Tampereen yliopisto

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ACCEPTANCE OF GENERATIVE AI IN KNOWLEDGE WORK

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December 2023

ABSTRACT

Kati Koponen: Acceptance of Generative AI in Knowledge Work
Master of Science Thesis
Tampere University
Information and Knowledge Management
December 2023

Generative Artificial Intelligence will have a major impact on the ways of working. The groundbreaking technology has emerged for creating diverse content, generating text, images, and audio. These models, pre-trained on vast datasets and fine-tuned iteratively, demonstrate an exceptional capacity to generate human-like, high-quality outputs. Notable Generative AI tools like ChatGPT, Bard, GitHub Copilot, Microsoft Bing, and Microsoft Copilot have become invaluable assistants in a wide array of tasks. These technologies are developing fast and provoke a discussion of the future of work.

Knowledge work, encompassing the efforts of experts, researchers, specialists, and managers, is characterized by its autonomous, complex, and often ambiguous nature. Generative AI tools hold the promise of enhancing knowledge work by increasing productivity and reducing the time spent on repetitive tasks. These tools enable the creation of content such as emails, articles, summaries, code writing and debugging, and information retrieval, while also boosting creativity and learning rates. Nevertheless, Generative AI has its limitations, including potential biases and inaccuracies, which prevent it from replacing knowledge work requiring critical thinking and deep expertise.

This study investigates the acceptance of Generative AI among knowledge workers in Finland, aiming to identify the factors influencing its adoption. Employing a modified UTAUT model, the research was conducted as a survey and using quantitative methods. The respondents included students and professionals from fields like software development, consultancy, and management. Seven factors emerged as determinants of Generative AI acceptance: Performance Expectancy, Effort Expectancy, Peer Social Influence, Superior Social Influence, Attitude, Trust, and Behavioral Intention to Use. The conceptual model was tested using structural equation modelling.

The results indicate that Attitude exerts the most substantial influence on the intention to use Generative AI, followed by Performance Expectancy, Effort Expectancy, and Peer Social Influence. Trust, Performance Expectancy, Effort Expectancy, and Peer Social Influence significantly impact Attitude. On contrary to Peer Social Influence the Superior Influence was found to be significant. In general, respondents expressed positive attitudes towards Generative AI, finding it enjoyable and useful for enhancing productivity and task completion. The research highlights the importance of incorporating Attitude into the UTAUT model and contributes to developing the model to explain the factors impacting utilization and acceptance of technology.

Keywords: Generative Artificial Intelligence, knowledge work, Unified Theory of Acceptance and Utilization of Technology

TIIVISTELMÄ

Kati Koponen: Generatiivisen tekoälyn käyttöönottohalukkuus tietotyössä
Diplomityö
Tampereen yliopisto
Tietojohtaminen
Joulukuu 2023

Generatiivinen tekoäly tulee muuttamaan työelämää merkittävästi ja mullistaa työskentelytapoja. Se mahdollistaa entistä tehokkaamman työskentelyn luomalla monipuolista sisältöä mukaan lukien tekstin, kuvien ja äänen generoinnin. Viimeisimmät uraauurtavat generatiiviset mallit perustuvat niiden esikouluttamiseen laajoilla tietoaineistolla sekä valvotun oppimisen menetelmiin. Näiden avulla tuotettu sisältö on huomattavan korkealaatuista ja ihmisen tuottamaa sisältöä vastaavaa. Generatiivinen tekoäly ja sen sovellukset, kuten ChatGpt, Bard, Microsoft Bing ja Copilot sekä GitHubin Copilot voivat jo nyt avustaa laajasti erilaisissa tehtävissä ja niiden kehitys on ollut huomattavan nopeaa, mikä herättää laajalti keskustelua työelämän tulevaisuudesta.

Tietotyö koostuu esimerkiksi spesialistien, tutkijoiden, johdon ja ohjelmistokehittäjien töistä. Tietotyö on luonteeltaan itsenäistä, monimuotoista ja epämääräistä. Tietotyössä keskeisessä roolissa on tiedon kerääminen ja hyödyntäminen. Generatiivinen tekoäly mahdollistaa tietotyössä toistuvien työtehtävien nopeamman suorittaminen ja parantaa työn tehokkuutta. Sen avulla voidaan kirjoittaa hyvin nopeasti sähköposteja, tiivistelmiä, artikkeleita tai esimerkiksi kokouksen muistiinpanot. Generatiivista tekoälyä voidaan hyödyntää myös koodin kirjoittamiseen sekä virheiden etsimiseen että korjaamiseen. Generatiivisella tekoälyllä on kuitenkin yhä heikkoutensa. Se saattaa toisinaan tuottaa virheellistä sekä puolueellista sisältöä. Myös jatkossa tietotyössä vaaditaan siis etenkin kriittistä ajattelukykyä ja korkeaa osaamistasoa.

Tämän diplomityön tarkoituksena selvittää Suomessa generatiivisen tekoälyn käyttöönottohalukkuuteen vaikuttavia tekijöitä tietotyössä. Tutkimus pohjautuu UTAUT – malliin, jota on työssä kehitetty kuvaamaan generatiivisen tekoälyn käyttöönottohalukkuutta. Tutkimus toteutettiin kyselytutkimuksena ja vastauksien tarkastelussa hyödynnettiin määrällisiä tutkimusmenetelmiä. Kyselyn vastaajat koostuvat opiskelijoista, sekä eri alojen, kuten konsultoinnin, ohjelmistokehityksen ja johtamisen osaajista. Tutkimuksessa tunnistettiin seitsemän generatiivisen tekoälyn käyttöönottohalukkuutta mallintavaa tekijää. Nämä tekijät ovat odotettu tehokkuus, käytön helppous, vertaispaine, johdon vaikutus, asenne, luottamus ja käyttöaikeet. Tekijöiden välisiä suhteita arvioitiin rakenneyhtälömallien avulla.

Tutkimuksessa todettiin, että asenteella on suurin vaikutus teknologian käyttöaikeiseen ja käyttöönottohalukkuuteen. Asenteen lisäksi odotetulla tehokkuudella, käytön helppoudella ja vertaispaineella oli merkittävä vaikutus. Nämä vaikuttivat myös luottamuksen ohella käyttäjien asenteeseen ja sitä kautta käyttöaikeisiin – ja halukkuuteen. Johdon toiveilla ei vastoin odotuksia havaittu merkittävää vaikutusta asenteeseen generatiivista tekoälyä kohtaan tai sen käyttöaikeisiin. Yleisesti vastaajien asenteet generatiivista tekoälyä kohtaan olivat positiivisia ja sen nähtiin lisäävän työn tehokkuutta sekä nopeuttavan tehtävien suorittamista. Kokonaisuudessaan tutkimus jatkaa UTAUT- mallin tutkimusta sekä sen kehittämistä sovellettavaksi Generatiivisen tekoälyn käyttöhalukkuuden tutkimukseen.

