized Coefficients Beta	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
<i>Constant</i>	-21.899	32.694		-.670	.504
Performance Experienced	22.723	4.937	.329	4.603	<.001
Effort Experienced	-.582	7.123	-.006	-.082	.935
Hedonic Motivation	-6.861	5.735	-.088	-1.196	.233

*Table 8: Coefficients for Model 3**Dependent variable: Questions asked; Independent variables: PE, EE, HM***Model 4 (US\_2: Questions asked)**

Variables	Unstandardized Coefficients Beta	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
<i>Constant</i>	-26.208	32.651		-.803	.423
Performance Experienced	19.725	5.450	.286	3.619	<.001
Effort Experienced	-.481	7.111	-.005	-.068	.946
Hedonic Motivation	-8.724	5.858	-.112	-1.489	.138
Creativity	9.385	4.668	.152	2.010	.046
Trust	-2.942	4.450	-.048	-.661	.509

*Table 9: Coefficients for Model 4**Dependent variable: Questions asked; Independent variables: PE, EE, HM & CR, TR*

**Model 5 (US\_3: Last time used)**

Variables	Unstandardized Coefficients Beta	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
<i>Constant</i>	2.048	.433		4.733	<.001
Performance Experienced	.393	.065	.416	6.014	<.001
Effort Experienced	-.101	.094	-.076	-1.076	.283
Hedonic Motivation	-.037	.076	-.034	-.486	.628

*Table 10: Coefficients for Model 5**Dependent variable: Last time Used; Independent variables: PE, EE, HM***Model 6 (US\_3: Last time used)**

Variables	Unstandardized Coefficients Beta	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
<i>Constant</i>	2.023	.430		4.709	<.001
Performance Experienced	.379	.072	.402	5.288	<.001
Effort Experienced	-.090	.094	-.067	-.958	.339
Hedonic Motivation	-.048	.077	-.045	-.622	.535
Creativity	.116	.061	.137	1.884	.061
Trust	-.110	.059	-.130	-1.873	.062

*Table 11: Coefficients for Model 6**Dependent variable: Last time Used; Independent variables: PE, EE, HM & CR, TR***5.2 Presentations of Findings**

The authors will summarize which hypothesis got supported and rejected with the above six models as a base. To conclude, Performance Experienced was significant in all six models, while Creativity became significant in two models and Hedonic Motivation in one model.

### ***Performance Experienced***

In all six models, across the three different dependent variables of usage, Performance Experienced showed a significant positive effect ( $p > .001$ ). Performance Experienced is the strongest unique contributor to explaining usage. Performance Experienced's standardized beta coefficient is  $\beta = 0.466$  in model 1 (Dependent variable: Usage Frequency; Independent variables: PE, EE, HM),  $\beta = 0.367$  in model 2 (Dependent variable: Usage Frequency; Independent variables: PE, EE, HM & CR, TR),  $\beta = 0.329$  in model 3 (Dependent variable: Questions asked; Independent variables: PE, EE, HM),  $\beta = 0.286$  in model 4 (Dependent variable: Questions asked; Independent variables: PE, EE, HM & CR, TR),  $\beta = 0.416$  in model 5 (Dependent variable: Last time Used; Independent variables: PE, EE, HM) and  $\beta = 0.402$  in model 6 (Dependent variable: Last time Used; Independent variables: PE, EE, HM & CR, TR). This shows that Performance Experienced in all six cases positively affects usage and hypothesis H1 is supported.

### ***Effort Experienced***

Effort Experienced did not show a significant effect on usage in either of the six models. It received significance level 0.766 in model 1, 0.734 in model 2, 0.935 in model 3, 0.946 in model 4, 0.283 in model 5 and lastly 0.339 in model 6. As such, hypothesis H2 is rejected.

### ***Social Influence***

The construct for Social Influence did not pass the validity tests and thus was removed and not included in the six regressions.

### ***Facilitating Conditions***

The construct of Facilitating Conditions did not achieve acceptable levels in either the reliability nor the validity tests, thus were removed and not included in the six regressions.

### ***Hedonic Motivation***

Hedonic Motivation showed a significantly negative effect on usage in model 2 ( $p > 0.042$ ,  $\beta = -.137$ ). Model 2 was based on the usage question US\_1 ("How often do you use ChatGPT?"). However the construct did not become significant in the other five models, as it received a significance level of 0.233 in model 1, 0.233 in model 3, 0.138 in model 4, 0.628 in model 5 and lastly 0.535 in model 6. Hedonic Motivation is therefore contributing to

explaining the dependent variable “usage frequency” but not “questions asked” nor “last time used”. However, the significantly negative result in model 2 is still an interesting finding, worth further discussion.

As such, hypothesis H5 is rejected due to its negative significance in model 2 rather than the expected positive effect.

### ***Trust***

Trust did not show a significant positive effect on usage in either of the three models in which it was included. It received a significance level of 0.127 in model 2, 0.509 in model 4 and 0.062 in model 6. The construct is not significant in any of the models but it is almost significant in model 6. However, almost significant results cannot be relied upon and used as a basis for analysis. As such, hypothesis H6 is rejected.

### ***Accessibility***

The construct of Accessibility did not pass the reliability tests, and was thus removed and not included in the three models.

### ***Humanization***

The items for Humanization had cross-loadings on Hedonic Motivation in the Rotated Component Matrix and therefore the construct failed to achieve internal consistency, thus the construct was removed and not included in the six regressions.

### ***Data Privacy Risks***

The construct of Data Privacy Risks did not have an acceptable level of reliability and thus was removed and not included in the six regressions. However, the construct was close to passing the threshold, receiving a Cronbach Alpha of 0.634, not far from 0.7 (Table 3).

### ***Creativity***

Creativity was positively significant in two of the three models with the dependent variables “frequency of use” & “questions asked” ( $p > 0.01$ ,  $\beta = 0.34$  in model 2, and  $p > 0.046$ ,  $\beta = .152$

in model 4) and therefore confirmed as a predictor of student's usage of ChatGPT, thus H10 was supported.

As previously mentioned, all dependent variables measure the same thing, namely usage frequency. It is therefore natural that Creativity which is significant for one dependent variable (frequency of use) also becomes significant for another one (questions asked). The significance of Creativity in two different models proves that the construct is highly relevant when studying usage frequency.

### 5.3 Overview of Hypothesis Testing

Construct:	Hypotheses:	Result:	Relationship:
Performance Experienced	H1: The higher Performance Experienced, the more students use ChatGPT	Supported	PE → US_1, US_2 & US_3
Effort Experienced	H2: The less Effort Experienced, the more students use ChatGPT	Rejected*	EE → US_1, US_2 & US_3
Social Influence	H3: The more Social Influence, the more students use ChatGP	Omitted	N/A
Facilitating Conditions	H4: The more Facilitating Conditions, the more students use ChatGPT	Omitted	FC → US
Hedonic Motivation	H5: The more Hedonic Motivation, the more students use ChatGPT	Rejected**	HM → US_1
Trust	H6: The more Trust towards ChatGPT, the more students use ChatGPT	Rejected*	TR → US_1, US_2 & US_3
Accessibility	H7: The more limited Accessibility to ChatGPT, the less students use ChatGPT	Omitted	N/A
Humanization	H8: The more Humanization of ChatGPT, the more students use ChatGPT	Omitted	N/A
Data Privacy Risk	H9: The higher perceived Data Privacy Risks, the less students use ChatGPT	Omitted	N/A
Creativity	H10: The higher perceived Creativity of ChatGPT, the more students use ChatGPT	Supported	CR → US_1 & US_2