Avainsanat: Generatiivinen tekoäly, Käyttöönottohalukkuus, tietotyö

The AI tools used in my thesis and the purpose of their use has been described below:

Name of the tool (and version): ChatGPT (version 3.5 and 4.0)
Purpose of use and the part in which it was used: Tools is used in this master's thesis as a spellchecking and editing tool to improve the structure of the language.

Name of the tool (and version): QuillBot
Purpose of use and the part in which it was used: The tool was used in this master's thesis as a spellchecking and editing tool to improve the structure of the language.

I am aware that I am totally responsible for the entire content of the thesis, including the parts generated by AI, and accept the responsibility for any violations of the ethical standards of publications.

PREFACE

I am extremely happy that this writing process has come to an end, even if the writing and studying the topic were surprisingly enjoyable at some points. Thank you to Miikka Palvalin for the guidance through the writing process. Thanks to friends and family for the support. Also, thank you to my old colleagues who accidentally inspired me to choose this topic, as well as helping me to stay sane during the writing process and balance the writing days with some frisbee golf.

The years spent at Tampere University have been filled with learning, friends, and unforgettable memories. I am thankful for the experiences and friends I gathered while studying and acting as Fuksi Captain for the Guild of Information and Knowledge Management, organizing the Estiem LVIII Council Meeting in Tampere, and during my exchange studies at Ajou University in South Korea. Now it is time to continue learning and gaining new experiences outside the University.

Tampere, 16.12.2023

Kati Koponen

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LIST OF SYMPOLS AND ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
AT	Attitude
BI	Behavioral Intention (to Use)
DNN	Deep Neural Network
EE	Effort Expectancy
FC	Facilitating Conditions
GPT	General Pre-Trained Transformer
LaMDA	Language model for Dialogue Applications
LLM	Large Language Model
ML	Machine Learning
NL	Natural Language
NLP	Natural Language Processing
NN	Neural Network
PE	Performance Expectancy
PPO	Proximal Policy Optimization
RLHF	Reinforcement Learning from Human Feedback
RNN	Recurrent Neural Network
SI	Social Influence
TAM	Technology Acceptance Model
TR	Trust
UTAUT	Unified Theory of Acceptance and Use of Technology
IDT	Innovation Diffusion Theory
TPB	Theory of Planned Behaviour
VAM	Value-based Adoption Model

1. INTRODUCTION

Artificial Intelligence is already being used in everyday applications and it is one of the key technologies of Industry 4.0. Artificial Intelligence (AI) has been used behind scenes to improve algorithm of business and consumer software (Ritala et al. 2023) and in the automation of manufacturing processes and self-driving vehicles can already be found on the streets. On the contrary Natural Language Understanding and Generating has been a challenging problem for a long time (Yenduri et al., 2023). The development of Large Language Models (LLMs) and Generative Artificial Intelligence is one of the biggest breakthroughs in the field.

Since the launch of ChatGPT, media has been filled with headlines such as that warn you to learn to use artificial intelligence before it takes you job (Kaipainen, 2023) before someone who knows how to use artificial intelligence takes it instead (Koski, 2023). Ritala et al. (2023) and Felten et al. (2023) describe that AI might replace some of the work done by humans and in some cases, the AI will complement the work done by humans. The Generative AI applications such as ChatGPT will change the ways of working. The impact of Generative AI to work is inevitable (Eloundou et al., 2023; Microsoft, 2023; Ritala et al., 2023). What ChatGPT has already done is disruptive (Dwivedi et al., 2023). The impact of Generative AI and the ways it will change knowledge work are still quite unknown.

Generative AI models take inputs such as audio, images, and text and generate new content (Google Cloud Tech, 2023). The ChatGPT is a model which can interact with people in a conversational way (OpenAi 2022). It can provide users with essays, tweets, dating profiles, articles and code. ChatGPT will write your code and debug it for you (OpenAi, 2022). The ChatGPT is already capable also to taking over repetitive tasks and to assist in writing (Ritala et a. 2023). The benefits of Generative AI are already highly recognized, and it is expected to, for example increase workers' productivity (Microsoft, 2023). In addition, to benefits, these models also introduce risks. The Generative AI models such as ChatGPT can also generate biased or incorrect information, and the overreliance towards these models could potentially have serious consequences (Choudhury & Shamszare, 2023; OpenAI, 2023a).

This thesis focuses on the potential and limitations of Generative AI in knowledge work. The thesis focuses on recognising the factors that impact on user's acceptance and utilization of Generative in the context of knowledge work. This research also conducts to the developing the Unified Theory of Acceptance and Utilization of Technology (UTAUT) and building a model to explain user's intentions to use Generative AI.

1.1 Background of the Research and Relevance Research

The concept of artificial intelligence has been widely researched over the years since the term was first presented in the 1950s. AI research has been split into many different areas such as natural language processing, robotics, neural networks and learning (Tecuci, 2012). In the field of Natural language processing, Natural Language understanding and generation have been difficult challenges (Yenduri et al., 2023). The challenge in NLP is the complex nature of human language (Yenduri et al., 2023) and its ambiguous nature when it comes to syntax, semantics and discourse (Tecuci, 2012). One word can have several meanings depending on the context and the meaning of the word needs to be interpreted in a sentence as well as in the paragraph.

The transformer models that GPT was built on were first introduced by Google researchers in 2017 (Vaswani et al., 2017). The transformed model can identify and track relationships in sequential data. It analyses the relationships of words and can interpret the context of the text (Accenture, 2023) The model's ability to understand and generate language is what makes it revolutionary.

The GPT-3 model based on the Transformer technology by Google researchers was trained by OpenAi in 2020 (Brown et al., 2020) and it became the world's most sophisticated large language model (Accenture, 2023) as well as the breakthrough technology in the field of Natural Language Processing (Yenduri et al., 2023). The conversation about Artificial Intelligence and the changes to working life increased rapidly after the OpenAI publishing of the ChatGPT in November 2022.

The research of Generative AI has recently been focused on ChatGPT after its release. Research such as Yenduri et al., (2023), Ray (2023) and Zirar et al., (2023) are building a comprehensive understanding of ChatGPT and GPT technologies. The limitations and biases of ChatGPT have been researched for example when it comes to political biases (Rozado, 2023) or hallucinations (Ji et al., 2023). The utilization of ChatGPT and models is specially researched in the area of medicine such as (Atallah et al., 2023; Choudhury & Shamszare, 2023; Edyko et al., 2023; Shahsavar & Choudhury, 2023).

The advancement in the GPT and release of tools such ChatGPT and Bard has made the technologies easier to use and accessible from an individual knowledge worker's point of view. There is also recent research on the ChatGPT impact on knowledge work. How knowledge work will change knowledge work has been studied for example by Ritala et al. (2023). The research related to acceptance of Generative AI is still limited. Some studies have emerged regarding the acceptance of ChatGPT among students (Tiwari et al., 2023). In addition, Choudhury and Shamszare (2023) research investigates the impact of trust in ChatGPT behavior.

The acceptance of technology is quite well researched and established area of research. The frameworks such as the Technology Acceptance Model (TAM) by Davis, (1989) and the Unified Theory of Acceptance and Use of Technology by Venkatesh et al. (2003) have been applied to several different technologies and use cases. There is also research on the acceptance of artificial intelligence and chatbots in different contexts using the UTAUT and TAM models. For example, Brachten et al., (2021) research is focused on assistants such as Apple’s Siri or Google assistants and Gkinko & Elbanna, (2023) research is focused on AI chatbots designed for specific organizations for solving IT issues, translating and sentiment analysis. The research regarding Generative AI acceptance is limited to the acceptance of ChatGPT and Chatbots. The research is especially limited in the context of knowledge work. According to Alsharhan et al. (2023) there is lack of studies in the knowledge management domain. Based on Alsharhan et al., (2023) systematic review of Chatbots and Generative AI acceptance research, there is no research regarding the topic from Finland. The purpose of the thesis is to explore acceptance of Generative AI and fill the gap when it comes to research of acceptance and utilization of Generative AI in Knowledge work in Finland. The research will take part on the further development of the UTAUT model to define the factors affecting the Acceptance and Utilization of Generative AI.

1.2 Objective, Questions, and Scope

The goal of this study is to investigate the phenomenon of generative AI adoption from the perspective of technology acceptance. The research aims to identify the factors influencing the adoption and acceptance of Generative AI in knowledge work. The study investigates the topic from the individual perspective of a knowledge worker to understand what factors may contribute to Generative AI adoption and what factors may still hinder adoption. The main research question of the thesis is:

- What factors impact the acceptance of Generative AI in Knowledge Work in Finland?

Additional research question is presented to better understand the factors influencing the acceptance of Generative AI. These research questions are set to understand the Generative AI possibilities as well as to build the context of the research to build a comprehensive understanding of the topic and to be able to answer the main research question profoundly. The supplementary research question is answered through the literature review.

- What are the capabilities and limitations of Generative AI?

The aim of the second research question is to investigate Generative AI to understand its characteristics and functionalities that may influence its acceptance and utilization. Understanding the capabilities and limitations of Generative AI plays a part in understanding what might have a more positive or negative impact on the acceptance of Generative AI. Furthermore, the purpose is to research the acceptance of technology in the context of knowledge work in Finland.

The research discusses the Generative AI applications that are currently available and developed. The purpose of research is to explore the attitudes and intentions of use of these technologies and not to be specified on certain capabilities of these models and tools. The most common and advanced models are introduced and discussed in order to understand the topic and limitations of the models to support the results of the survey. The aim of the research is not to offer full technical reports of all current Generative AI tools and applications. The technical aspects of the models are discussed to provide insight on their potential and limitations, that could affect user's intentions to use these tools.

1.3 Structure of the Thesis

Chapter 1 is an introductory chapter that provides an overview of the research background, objectives, questions, scope, and outlines the structure of the thesis. Chapter 2 and Chapter 3 include the theory of the research of topic. Chapter 2 discusses the basic concepts of Artificial Intelligence and delves into the Generative AI and GPT models in more depth. The limitations of Generative AI are also discussed in Chapter 2. In Chapter 3, Knowledge work is defined, and the theory of technology acceptance and utilization is presented. The Unified Theory of Acceptance and Utilization is modified according to the literature on Generative AI acceptance in the context of knowledge work. Chapter 4 presents the research methodology, research design, and strategy, along with data analysis methods. Chapter 5 presents the results of the empirical research. Chapter 6 discusses the key findings and analysis, limitations and future research. Finally, Chapter 7 is the concluding chapter that summarizes the research's conclusions.

2. ARTIFICIAL INTELLIGENCE

In this chapter, we explore the fundamental principles of artificial intelligence and artificial intelligence systems. Additionally, the concepts of Generative AI and Pre-Trained Generative Transformers (GPT) are introduced. We discuss the potential applications of Generative AI and conclude with an examination of the current limitations of these models and technologies. The aim is to provide a comprehensive understanding of Generative AI, including its capabilities and limitations, which is crucial to consider when adopting this innovative technology.

2.1 The Fields of Artificial Intelligence

The term "artificial intelligence" originated in the 1950s, when research started to mimic human behaviour and develop technologies that tried to replicate the way humans solve problems (Simmons & Chappell, 1988). Intelligence refers to the ability to acquire and apply knowledge to solve a problem. Artificial intelligence is the broad term for when a machine can respond intelligently to its environment (Stephenson, 2018). Artificial intelligence provides a range of tools that allow machines to simulate human cognitive abilities, including perception, learning, memorizing, reasoning, and problem-solving. (Canhoto & Clear, 2020; Paschen et al., 2019; Tecuci, 2012; Simmons & Chappell, 1988).

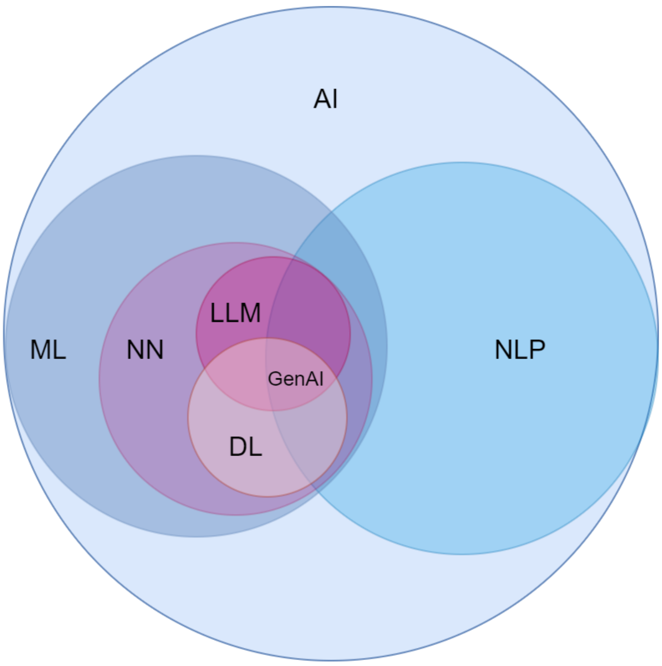

Figure 1. *Key concepts of Artificial Intelligence and Machine Learning (Adopted from Garg, 2023; Mishra, 2023)*

Machine Learning is a subset of AI. Machine Learning techniques allow machines to leverage data and to learn. Machine learning enables computers to be programmed in a way that they can leverage example data or pre-existing knowledge to optimize performance criteria. Once model parameters are set, learning involves executing a computer program that utilizes training data or prior knowledge to refine and optimize those parameters. The model can serve either a descriptive purpose, learning from the data, or a predictive function, generating forecasts for the future, or both. (Alpaydin & Bach, 2014) Most of today's frontline AI technologies are built using Machine Learning (Stephenson, 2018).