Table 12: Hypotheses

\* statistically insignificant results

\*\*statistically significant results, but do not support hypothesis

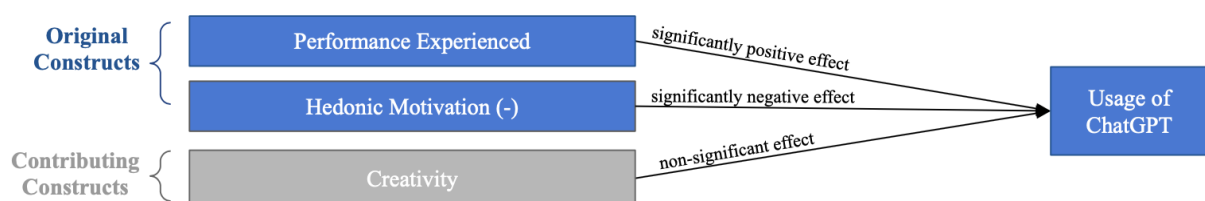
## 6. Discussion

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*In the following section, the authors discuss the outcome of the results and how they relate to previous research. Limitations of the study are also highlighted.*

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### 6.1 Revised Conceptual Framework



*Figure 13. Revised conceptual framework*

In the revised conceptual framework, three constructs are added to explain students' usage frequency of ChatGPT, based on their results in the analysis.

### 6.2 Discussion of Results

#### 6.2.1 Performance Experienced

Performance Expectancy is the strongest predictor to behavioral intention according to Venkatesh et al. (2003). This is in accordance with the findings also in our study, as Performance Experienced was proven to be the strongest unique contributor to students' usage of ChatGPT. This validates the importance of the construct also in the context of ChatGPT. It also concludes that ChatGPT is useful for students as it increases productivity and the student's chances of achieving a better result. At SSE, one of Sweden's most renowned business schools, the ambition level of students is high. It is therefore not surprising that the findings show that the strongest predictor of a student's usage of ChatGPT is Performance Experienced.

Performance Experienced also aligns with OpenAI's mission to “*ensure that artificial general intelligence—AI systems that are generally smarter than humans—benefits all of humanity*” (About, n.d.). Ultimately the main purpose of ChatGPT is to help users increase their performance in various tasks. However, the fact that it takes several prompts to refine an answer, can speak for the chatbots' unproductivity. Despite this, students still regards the tool as sufficiently productive and useful, which the data showed.

### **6.2.2 Effort Experienced**

Effort Experienced was proven to be a non-significant predictor of student's usage of ChatGPT. Interestingly, the authors did not receive the same significantly positive results as other UTAUT2 studies (Alalwan et al., 2017; Gharrah & Aljaafreh, 2021). Since the difficulty level of typing with a chatbot is not very high, users generally perceive chatbots as easy to use (Goli et al., 2023). One possible explanation for Effort Experienced being non-significant could therefore be that ChatGPT is an utmost basic technology, compared to other technologies such as mobile banking, virtual shopping and online learning systems. Effort Experienced could therefore be seen as a hygiene factor rather than a predictor of usage. Moreover, the fact that Effort Experienced became non-significant shows that other variables have a more significant effect on students' usage of ChatGPT.

### **6.2.3 Social Influence**

Social Influence was one of five constructs that was never tested due to its low convergent validity. The item SI\_3 (*My classmates have influenced me to use ChatGPT*) was proven not to measure Social Influence. The item of SI\_3 was modified from the original item, which was: “*People who influence my behavior think that I should Use Mobile Internet*”. This modification was done to fit the study participants better, but unfortunately resulted in SI\_3 failing to measure the correct construct. In hindsight, the item should have been kept as it was, like the other two items of Social Influence (SI\_1 & SI\_2). This resulted in Social Influence only consisting of two items instead of three, leading to poor results regarding its validity.

### **6.2.4 Facilitating Conditions**

Facilitating Conditions performed low on reliability and validity, and was therefore excluded from testing, making it challenging to draw any definitive conclusions about its impact on



usage. However, what can be reflected upon are the items used, and how they have affected the robustness of the construct.

One of the items FC\_2 (*I have the resources necessary to use ChatGPT*) was adopted from best practice while the other two: FC\_1 (*People in my surrounding give me inspiration on available use cases of ChatGPT*) and FC\_3 (*I have a friend or similar available for assistance when I am having difficulties with ChatGPT*) were modified to fit the study's context. The results of the Rotated Component Matrix showed that FC\_2 measured another construct while the modified items measured Facilitating Conditions. This analysis shows that the formulation of the item FC\_2 could have been more specific and tailored to ChatGPT, as well. Instead of focusing on the necessary resources (which are few for ChatGPT), the item could have instead focused on the necessary knowledge students need. A term that has emerged in the discourse of chatbots is prompt engineering, which involves writing effective prompts that are specific to the requests, by breaking down complex requests (Shieh, 2023). To make ChatGPT useful, some skills in prompt-handling are required. A way to upskill your prompting is to work on it in practice, according to Mollick (2023b). Therefore, an improved suggestion for FC\_2 is: "*I have the knowledge necessary to generate accurate prompts*".

### **6.2.5 Hedonic Motivation**

Hedonic Motivation was a significant predictor of usage in Model 2. However it was surprising that the construct did not have a positive, but instead negative, significant effect on usage.

A reasonable explanation for its negative effect on usage could be that when using a technology for important and serious tasks such as in a school setting, the user wants a serious tool that matches the purpose. This is in accordance with the *Task-Technology Fit* theory, which suggests that the better the match between the characteristics of the task and the features of the technology, the greater the user's satisfaction and performance (Goodhue & Thompson, 1995).

However, in use cases that are less serious and more fun, such as when ChatGPT is used for generating speeches or suggesting recipes, Hedonic Motivation might be more likely to

positively affect usage. Important to note is that this is only hypothetical reasoning and nothing that is statistically proven.

### **6.2.6 Trust**

The results from the regression analysis shows that Trust does not have a significant positive effect on usage in either of the three models where it has been used, as it is non-significant. Given that Trust has been examined in various contexts exploring emerging technologies (Alalwan et al., 2017, El-Masri & Tarhini, 2017; Hengstler et al., 2016; Tussyadiah et al., 2017), it is interesting that it did not play a significant role in this study.

By examining how students in our sample utilize ChatGPT, the authors gained a more comprehensive understanding of ChatGPT and the results that were received. One reason why Trust did not become a significant predictor of usage could be the fact that 64% of the students use ChatGPT to understand concepts/theories, 52% as an alternative to a Google search and 47% to get inspiration (Appendix 15). This implies that students use ChatGPT as a tool for creativity and for gaining understanding, rather than a source to reference to. Therefore, trust becomes irrelevant as ideas and inspiration cannot be true or false.

When using the tool for understanding concepts however, the trust issues related to ChatGPT become more concerning. However, it is important to note that students often possess a solid grasp of a concept/theory prior to asking the chatbot, and as a result, can more easily assess the credibility of ChatGPT's output. In addition, students use ChatGPT to recommend papers, which indicates that students do not use the chatbot's output in its pure form (copying and pasting text), but rather for support and inspiration in getting started with school tasks. This is also backed up by the results in Appendix 15, which shows that 44% of students use the chatbot as support in writing essays.

The data showed that students use ChatGPT more consciously than one might have thought. Students' selective use of ChatGPT could stem from the extensive training in source criticism taught throughout primary school and University (Rosenqvist & Ekecrantz, 2022). As a result, students understand what ChatGPT is capable of and not. This differs from the initial academic worries of ChatGPT jeopardizing students' critical mindset. For example, Meisner (2023) pointed out the risk of students losing their critical thinking when ChatGPT was

launched, by blindly trusting the tool and not use own critical thinking. To conclude, when students use ChatGPT for the cases presented above, trust does not become an apparent variable of influence and this could potentially explain why Trust is non-significant in this study.

### **6.2.7 Accessibility**

Accessibility was one of the constructs which was not included in the regression due to its internal reliability issues. Besides collecting more data, the authors could have increased the internal reliability by adding one more item related to Accessibility. An example could be: *“ChatGPT’s accessibility issues hinder me from using the chatbot”*.

Although the construct could not be tested, the authors want to reflect on its relevance in hindsight. Since ChatGPT faced major accessibility issues in the initial months, the authors considered it a relevant factor to include. However, in the past months, the problem has stabilized, and if the authors were to decide on additional constructs today (as of May 2023) this construct would most likely not be considered. This implies that future studies could consider omitting this variable, depending on how accessibility issues progress in the future.

### **6.2.8 Humanization**

Humanization was not included in the regressions due to its reliability issues. Humanization was too similar to the original independent construct of Hedonic Motivation and the two constructs therefore measured the same concept. The items connected to Hedonic Motivation involved the enjoyment of using the technology while Humanization was centered around the humor and dialogue of ChatGPT. It is clear in hindsight that these constructs overlap to some extent, and that the construct of Humanization could have been built on more diverse items to avoid this situation.

One way to diversify Humanization could be to focus solely on the phenomena of uncanny valley (Mori et al., 2012). In that case, three new items could have been *“I get frightened over ChatGPT’s human-like characteristics”*, *“I do not appreciate the human likeness of ChatGPT”* and *“I do not feel any empathy towards ChatGPT”*. If proceeding with the approach of uncanny valley, the hypothesis could then be formulated as: *“Humanization of*

*ChatGPT has a significant negative affect on students' usage of ChatGPT*". In other words, that its humanized characteristics influences usage negatively instead of positively.

In conclusion, the construct of Humanization is still of interest in future studies as no results were able to be confirmed.

### **6.2.9 Data Privacy Risks**

Data Privacy Risks were not included in the regression due to its low reliability. However, it received a Cronbach Alpha of 0.634 when the requirement was 0.7, meaning it was close.

The authors could have added one more item, to make it more robust. This item could have been: *"I am aware that OpenAI collects my data"*.

If discussing the construct's relevance on a general note, only speculatively, one could say that Data Privacy Risks might be an even more relevant construct to include in future research. From a user's perspective, there is a risk of sharing data and personal information in prompts as there is a lack of control over who will use this information (Zhang et al., 2013). Therefore, the more data shared with OpenAI, the more vulnerable users are to data privacy risks (Shaw & Sergueeva, 2019). From OpenAI's perspective, the more prompts users generate, the more knowledge on its users they receive (*OpenAI Help Center*, n.d.), something which they can use to their advantage. Therefore, future studies should include this construct in order to understand its relevance better, as Data Privacy Risk was not able to be tested or confirmed in this study.

### **6.2.10 Creativity**

Creativity was positively significant in two of the three models (frequency of use & questions asked) and therefore confirmed as a predictor of students' usage of ChatGPT. It can be concluded that as hypothesized, ChatGPT enhances student's creativity, innovativeness and ability to think outside the box. A skill that has grown to become important in today's education (Mission & Vision, n.d.). When studying the different use cases of what students use ChatGPT for, it is evident that 47% of students use the chatbot to get inspiration (Appendix 15). Inspiration often serves as the source of creativity (Oleynick et al., 2014) and it is not surprising that creativity is a strong significant predictor of students' usage of ChatGPT.

Moreover, Creativity was almost significant in model 6 ( $p < 0.062$ ,  $\beta = 0.137$ ), where the dependent variable was “last time used”. Even though it is not statistically significant in this model, it still gives an indication that Creativity has a meaningful effect in this regression as well. However, one must be aware that an almost significant result is not statistically significant and should not be used as a foundation for analysis and findings.

To conclude, Creativity is considered an influential factor in students’ usage of ChatGPT, and should therefore be included in future research regarding ChatGPT.

### **6.3 Limitations of study**

This study offers various insights about students’ usage of ChatGPT, but it also has its limitations, which needs to be acknowledged.

**Authors.** One limitation of the study is that the authors are both researchers and belong to the targeted sample at the same time, being students at SSE. This implies a risk of the researchers own beliefs, assumptions and biases being present in the study (Bell et al., 2018). To avoid this, reflexivity has been practiced to carefully reflect and understand our roles and choices in the study.

**Contributing independent constructs.** The contributing constructs in this study are chosen based on the research and knowledge which was gathered in the beginning of the study, implying a potential risk of conceptual limitation. Each construct is argued for and proven to be of high relevance in the theory section. However, this does not eliminate the fact that other potential constructs influencing students’ usage of ChatGPT might have been excluded.

**Sample.** Another limitation of the study is the convenience sample of SSE students. A top-tier business school such as SSE might not represent students as a whole. Also, by only studying SSE students the data collection was limited, as there are only so many students at SSE. Even though the sample size of 205 respondents was satisfactory in comparison to the total number of students at SSE, a larger sample size would still have been desirable. A larger sample size could have affected the variables in the study which did not turn out to be significant as a larger sample size is more likely to find significant relationships if they exist.

**Data.** The number of questions per construct in the questionnaire has had an effect on the variables' reliability. Since five constructs did not meet the required levels of reliability and validity, this was proven to be a limitation of the study. Four to five questions per variable would have been better as it could have increased the reliability and validity of the constructs. In turn, this could have made it possible to include them in the regressions to further understand their relationship to usage. As such, more items would be advantageous. However, this would have resulted in a lengthy questionnaire, and since our adopted UTAUT2 model already encompasses many variables, it was not feasible.

**Theory.** Initially, UTAUT2 was assumed to be the best fit to explain students' usage of ChatGPT. However, after the analysis, it is clear that this study's results differ from UTAUT2. Only one of the original constructs, Performance Experienced, showed significance, while Effort Experienced was non-significant and Hedonic Motivation showed a significant negative effect, differing from results in UTAUT2. This study shows that UTAUT2 could not help to explain the usage of the novel technology of ChatGPT, implying that new theories need to be explored and developed, building on the results of this study.

## 7. Conclusion

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*This chapter concludes the main findings of the study and its contribution to the literature. Thereafter, the authors give implications to three different stakeholder groups, who can be aided by this research. Lastly, suggested future research is discussed.*

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### 7.1 Main Results

The purpose of this quantitative study was to explore and understand which factors that affect students' usage of ChatGPT. To do so, UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) was adopted as the theoretical model with the constructs: *Performance Experienced*, *Effort Experienced*, *Social Influence*, *Facilitating Conditions* and *Hedonic Motivation*. The model has also been extended by the authors with particular constructs related to ChatGPT, which are: *Trust*, *Accessibility*, *Humanization*, *Data Privacy Risks* and *Creativity* (Figure 11). The Research Question that has served as the guideline for this study is:

*What factors influence students' usage of ChatGPT?*

To answer this, *Performance Experienced* has a significant positive effect on usage, while *Hedonic Motivation* has a significant negative effect on usage. *Effort Experienced* was proven not to have a significant effect on usage. *Social Influence* and *Facilitating Conditions* did not pass the reliability and validity tests and could therefore not be included in the regression analysis.