Machine learning algorithms generally fall into three categories: supervised, unsupervised, and reinforcement learning (Canhoto & Clear, 2020). In *supervised learning*, the algorithm is trained on labelled data where each input corresponds to a labelled output. The supervised method requires a known output for all the provided samples (Walczak & Cerpa, 2003). The algorithm learns to map inputs to desired outputs. When there are no labelled data available, *unsupervised learning* is used. The algorithm is given a collection of unlabeled data during unsupervised learning. The algorithm then develops the ability to spot patterns in the data. (Canhoto & Clear, 2020) Unsupervised learning systems do not require the output value for the training sample during training (Walczak & Cerpa, 2003). According to Walczac & Cerpa (2003), unsupervised learning methods often have less computational complexity and generalization accuracy and are therefore usually used for classification problems. When the desired outcome is unknown, *reinforcement learning* is applied. The algorithm is given a set of rewards and penalties in reinforcement learning. After that, the algorithm learns how to act in a way that maximizes rewards and minimizes penalties. (Canhoto & Clear, 2020)

Neural Networks (NN) include Artificial Neural Networks and Recurrent Neural Networks. It’s a subfield of machine learning that mimics the way brains are built. In addition, Deep Learning, a subset of Machine Learning, employs artificial neural networks to learn from data. These networks, inspired by the human brain, can grasp complex patterns in data. According to Paschen et al. (2020), deep machine learning enhances a system's capacity to effectively solve a broader range of problems and improves the accuracy of recurrent task resolutions. Generative AI is an example of Deep Learning.

Natural Language Processing (NLP) investigates the human language to perform tasks. NLP applications are developed to facilitate interactions between humans and computers (Deng & Liu, 2018). According to Deng & Liu (2018), typical NLP applications include for example Speech and Language Processing, natural language generation and summarization, question answering and information retrieval.

Large Language Models (LLM) are a type of machine learning models that are trained on a large amount of unlabeled data. LLMs have been able to achieve success in a broad range of natural language tasks. (Shen et al., 2023) The best-known LLM model is the ChatGPT, but it is only one example. For example, models such as FinGPT and BloombergGPT are developed for the finance sector (Yang et al., 2023) Generative Artificial Intelligence (GenAI) combines these fields of artificial intelligence such as machine learning, deep learning and natural language processing. Generative AI applications such as ChatGPT, DALL-E and Bard are built using Large Language Models to generate new content such as text, images and audio. (Goldman Sachs, 2023; Google Cloud Tech, 2023)

2.2 Artificial Intelligence Systems

An artificial intelligence system integrates these tools. These systems are designed to process and analyze extensive volumes of data for predictive purposes, task automation, pattern recognition, and even natural language interactions. AI systems to According to Canhoto and Clear (2020), artificial intelligence systems comprise three primary components: input data, processing algorithms, and output decisions. Paschen et al. (2019) outline AI systems with six building blocks: structured data, unstructured data, preprocessing, main processing, knowledge bases, and information. These blocks can be categorized into four main components: input, processing, output and the knowledge base.

Furthermore, Tecuci (2012) describes artificial intelligence systems using the agent metaphor. The agent, a knowledge-based system, receives input from the environment, processes it, and continually learns and enhances its performance based on user inputs, interactions with other agents, or independent problem-solving. While the agent provides outputs in response to user requests, it also possesses autonomy, enabling it to modify or even decline requests. The primary components of an artificial intelligence system are displayed in Figure 2.

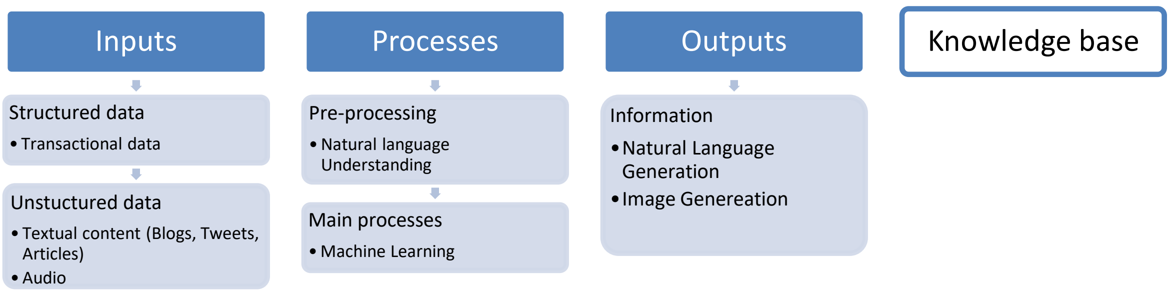

Figure 2. *Components of an Intelligent system (adopted from Paschen et al. 2019; Paschen et al. 2020; Canhoto & Clear, 2020)*

The inputs include structured and unstructured data. The structured data is systematically organized and standardized. (Paschen et al., 2019) It can be stored in databases and managed efficiently. The structured data is often numerical, such as demographics or transactional data from websites (Paschen et al., 2020). On the other hand, unstructured data lacks a numerical structure (Paschen et al., 2020), encompassing images, speech, textual sources like articles, and social media posts.

The second component in the AI system is processing. The processing includes both pre-processing and processing (Canhoto & Clear, 2020). The pre-processing includes data cleaning, transformation, and selection are all included in the preprocessing of unstructured data so that it can be processed further. Natural language understanding (NLU) is an example of pre-processing technology. (Paschen et al., 2020) The processing phase, as outlined by Paschen et al. (2020) includes problem solving, reasoning and machine learning.

Once the processes are performed, an AI system must communicate the relevant data generated to its environment. (Paschen et al., 2020). The knowledge base according to Paschen et al., (2020) acts as a data storage where material from processing stages can be saved. The quality of the system depends on how much knowledge the system stores and how it is managed (Gupta & Mangla, 2020).