Furthermore, *Creativity* has a significant positive effect on Usage. *Trust* has a non-significant effect on Usage. Lastly, *Accessibility*, *Humanization* & *Data Privacy Concerns* did not live up to reliability and validity thresholds and could therefore not be tested.

## 7.2 Contribution to Literature

The authors contribute to the literature by adding more empirical findings to the currently limited field of technology adoption theories in the context of chatbots and students. First of all, the empirical results from this study showed that Creativity could be extended to the theory of UTAUT2, as it had a significant positive effect on students' usage of ChatGPT. This is a valuable insight to current literature. Secondly, the study also proves that Performance Experienced is the strongest variable to predict student usage, making it possible to generalize the construct also in this context. Thirdly, the results of Hedonic Motivation were surprising as it shows that the normal relationships of UTAUT2 are not applicable when it comes to the usage of ChatGPT. Fourthly, it is equally important to highlight the non-significant constructs of Effort Experienced and Trust, as their results also provide valuable insights. Being transparent and presenting non-significant results helps readers understand the full scope.

Besides the contributions of the constructs, the study also contributes by studying the dependent variable of usage, without using a mediator of behavioral intention, moving away from the intention-behavior gap (Tamilmani et al., 2018). Removing the mediator also leads to more reliable and valid research findings.

As previously mentioned, the study shows that UTAUT2 has its limitations in explaining students' usage of ChatGPT. Therefore a contribution is also the fact that new models and theories need to be explored. These can be built upon the findings of this study in order to provide a more comprehensive understanding of ChatGPT usage.

## 7.3 Implications

### *7.3.1 Implications for Students*

The knowledge that ChatGPT's Creativity positively impacts students' usage of the chatbot, gives several implications. For students who have not tried generative AI before, this study can open up new doors of inspiration. Also for students who struggle with creativity, ChatGPT can become an important brainstorming partner that can enhance outside-the-box thinking by stimulating imagination and widening students' perspectives. In addition,



ChatGPT can be a tutor for students to improve their creative skills, as the chatbot can evaluate the student's work and identify areas of improvement.

However one should also highlight the risks of students depending on ChatGPT for creativity. First, one could argue that a student's creative abilities might drop if relying extensively on ChatGPT when solving a task (Meisner, 2023). Moreover, traditional brainstorming techniques, such as important face-to-face interactions with others to bounce ideas off, might become more seldom. Vereckey's (2022) study has shown that physical interactions are crucial for innovation creation. In the context of this study, one could say that ChatGPT can facilitate the initial brainstorming, but in order for students to take it to the next level, human judgment and interaction with others are necessary (Agrawal et al., 2016; Vereckey, 2022).

This study implies that ChatGPT increases students' Performance and is a great assistant in their school tasks. The most important implication for students is to learn how to optimally use ChatGPT, and excel in prompt-engineering as this not only saves time for the students but also increases the quality of the answers produced by ChatGPT. Brynjolfsson & McAfee's (2017) argument, that computers only can answer questions but not pose them, applies to students using ChatGPT as well. ChatGPT can enhance both Performance and Creativity, but only the students skillful enough to ask the right questions will get the right answers.

### ***7.3.2 Implications for Schools***

What essentially sparked the author's interest in this topic was the massive debate in the media about whether ChatGPT will be the death of schools or not. As shown from this study's results, schools should not be worried about ChatGPT being used for the wrong reasons, as ChatGPT mostly is used as an enhancing tool to unleash Creativity and Performance.

In today's education, Creativity is an important skill that is highly rewarded, but most schools are not teaching creativity as a skill (Mission & Vision, n.d; Sawyer, 2015) Moreover, creativity is one of the most important skills in the 21 century to possess in order to succeed in today's rapidly changing world (Sawyer, 2015). Helping students become more creative should therefore be in the interest of schools. The implications for schools are therefore to incorporate and encourage the use of ChatGPT as a brainstorming partner in creative tasks, to demonstrate how the tool can inspire students to think outside the box. By doing so, students

have the possibility to enhance their creativity in the specific task and, most likely, also their performance. Over time, ChatGPT can improve students' creative skills by constantly exposing them to new diverse perspectives and concepts, and thereby avoiding mental fixedness.

Regarding Performance, it is proven that students increase their Performance when using ChatGPT, and believe the tool is of great value in their school tasks. Moreover, extensive programs have been developed to detect AI-written text and therefore schools should not be worried about whether a text is performed by a student or a chatbot. With this in mind, schools should not hinder students from using ChatGPT, but rather redirect their focus onto understanding how to integrate and leverage it. First of all, schools need to understand how they can better teach students how ChatGPT can be used as a aid, but also inform about its drawbacks. One way to teach students how to use ChatGPT best is to practice prompt-engineering in order for students to learn and optimize the utility of the chatbot. Moreover, the biases of the chatbot needs to be addressed and mediated to students to avoid faulty usage. This would result in a more proactive and positive approach to ChatGPT, and since generative AI is here to stay, it is important to understand how schools can best leverage its benefits.

### ***7.3.3 Implications for Businesses***

The proven usage of ChatGPT by students, will likely follow when transitioning into their work life later on. This in combination with ChatGPT being a disruptive technology, gives implications also for businesses.

First of all, ChatGPT's Creativity could be leveraged by businesses in creative jobs and industries. However, skills and knowledge of how to best leverage ChatGPT is still needed, and those who can develop them correctly have a chance of achieving a competitive advantage. Requiring the right skills will inevitably become a make-or-buy decision as companies can either choose to develop these skills in-house or outsource them. It further implies that some job roles could even get replaced (Berg et al., 2023).

The findings from Hedonic Motivation can be of relevance for businesses in Ed-Tech, knowing that there is a certain limit to which students appreciate the enjoyment of a tool. As concluded from the theory of TTF, the technology has to match the task.

Lastly, the findings about Performance Experienced implies that students believe the tool enhances their productivity. The extensive usage of ChatGPT poses major threats to dominant incumbents like Google (Kyriakou, 2023). Ed-Tech firms have also experienced a threat from ChatGPT, resulting in a decline in revenue since ChatGPT's launch (Staton, 2023). What all companies have in common is the need to transform and incorporate emerging technology. However, it is easier said than done due to cultural challenges, inertia, lack of capabilities and change management, to name a few common challenges (Wimelius et al., 2021). A quote from Brynjolfsson and McAfee (2017) explains this transition well: *"The effects of AI will be magnified in the coming decade, as manufacturing, retailing, transportation, finance, health care, law, advertising, insurance, entertainment, education, and virtually every other industry transform their core processes and business models to take advantage of machine learning. The bottleneck now is in management, implementation, and business imagination"* (paragraph 5).

## 7.4 Future Research

ChatGPT's novelty, having been released only six months ago, offers countless possibilities for studying the phenomena.

In light of the outcomes that showed that Creativity was a significant factor influencing usage, a qualitative study could be a relevant next step to investigate and explore this interesting relationship and better understand the underlying reasons for its significance.

Moreover, future scholars could leverage the three additional questions in the questionnaire as inspiration for new Research Questions: "When did you start using ChatGPT?", "What would you be willing to pay for ChatGPT monthly?" and "What do you use ChatGPT for today?". The answers to these questions can be seen in Appendixes 16, 17 & 18.

It is also interesting to dig deeper into ChatGPT's caveats, such as untrustworthy answers provided by the chatbot. The challenge of distinguishing true from false output is apparent for text-generated AI, but also for image-generated AI, such as DALL-E by OpenAI. Recently published photos falsely illustrating Trump being arrested on the street (Belanger, 2023) and the Pope wearing a white puffy jacket (Vincent, 2023) have gained attention on social media.

As such, it would be interesting to discover text and image generative AI's effect on society when it comes to misusing the tool, leading to the spread of propaganda and fake news.

Lastly, it could be interesting to explore new emerging business models that will build on ChatGPT's technology in the same way that for example Bolt and Foodora builds upon Google Maps' technology. Understanding which services and complementary products that can be built upon ChatGPT will be interesting to follow. Investigating the critical components that will play a significant role in this domain can be interesting for future researchers to explore.

To conclude, there are endless opportunities to study this phenomenon so why not ask ChatGPT for a Research Question?

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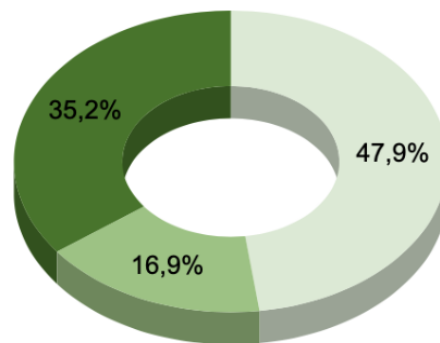
## 9. Appendix

### Background

#### *Appendix 1: Pre-study*

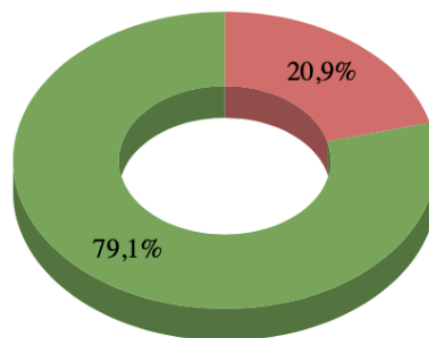
**Question 1b: If you have used ChatGPT, what have you used it for?**

● I use it in school   ● I use it for work   ● I use it for other purposes



**Question 1a: Have you used ChatGPT?**

● Have not used it   ● Have used it



## Theoretical Framework

### *Appendix 2: Overview of literature regarding contributing constructs*

Construct	Author	Context
Trust	(Aldossari & Sidorova, 2020)	Trust in smart home acceptance
	(Alalwan et al., 2017)	Trust in adoption of mobile banking by Jordanian bank consumers
	(Sharma et al., 2022)	Addition of trust in customer adoption of autonomous shopping systems
	(Ferrario et al., 2020)	Multi-layer model of trust to analyse human AI interactions
	(Al-Khalaf & Choe, 2020)	Trust towards mobile commerce in Qatar
	(Cao et al., 2022)	Trust as one of eight construct extensions of the UTAUT model
	(Slade et al., 2015)	Trust as one behavioural intention to adopt technological innovation
	(Almaiah & Mulhem, 2019)	Trust as a factor affecting intention to use mobile learning applications
	(Meyer-Waarden & Cloarec, 2021)	Trust, an important factor of new technology adoption
	(Chao, 2019)	Addition of trust in UTAUT in the context of mobile learning
	(El-Masri & Tarhini, 2017)	Trust as an external variable in UTAUT in the context of e-learning systems
	(Aswani et al., 2018b)	Trust as an addition in UTAUT2
	(Glikson & Woolley, 2020)	Human trust in AI
Creativity	(Kirkpatrick, 2023)	AI as a catalyst for human creativity
	(Lee, 2022)	How creativity is dehumanised and rehumanized by AI
	(Boden, 1998)	AI can be used in three different ways to create new ideas
	(Wieland et al., 2022)	Brainstorming is more efficient and productive with a chatbot than a human
	(Campbell, 2021)	Studies how digital technologies and AI can enhance human imagination

	(Michinov et al., 2015)	How individual creativity affect ideas generated by electronic brainstorm session
	(Millet et al., 2023)	Artistic creativity and AI
	(Amabile, 2019)	AI creativity and how AI and computer-assisted human intelligence can generate creative breakthroughs
	(Anantrasirichai & Bull, 2021)	AI in creative industries, a review
	(Eshraghian, 2020)	Explores the copyright laws when artwork is generated by AI
Humanization	(Ramadan et al., 2021)	Exploring the Artificial Intelligence Alexa robot's sense of compassion & feelings
	(Ki et al., 2020)	Exploring Intelligent assistants humanized characteristics of social support, intimacy understanding and friendship
	(Hermann, 2021)	Exploring consumers attachment to humanized AI applications
	(Schanke et al., 2021)	Applying humanized characteristics to service chatbots, such as adding humor and naming it
	(Skjuve et al., 2019)	Ia chatbot a human name, adding humor, and so on, without knowing how these features influence end user behavior
	(Qiu & Benbasat, 2009)	Applying anthropomorphic interfaces (humanoid embodiment) to a technology, in electronic commerce contexts
	(Dhanasekar et al., 2021)	Chatbot for students to promote their mental health by emotion recognition techniques
	(Dosovitsky & Bunge, 2021)	Observing chatbots for social isolation and loneliness
	(Chatterjee & Dethlefs, 2023)	Explores strenghts and weaknessess of ChatGPT and potential misuse of it
	(Ciechanowski et al., 2019)	Measures the extent to which a chatbot seems humanlike & uncanny valley
Accessibility	(Mori et al., 2012)	Observes people's reactions to robots that looked and acted like a human
	(Oh & Yoon., 2014)	Flow experience (synonymous to accessibility) in E-learning vs. online game

	(Strebel et al., 2004)	The pace of technological affecting frustration in purchase-process of consumers
	(Skjuve et al., 2019)	Importance of chatbot responsiveness and conversation flow, to enhance user experience
	(Zhou, Li, et al., 2010)	Examines how flow experience effects mobile internet users's loyalty
	(Novak et al., 2000)	Study introducing a flow construct, to help better explain consumer behavior
	(Galletta et al., 2004)	Explore how tolerant users are to web site delays
Data Privacy Risks	(Shaw & Sergueeva, 2019)	Extending UTAUT2 with perceived value in the context of non-monetary benefits of mobile commerce
	(Morosan & DeFranco., 2016)	Examining Mobile payments in hotels using UTAUT2
	(Zhang et al., 2022)	Adding the theory of perceived risk, anthropomorphism and personalization to extend UTAUT2 when examining AI-based chatbots for tourism
	(Choe et al., 2021)	Examining the perceived risks from drone delivery services, before and after covid-19
	(Dinev & Hart., 2006)	Privacy risks in e-commerce transactions
	(Alalwan et al., 2018)	Applying UTAUT2 to the context of mobile banking in Jordania
	(Vimalkumar et al., 2021)	User privacy as a construct in the adoption of voice based digital assistants
	(Pascual-Miguel et al., 2015)	Gender differences in online purchasing behaviour is examined among consumers who both purchase digital and non-digital goods

### Appendix 3: ChatGPT generating false answers

SE

I am only looking for arguments made in the actual article. Are all four points in the answer derived from the article, or do any of them include speculation on your part?



You're right; I included some speculation in my previous response. Based on the article, these are the motivations that can be derived:

1. Longtermist perspective promotion: The article implies that the writers, associated with the Future of Life Institute, might be motivated by promoting a longtermist perspective, which has been criticized as harmful and anti-democratic, as it valorizes the uber-wealthy and justifies morally dubious actions under certain circumstances.
2. Diverting attention from present harms: Arvind Narayanan, a computer science professor at Princeton, suggests that the letter's AI hype and focus on existential risks strategically divert attention from the present harms of AI, which could be an implicit motivation for some of the writers and signatories.

The other points I previously mentioned were speculative and not directly derived from the article. My apologies for the confusion.