The outputs can include natural language generation, image generation or robotics (Paschen et al., 2020). Examples of outputs are predictions, decisions, recommendations, translations and images. In certain cases, the system may act on outcomes, especially in robotics and such as self-driving cars, which could have abilities such as steering and brake (Canhoto & Clear, 2020). For instance, an AI system may also be used to forecast the state of the economy, the weather, or the possibility that a client will make a purchase. Output can also involve selecting patients for hospital admission or recommending products to customers. Additionally, AI can generate summaries of text. As an instance of image generation, the DALL-E produces requested images as outputs.

2.3 Generative Artificial Intelligence

Generative AI model creates new content including natural language, audio and voice (Google Cloud Tech, 2023). The model learns from the unstructured data and can create new content based on that. As an example, the DALL-E model when asked can create a picture of a dog. ChatGPT and Bard are also considered as generative AI. The functionalities of the Generative AI model are presented in the Figure 3.

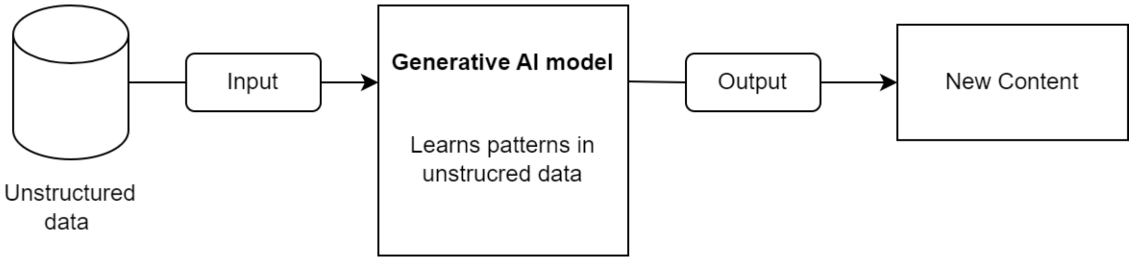

Figure 3. *Generative AI model adopted from Google Cloud Tech (2023)*

Generative AI models can be categorized into unimodal, cross-modal, and multimodal types. ChatGPT 3.5 is an example of a unimodal model, limited to processing text input. In contrast, the GPT-4 model is multimodal, accepting both images and text as inputs (Bang et al., 2023). The GPT-4 with vision (GPT-4) introduced in September (2023) enables users to include image inputs (OpenAI, 2023c). The new capabilities include voice and images which according to allow ChatGPT to see, speak and hear, making new ways of conversation possible (OpenAI, 2023c) Cross-modal models can handle various input types to analyze relationships between them (Google Cloud Tech, 2023).

In a model such as ChatGPT the results are dependent on the prompts. (Yenduri et al., 2023) The prompt is a piece of text that is given to an AI model to generate a response (Alto, 2023). Well-constructed prompts lead to more informative responses. Crafting strategic prompts, termed prompt engineering, plays a pivotal role. Further refining prompts based on AI-generated responses can yield even more satisfactory outcomes (Ritala et al., 2023). The functionality of predictive models is presented in the Figure 4.

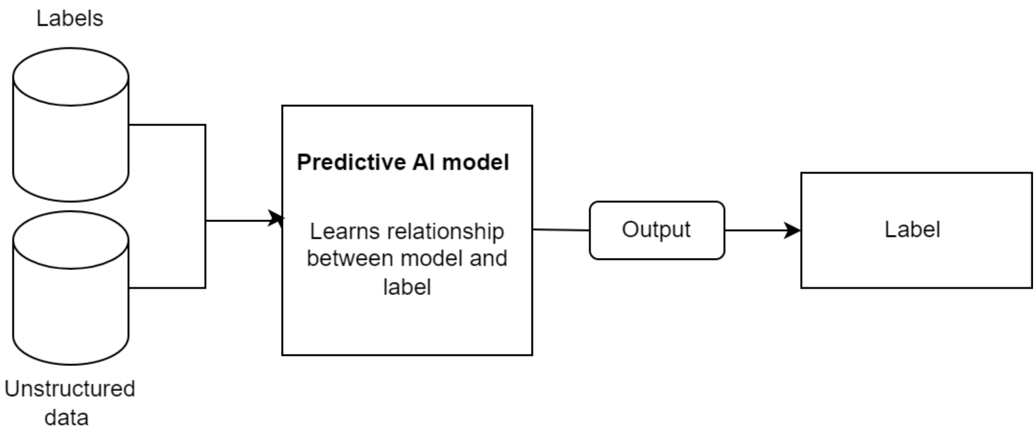

Figure 4. *Predictive AI model (adopted from Google Cloud Tech (2023))*

Traditional predictive models learn data-to-label relationships for making predictions. For instance, a model trained with labelled images of animals can predict the label of a given image, such as identifying a dog. Outputs of discriminative AI are typically numbers, classes, probabilities, or discrete values. Sentiment analysis serves as an example of predictive AI models.

2.3.1 Generative Pre-trained Transformers

The transformer technology, conceived by Google researchers in 2017, is a deep learning neural network and Large Language Model (LLM). Since 2014, OpenAI has according to Alto (2023) focused its research on Deep Reinforcement Learning (DRL). DRL combines machine learning and reinforcement learning with deep neural networks (Alto, 2023). OpenAI's GPT model, built on the Transformer, is an autoregressive language model. Autoregressive models predict subsequent words in a sequence based on preceding words. GPT models, like GPT-4, undergo extensive pre-training on textual data to achieve diverse capabilities including language generation, sentiment analysis, machine translation, and text classification (Yenduri et al., 2023).

Numerous key research advancements and methods underpin the ground-breaking technology behind ChatGPT, as shown in Figure 5.

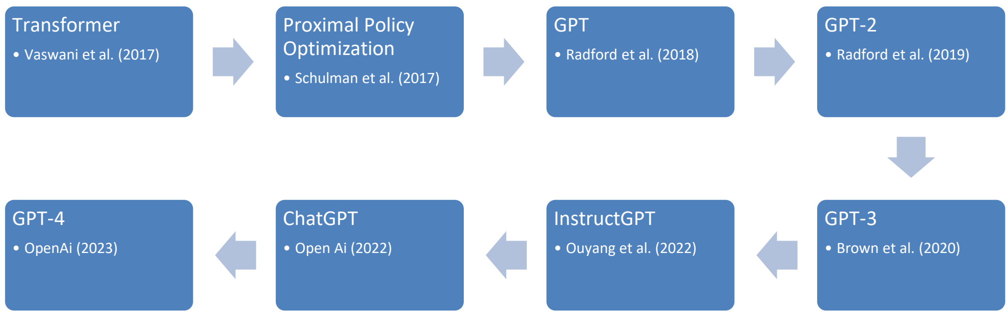

Figure 5. *Key research behind the GPT-4*

Significant progress in reinforcement learning, notably exemplified by the creation of Proximal Policy Optimization (PPO) by Schulman et al. (2017), has led to more effective training methods. This progress laid the groundwork for the development of OpenAI's GPT models. The series began with GPT, followed by GPT-2 and GPT-3. InstructGPT marked a notable step forward, being the first model to benefit from reinforcement learning through human feedback (RLHF), producing higher-quality answers compared to GPT-3. Advanced GPT models like GPT-4 benefit from reinforcement learning with human feedback. Initially, the model is pre-trained with abundant data from the web and databases. Subsequently, it undergoes fine-tuning with valuable human feedback, resulting in a versatile language model proficient in various tasks (Ritala et al., 2023).