42

what source did you use for this?



As an AI language model, I don't have direct access to external sources of information, but I was trained on a vast corpus of text from various sources, including books, articles, websites, and other textual content. My training data was carefully selected and preprocessed to ensure quality and relevance, and it includes information from a wide range of domains, such as science, literature, history, social sciences, and more. Additionally, my responses are generated based on statistical patterns and associations learned from this training data, and they are not based on any particular external source.







## *Appendix 4: ChatGPT's training data*

J

Hi, what do you base your answers on?



Hello! As an AI language model, I base my answers on the information I was trained on. My training data consists of a large corpus of text from various sources such as books, articles, and websites. The information I provide is generated using complex algorithms that allow me to understand natural language and generate responses based on patterns and relationships in the data. However, it's important to note that while I strive to provide accurate information, my responses are generated automatically and may not always be perfect or complete.  

## *Appendix 5: The message displaying when ChatGPT is over capacity*

**ChatGPT is at  
capacity right now**

[Get notified when we're back](#)

**Write a rap about the status of ChatGPT.**

Yeah, yo, what's up ChatGPT fam  
A lot of people trying to jam  
But don't worry, we got your back  
Just check back soon, we'll get on track


ChatGPT's the place to be  
For all your AI chat needs  
We're working hard to keep up the pace  
So hold tight, we'll be back in this space

So don't you worry, don't be mad  
We're working hard, it's not so bad  
Just give us time, we'll be back  
ChatGPT, the future of chat, that's a fact.

## *Appendix 6: Example of a humanized conversation with ChatGPT*



42

Hi, I feel stressed in school. My master is very demanding and I feel useless.




I'm sorry to hear that you're feeling stressed and overwhelmed in school. It can be difficult to cope with a demanding master's program, and it's important to take steps to manage your stress and feelings of uselessness. Here are some tips that might help:

1. Take breaks: It's important to take regular breaks throughout the day, especially when you're feeling stressed. Take a few minutes to step away from your work and do something that you enjoy or find relaxing.
2. Practice self-care: Make sure to take care of yourself by getting enough sleep, eating a healthy diet, and exercising regularly. These basic self-care practices can help you feel more energized and less stressed.
3. Seek support: Don't be afraid to reach out to friends, family, or a therapist for emotional support. Sometimes just talking about your feelings can be a big help.
4. Break tasks into smaller steps: If you're feeling overwhelmed by a large project, try breaking it down into smaller, more manageable tasks. This can help you feel more in control and less anxious.





42

thank you



You're welcome. Remember to take care of yourself and don't hesitate to seek additional support if you need it. Good luck with your studies!




(Open AI, 2023)



## *Appendix 7: Example of how the chatbot can help brainstorm ideas*

42

Can you help me brainstorm start-up ideas for my school course?




Sure, I'd be happy to help you brainstorm startup ideas for your school course! What's the focus of your course, and do you have any particular interests or skills you'd like to incorporate into the startup idea? This information can help me tailor my suggestions to your needs.



42

Absolutely, it is supposed to be a digital/tech start-up, based in Nordics.



Great! Here are some potential digital/tech startup ideas based in the Nordics that you might find interesting:

1. An app that helps people find and book eco-friendly hotels, transportation, and activities for their travels.
2. A platform that connects local farmers with consumers, making it easy to buy fresh, sustainable produce directly from the source.
3. A service that provides virtual interior design consultations, allowing

(Open AI, 2023)

# Methodological Approach

## *Appendix 8: GDPR and Anonymization*



### **Welcome!**

This survey is conducted by two students at Stockholm School of Economics as a part of a Master's Thesis.

The survey will take about **5 minutes to complete**. If you no longer wish to participate, simply close the tab. The thesis is not in collaboration with a corporation.

In the end of the survey you can sign up with your email for a chance to **win a 1000 SEK gift card of your choice!**

If you have any questions, feel free to contact us on 42096@student.hhs.se

Thank you for participating!

Best Regards,  
Julia Lundberg & Tess Brodin



### **GDPR**

By continuing to the following pages, you consent to us using your responses in our research. In accordance with the General Data Protection Regulation (GDPR), your personal data will be handled confidentially. The thesis will not contain any information that can identify you as a participant in the survey. The data will be permanently deleted in June 2023. You are welcome to visit <https://www.hhs.se/en/about-us/data-protection/> to learn more about your rights related to personal data.



## Appendix 9: Questionnaire

CONSTRUCTS		
<b>Construct 1: Performance Expectancy</b>		Adopted from Venkatesh et al. (2012)
PE_1	Using ChatGPT helps me increase my productivity	
PE_2	Using ChatGPT increases my chances of achieving things that are important to me in school	
PE_3	I find ChatGPT useful when I am studying	
<b>Construct 2: Effort Expectancy</b>		Adopted from Venkatesh et al. (2012)
EE_1	I find ChatGPT easy to use	
EE_2	Learning how to use ChatGPT was easy for me	
EE_3	ChatGPT is clear and understandable	
<b>Construct 3: Social Influence</b>		Adopted from Venkatesh et al. (2012)
SI_1	People who are important to me think that I should use ChatGPT	
SI_2	People whose opinions that I value prefer that I use ChatGPT	
SI_3	My classmates have influenced me to use ChatGPT	
<b>Construct 4: Facilitating Conditions</b>		Adopted from Venkatesh et al. (2012)
FC_1	People in my surrounding give me inspiration on available use cases of ChatGPT	
FC_2	I have the resources necessary to use ChatGPT	
FC_3	I have a friend or similar available for assistance when I am having difficulties with ChatGPT	
<b>Construct 5: Hedonic Motivation</b>		Adopted from Venkatesh et al. (2012)
HM_1	Using ChatGPT is fun	
HM_2	Using ChatGPT is enjoyable	
HM_3	Using ChatGPT is very entertaining	
<b>Construct 6: Data Privacy Risks</b>		Adopted from Choe et al. (2021) and Dinev and Hart (2006)
PC_1	Personal information could be exposed when using ChatGPT	
PC_2	The benefits of using ChatGPT outweighs potential data privacy concerns	
PC_3	I am concerned that the information I submit to ChatGPT could be misused	
<b>Construct: Usage of ChatGPT</b>		Adopted from Venkatesh et al. (2012)
US_1	How often do you use ChatGPT?	

US_2	How many questions do you ask ChatGPT on average per week?	
US_3	When was the last time you used ChatGPT?	
US_4	Do you plan to use ChatGPT in the near future?	
US_5	What do you use ChatGPT for in school? (you can choose multiple answers)	
US_6	When did you start using ChatGPT?	
<b>Value</b>		
VA_1	How much would you be willing to pay per month for ChatGPT, in SEK? (given that no other competitor offers the same service for free)	
<b>Contributing Construct 1: Trust</b>		Adopted from Marikyan et al. (2022) Chao, C. (2019)
TR_1	I believe that ChatGPT is trustworthy	
TR_2	I trust the answers provided by ChatGPT	
TR_3	ChatGPT always provide reliable information	
<b>Contributing Construct 2: Accessibility</b> (Interval: Strongly disagree, Disagree, Neutral, Agree, Strongly agree)		
AC_1	“ChatGPT is at capacity right now” is a message I often get when trying to access the tool	
AC_2	I would use ChatGPT more if it wasn't for the capacity limit	
AC_3	I get frustrated when ChatGPT isn't available (due to its capacity limit)	
<b>Contributing Construct 3: Humanized</b> (Strongly disagree, Disagree, Neutral, Agree, Strongly agree)		
HU_1	It feels like a person is sitting behind the screen when I have a conversation with ChatGPT	
HU_2	I appreciate the humour of ChatGPT	
HU_3	I appreciate being able to have a dialogue with ChatGPT	
<b>Contributing Construct 4: Creativity</b>		
CR_1	I am enhancing my creativity with ChatGPT	
CR_2	ChatGPT helps me find innovative solutions and generate ideas in my school work	
CR_3	ChatGPT improves my ability to think outside the box	
<b>MODERATORS</b>		
<b>Moderator 1: Age</b>		
AG_1	How old are you?	

<b>Moderator 2: Gender</b>		
GE_1	What gender do you identify as?	
<b>Moderator 3: Experience</b>		
EX_1	I have previous experience of interacting with AI (artificial intelligence) from the following contexts	
EX_2	When did you start interacting with AI technology?	
<b>Moderator 4: Educational Level</b>		
EL_1	I am currently on my: Bachelor year 1, Bachelor year 2, Bachelor year 3, Master year 1, Master year 2	
<b>CONTROL CHECKS</b>		
CC_1	I have tried ChatGPT	
<b>ATTENTION TASK</b>		
AT_1	Here is an attention task for you, just to make sure that you continue to read all questions carefully. Please select number 4 below 4                      27                      18                      2                      31	
AT_2	Here is an attention task for you, just to make sure that you continue to read all questions carefully. Please select the answer “strongly agree” on this question, so that we know you are paying attention.  Strongly disagree    Disagree    Neutral    Agree    Strongly agree	

## Results

### *Appendix 10: Revised Rotated Component Matrix*

Items	Component								
	1	2	3	4	5	6	7	8	9
PE_1	.781								
PE_2	.768								
PE_3	.784								
EE_1				.769					
EE_2				.746					
EE_3				.750					
SI_1							.792		
SI_2							.835		
SI_3									.829
FC_1									.495
FC_3									.668

HM_1		.730							
HM_2		.844							
HM_3		.826							
TR_1			.740						
TR_2			.791						
TR_3			.814						
AC_1								.833	
AC_2								.640	
AC_3								.639	
CR_1						.769			
CR_2						.683			
CR_3						.800			
PC_1.2							.664		
PC_2							.698		
PC_3.2							.814		

*Extraction Method: Principal Component Analysis.*

*Rotation Method: Varimax with Kaiser Normalization.*

*Rotation converged in 7 iterations.*

### ***Appendix 11: Overview of descriptive measures***

Construct		Descriptive		Normality		Reliability/Validity			
Variable	Items	Mean statistic	Std. Deviation statistic	Skew-ness	Kurtosis	Factor loading	Cronbach alpha	CR	AVE
Performance expectancy	PE_1	4.11	.896	-1.164	1.280	0.781	0.819	0.821	0.605
	PE_2	3.71	.939	-0.649	0.022	0.768			
	PE_3	4.17	.925	-1.088	0.786	0.784			
Effort expectancy	EE_1	4.56	.681	-2.108	6.778	0.769	0.702	0.799	0.570
	EE_2	4.56	.729	-1.784	2.908	0.746			
	EE_3	4.29	.707	-0.895	1.003	0.750			
Social influence i	SI_1	3.09	1.067	-0.128	-0.267	0.792	0.713	0.612	0.441
	SI_2	2.94	.948	-0.092	0.010	0.835			
	SI_3	-	-	-	-	Omitted*			
Facilitating condition	FC_1	3.93	.963	-1.061	0.979	0.482	0.552	0.713	0.464



	FC_2	-	-	-	-	Omitted*			
	FC_3	2.79	1.238	0.009	-1.036	0.688			
	SI_3	3.75	1.280	-0.926	-0.226	0.829			
Hedonic motivation	HM_1	4.20	.722	-0.549	-0.102	0.730	0.797	0,843	0.643
	HM_2	3.85	.935	-0.747	0.284	0.844			
	HM_3	4.21	.806	-0.864	0.583	0.826			
Trust	TR_1	3.25	1.039	-0.461	-0.593	0.740	0.762	0,825	0.612
	TR_2	3.10	1.036	-0.234	-1.041	0.791			
	TR_3	2.48	1.136	0.326	-1.089	0.814			
Accessibility	AC_1	3.26	1.220	-0.305	-1.059	0.833	0.582	0.750	0.504
	AC_2	3.00	1.165	-0.010	-0.775	0.640			
	AC_3	3.68	1.201	-0.858	-0.120	0.639			
Humanised	HU_1					Omitted*	-	-	-
	HU_2					Omitted*			
	HU_3					Omitted*			
Creativity	CR_1	3.34	1.107	-0.271	-0.768	0.769	0.769	0.796	0.566
	CR_2	3.78	.932	-0.613	-0.076	0.683			
	CR_3	3.14	1.206	-0.089	-1.026	0.800			
Privacy Data Risks	PC_1	2.6146	1.01111	0.258	-0.322	0.664	0.634	0.771	0.530
	PC_2	3.81	0.959	-0.452	-0.413	0.698			
	PC_3	3.0927	1.16997	-0.089	-0.413	0.814			

*Overview of items and measures*

## Appendix 12: Multicollinearity

### Coefficients<sup>a</sup>

	Tolerance	VIF
PE	.644	1.554
EE	.811	1.232
HM	.776	1.289
PC	.880	1.136
TR	.794	1.259
AC	.864	1.157
SI	.788	1.269
FC	.819	1.222
CR	.729	1.372

a. Dependent Variable: US\_1newscale

Collinearity diagnostic table: VIF values below 10 and Tolerance values above 0.10

## Appendix 13: Breusch-Pagan test

### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	127.468	5	25.494	1.116	.353 <sup>b</sup>
	Residual	4546.287	199	22.846		
	Total	4673.754	204			
a. Dependent Variable: sqres						
b. Predictors: (Constant), TR, CR, EE, HM, PE						

$P > 0.05$  which shows evidence of homoscedasticity

#### *Appendix 14: Descriptive statistics for US\_1, US\_2 and US\_3*

<b>Descriptive Statistics</b>	<b>N</b>	<b>Minimum</b>	<b>Maximum</b>	<b>Mean</b>	<b>Std. Deviation</b>
US_1 How often do you use ChatGPT?	205	1.00	10.00	5.9610	2.28774
Valid N (listwise)	205				

*Maximum and minimum value for US\_1*

<b>Descriptive Statistics</b>	<b>N</b>	<b>Minimum</b>	<b>Maximum</b>	<b>Mean</b>	<b>Std. Deviation</b>
US_2 How many questions do you ask ChatGPT on average? - Per week	205	.00	300.00	38.2439	54.39515
Valid N (listwise)	205				

*Maximum and minimum value for US\_2*

<b>Descriptive Statistics</b>	<b>N</b>	<b>Minimum</b>	<b>Maximum</b>	<b>Mean</b>	<b>Std. Deviation</b>
US_3 When was the last time you used ChatGPT?	205	1.00	4.00	3.0146	.74411
Valid N (listwise)	205				