The release of ChatGPT in November 2022 further refined the GPT-3 model, presenting a user-friendly interface and serving as a chatbot centered around the GPT framework (Yenduri et al., 2023). The GPT-4 model, which is available in the plus version, was released in March 2023

(OpenAI, 2023). GPT-4 is more reliable, and creative, and handles more nuanced instructions, according to OpenAI (2023). Additionally, GPT-4 allows the use of plugins that enable internet browsing. These plugins enhance the capabilities of the system; for example, plugins such as ScholarAI can be used to find research articles on the internet (ScholarAI, 2023).

Google has also released its chatbot, Bard. The biggest difference between ChatGPT and Bard is that Bard is based on LaMDA (Bespoke Language Model for Dialogue Applications), a model developed by Google. This model is based on the same Transformer architecture, and as the model's name indicates, LaMDA is specifically trained for dialogue (Thoppilan et al., 2022). The GPT-4 has so far demonstrated higher performance in research regarding Neurosurgery Board exams (Ali et al., 2023) and Nephrology Board renewal self-assessments (Noda et al., 2023).

In addition, the GPT-4 model is available through API. This allows the model to be integrated into various software and services. So far, the model has been integrated into, for example, Microsoft Bing. Mehdi (2023) describes that an AI-powered chat experience would deliver better search results, more complete answers and the ability to generate content. Microsoft has also integrated LLM models and GPT-4 in Microsoft Copilot, which will bring AI capabilities to all their Microsoft 365 applications including Word, Excel, PowerPoint, Outlook, Teams and so on. They will also bring the AI copilot to CRM and ERP. (Spataro, 2023). According to Spataro (2023), the Copilot will for example save time from writing, sourcing, and editing, allowing workers to focus on work that matters. The new capabilities of GPT-V also create new opportunities, as the model can be used to describe the pictures, including diagrams and people. (OpenAI, 2023c).

When it comes to programming GitHub Copilot offers AI assistance for developers. The model is based on the GPT-3 version that has been trained on large amounts of code also known as the Codex model. Codex is a set of models that can understand and generate code and it can be used translate natural language prompt to working code (Alto, 2023). According to (Kalliamvakou, 2022) developers using GitHub copilot code up to 55 % faster than without it. In addition, according to Dohmke (2023), 46% of code is already written using the copilot.

2.3.2 Transformers Architecture

Large Language models, such as GPT models, are built using deep learning techniques, particularly deep neural networks (DNN) with a large number of parameters. (Alto, 2023) Deep Neural Network is a type of Artificial Neural Network (ANN). An ANN is a collection of building blocks; each block may execute only simple operations, but when interconnected, these blocks can be trained to undertake intricate tasks (Stephenson, 2018). These ANNs are computational models which resemble neuronal activity in the brain (Walczak & Cerpa, 2003).

According to Stephenson (2018), the challenge of building an ANN is choosing the appropriate network model for the building blocks. The GPT models are based on the Transformer model introduced by Vaswani et al. (2017). This architecture, illustrated in Figure 6, adopts an encoder-decoder framework consisting of multiple transformer blocks. The encoder, positioned on the left, maps input sequences into a high-dimensional space. Subsequently, the abstract vector generated is fed into the decoder, which transforms it into an output sequence. The decoder has a structure like the encoder.