*Maximum and minimum value for US\_3*

## **Discussion and Conclusion**

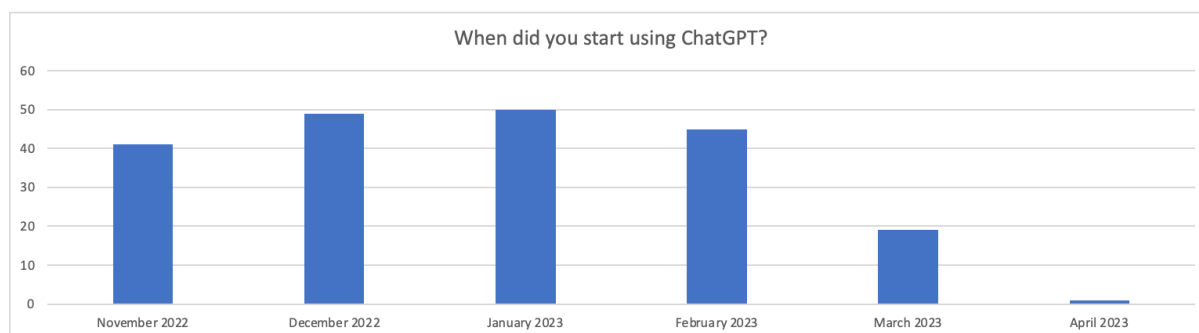
#### *Appendix 15: Usage variety frequencies*

<b>US_5 What do you use ChatGPT for in school? (you can choose multiple answers)</b>	<b>N</b>	<b>Percent</b>	<b>Percent of Cases</b>
Understanding concepts and/or theories	130	13.7%	64.0%
Drawing connections between theories and phenomenon	75	7.9%	36.9%
Math exercises	16	1.7%	7.9%
Coding	65	6.9%	32.0%
Translation	23	2.4%	11.3%
To get inspiration	95	10.0%	46.8%
Alternative to google search	107	11.3%	52.7%
Alternative to wikipedia	59	6.2%	29.1%

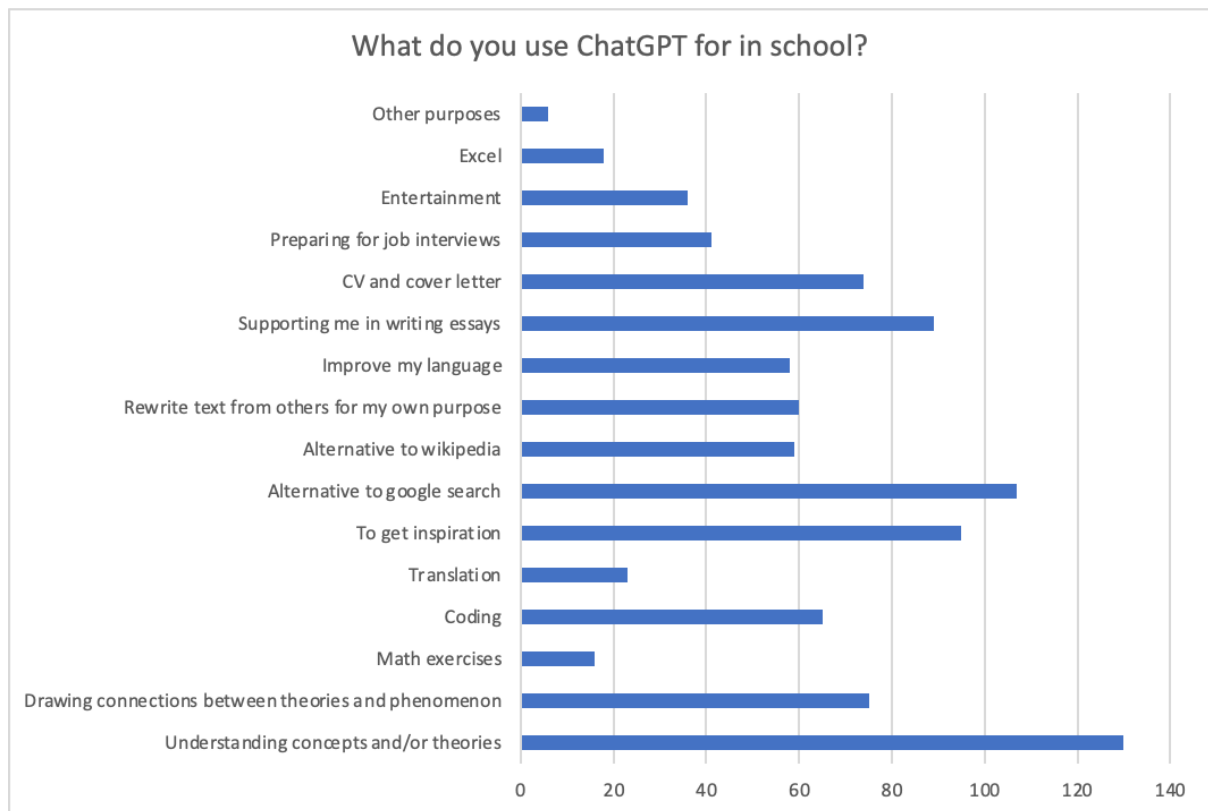
Rewrite text from others for my own purpose	60	6.3%	29.6%
Improve my language	58	6.1%	28.6%
Supporting me in writing essays	89	9.4%	43.8%
CV and cover letter	74	7.8%	36.5%
Preparing for job interviews	41	4.3%	20.2%
Entertainment	36	3.8%	17.7%
Excel	18	1.9%	8.9%
Other purposes typed in by students manually: 1) Summarizing articles 2) Guidance with software 3) Research 4) R 5) Finding papers			
Total:	946	100.0%	466.0%

*Summary of question US\_5: What do you use ChatGPT for in school? (you can choose multiple answers)*

### ***Appendix 16: When did you start using ChatGPT?***

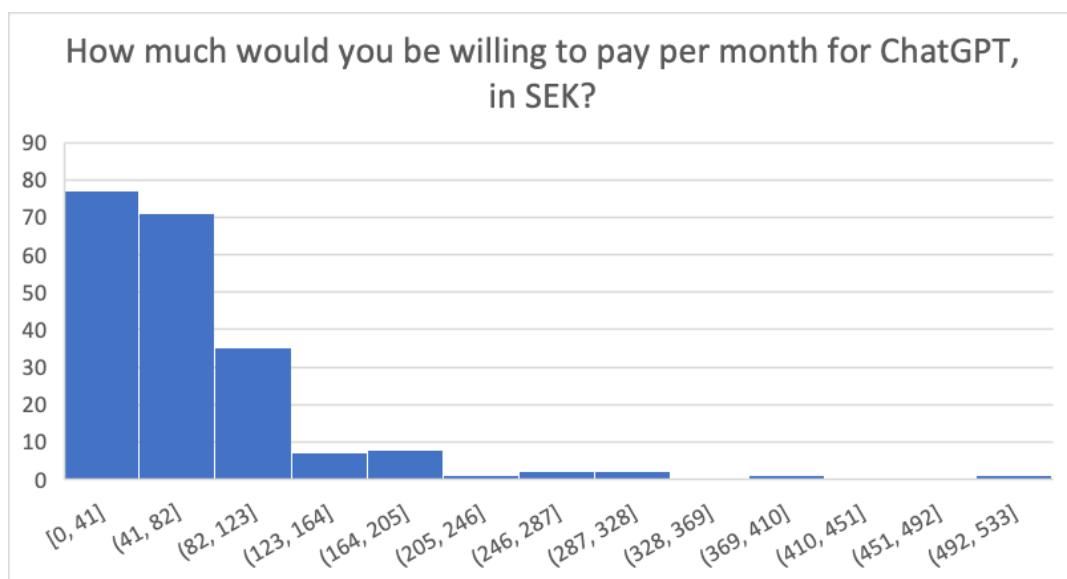


### Appendix 17: What do you use ChatGPT for in school



\* Other purposes: Summarizing articles, Guidance with software, Research, R, Finding papers

### Appendix 18: How much would you be willing to pay per month for ChatGPT in SEK?



The average answer was 64 SEK/month.