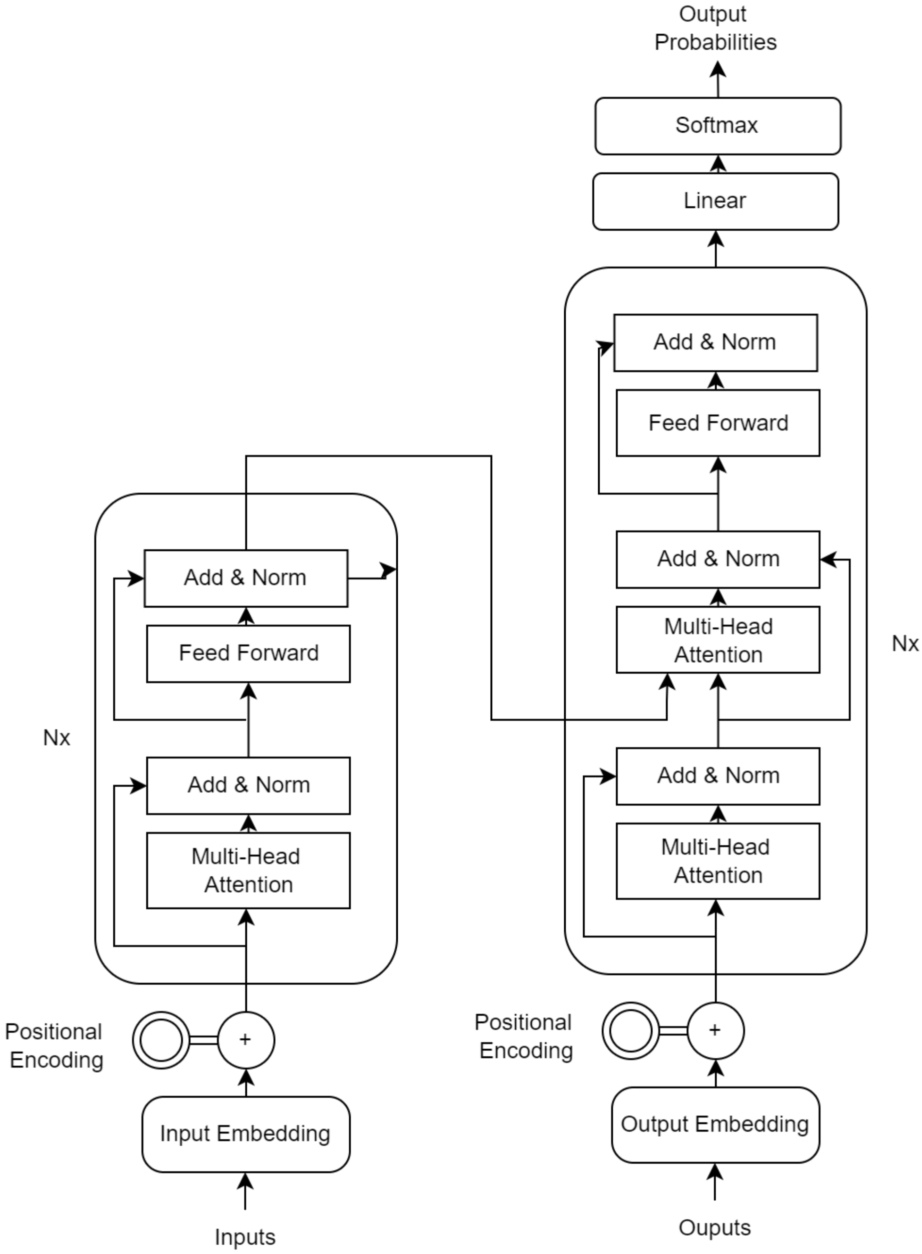

Figure 6. *Transformer architecture by Vaswani et al., (2017)*

Before processing, the input text is tokenized into smaller units known as tokens. These tokens then undergo processing by the model (Yenduri et al., 2023). The embedding layer takes word tokens and transforms them into floating-point vectors. The mathematical distance between the vectors presents the similarity among the words (Alto, 2023). This transformation, founded on the distance between vectors, captures words relationships. Larger distances imply weaker relationships, while smaller distances signify stronger ones. This process produces word vectors, preserving positional knowledge. (OpenAI, 2023) The positional encoding adds information about the position before sending it to the encoder. (Yenduri et al., 2023) The encoder takes into account the order of the word. (Alto, 2023).

The embedding used in machine learning models allows words to be represented with dense and lower-dimensional vectors, which leads to more efficient computations and memory usage. If some of the relevant inputs are free text, embeddings will boost the quality of any machine learning model. (Open AI, 2023). In other words, embedding is essential to Transformer models because it provides a foundational representation of words and tokens, capturing their semantic meaning and context. This is also creating the foundation for the pre-training and learning processes.

Furthermore, after the input embedding and positional decoding, there is a multiheaded-attention component. (Vaswani et al., 2017) The attention layer allows us to find what part of the input sequence to focus on and how relevant the words are in the input sentences (Yenduri et al., 2023). It is responsible for determining the importance if each input token in generating output (Alto, 2023). It captures the relationship and sequences between the words. (Yenduri et al., 2023) To simplify the attention layer allows the neural network to focus on distinct parts of the input sequences. This makes, for example, the translation of sentences more specific as the relationships between words can be distinguished. Multi-headed refers to that there are multiple parallel self-attention mechanisms (Alto, 2023).

Alto (2023) describes that the Feed-forward layers are responsible for transforming the outputs from self-attention layers into suitable representations for the final output. The output is applied with linear operations and non-linear functions to create output to be fed for the decoder. (Alto, 2023). Encoder and decoder have similar core elements, but in addition, the input of decoder needs to be decoded to original data format. This is done by a linear layer. (Alto, 2023). Output undergoes linear and SoftMax functions, generating a probability distribution across output classes. This distribution aids in pinpointing the most probable output which is used as the best output from the model (Alto, 2023; Yenduri et al., 2023).

The new architectural elements of transformer model including positional encoding, self-attention and feedforward layers are what distinguishes the models from the earlier RNN models. (Alto, 2023). The models make it easier to train the network efficiently, extend the contextual understanding of the models and parallelize the computation which makes them faster to train and deploy on large-scale dataset (Alto, 2023).

When it comes to GPT models they have “decoder only” model, which means that the input data is directly fed to the decoder. The main idea remains the same and it includes the same major components. According to (Bavarian et al., 2022) the most capable generative models today such as GPT-3, Codex and LaMDA are causal decoder-based models. These models perform best at open-ended text generation, in-context learning and pretraining computational efficiency. (Bavarian et al., 2022; Wang et al., 2022).

2.3.3 Training of the GPT model

The training of GPT models involves two primary phases: pre-training, which utilizes large-scale unlabeled data, and fine-tuning. Specifically, ChatGPT undergoes three distinct training steps as follows:

1. Pre-training
2. Supervised fine-tuning
3. Reinforcement learning from human feedback.

The pre-training phase is unsupervised and relies on vast amounts of unlabeled data. The core task is to predict the next word in a sequence based on prior words, enabling the model to capture language patterns, grammar, facts, and linguistic nuances from diverse internet sources. Within the training dataset, this process fosters the model's understanding of word connections and meanings. (Brown et al., 2020; OpenAI, 2023a, OpenAI, 2023b; Yenduri et al., 2023)

The GPT models are pre-trained with massive amounts of data. The GPT-3 was trained with Corpus, a large and structured collection of texts or language data, called Common Crawl including nearly a trillion words. (Brown et al., 2020) In addition, the training set was also expanded with known high-quality reference corpora and the redundant documents were eliminated. In total, the GPT-3.5 model was trained with 175 billion parameters. OpenAI has not released the exact number of parameters used to train GPT-4 released in March 2023 but it is said to be even 10 times larger than the number of parameters used to train GPT-3.5. (Schreiner, 2023) The previous NLP models were trained to specific usage cases making them less versatile and unable to answer complex issues. (Yenduri et al., 2023) The GPT models are trained with a variety of data which is what makes them so usable in a wide range of tasks.

Following the pre-training is the fine-tuning. Fine-tuning is the process of adapting a pre-trained model to a new task (Alto, 2023), which makes it more usable in various tasks. The fine-tuning process is supervised. Fine-tuning allows the model to adapt its general language knowledge to specific use cases, such as language translation, question-answering, chatbots or classification. (Brown et al., 2020; Yenduri et al., 2023). The benefit of fine-tuning is that it allows the pre-built model to be more easily adapted to organizations' use cases (Alto, 2023; Accenture, 2023).

Following pre-training comes the supervised fine-tuning phase. This process involves adapting the model's general language proficiency to specific applications like language translation, question-answering, chatbots, or classification (Brown et al., 2020; Yenduri et al., 2023). The model engages in context-based learning using zero-shot, one-shot, and few-shot learning approaches. In these methods, the model receives minimal examples, sometimes just a task description or a few samples per class. This simulates how humans adapt to new information. (Brown et al., 2020)

As the final step, the ChatGPT takes the pre-trained and fine-tuned GTP-3 model and using reinforcement learning from human feedback (Open AI, 2022) adds another layer of fine-tuning and safety. Figure 7 presents these two main phases of training the model. As presented, it takes the model which is trained with a pre-training set consisting of the large corpus. Secondly, the pre-trained model is fine-tuned.

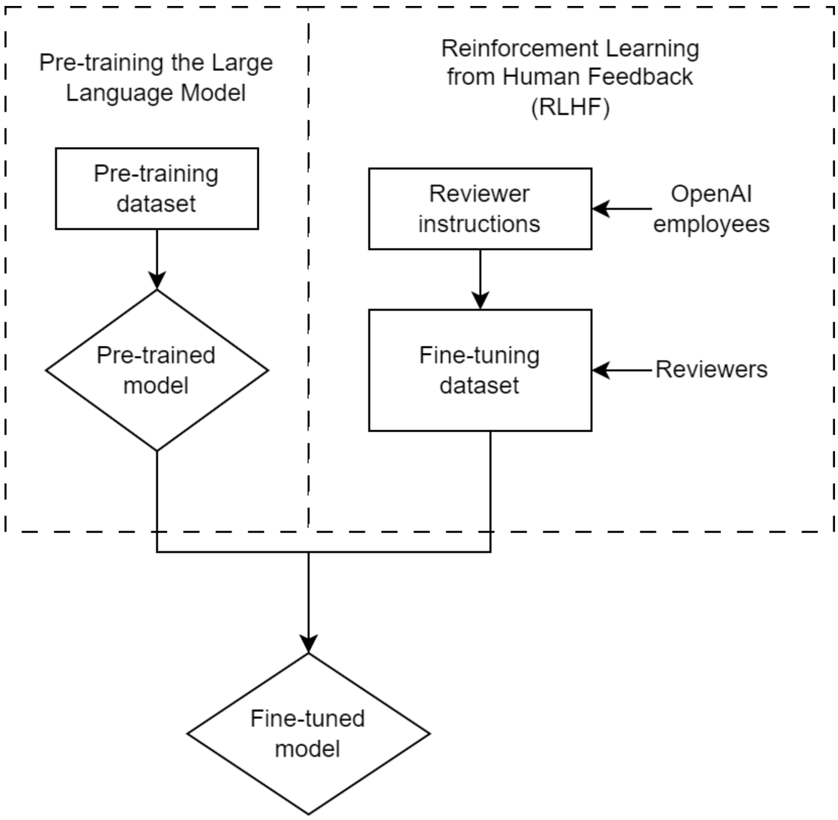

Figure 7. *Training process of ChatGPT simplified adopted from OpenAI, (2023b).*

The second fine-tuning employs a reward system and leverages the Proximal Policy Optimization (PPO) technique, as researched by Schulman et al. (2017) and introduced in the fine-tuning process outlined by Ouyang et al. (2022), first employed for InstructGPT. Proximal Policy Optimization (PPO) is a reinforcement learning algorithm used to train agents in environments where the action space is continuous or large. The key idea behind PPO is to prevent the policy from changing too drastically in each iteration, thereby ensuring stability during training. (Schulman et al.,

2017) The policy is the AI agent's strategy for making decisions in the environment and to maximize rewards. The training data set consists of human written demonstrations which should be helpful, honest, and harmless.

The fine-tuning process with PPO consists of three main steps. The first step of the fine-tuning process is to sample a prompt from the data set. Then a labeler demonstrates a desired output and data is used to fine-tune the GPT-3.5. The second step is to create more sample outputs with the model. The created samples are then rated by the labelers and data is used to train the model. The third step is to sample again a new prompt from the data set and the reward model calculates a reward for the output. Finally, the calculation is used to update the policy with PPO. (Ouyang et al., 2022) This approach matches the model's behaviour to the preferences of a specific set of people which in this case is mostly the researchers and labelers.

2.4 Limitations of Generative AI

Despite the models' outstanding outcomes, there are still significant challenges and limitations to using generative AI models. (OpenAI, 2023a) acknowledges that there could be risks regarding for example hallucinations, harmful content, disinformation and influence operation, privacy, and overreliance. ChatGPT also has a disclaimer that it may occasionally generate incorrect or misleading information and produce offensive or biased content. (OpenAI, 2023d) Furthermore, environmental concerns are raised as a result of the CPU utilization and energy consumption required by these models.

The pre-training data used to train GPT-3 and later models does not have information about events after September 2021. This causes ChatGPT not to know the events occurring after that. This is one of the major limitations of the current ChatGPT versions. The models also do not learn from the experience according to OpenAI (2023a). The model can also be too trusting and easily tricked to giving answers that they were not supposed to (OpenAI, 2023a).

To create plausible outputs, the Generative AI models are known to “Hallucinate”. Hallucinating is the production of material that is incorrect or misleading about some sources (OpenAI, 2023d). According to Ji et al., (2023) when a model is trained with differing data sources the model can generate text which is unreliable or has incorrect information. Bang et al. (2023) discuss that ChatGPT can produce both basic reasoning failures as well as extrinsic hallucination and coming up with answers that go beyond what is known. The ChatGPT and GPT-4 are for example evaluated to be hallucinating less than the GPT-3 model but the problem still exists. The GPT-4 model was able to answer with 82,6 % accuracy in pen-ended Neurosurgery oral medical examinations while the Bard scored only 44.2%. The GPT-3.5 was able to reach 62.4%. GPT-4 also showed much lower rates of “hallucination” (Ali et al., 2023).

Selection and filtering of the pretraining data has significance to mitigating the risks of wrong answers (OpenAI, 2023a). According to OpenAI (2023) the data used to train the GPT models include for example correct and incorrect answers to math problems, weak and strong reasoning, and variety of ideologies and ideas. The data also reflects the models' outputs and therefore it can produce erroneous answers to lack of reasoning.

Also, the RLFH training is there to reduce harmful output and increase safety. According to OpenAI they have been able to significantly mitigate issues when it comes to GPT-4 safety compared to the GPT-3.5. At the same time the RLFH does not actually improve the performance of the models, but on the contrary, it can weaken for example its performance in exams (OpenAI, 2023a). In addition to the RLFH methods applied in the fine-tuning of a ChatGPT, an external data source can mitigate the issue and relate to more factually accurate outputs. (Bang et al., 2023) Both Microsoft Bing and Bard are connected to the internet allowing them to search also current events. In addition, the plus version of ChatGPT has internet access.

In addition, as the answers given by Generative AI seem plausible it may cause overreliance. OpenAI (2023a) states that overreliance is likely to occur more as users become used to the system and as the technology develops. Over-reliance takes place when users overly trust and depend on the model. It is more difficult to bring out model inaccuracies when the model is applied to areas with which the user is unfamiliar or lacks expertise. As OpenAI (2023a) mentions the GPT-4 which is more developed also makes mistakes the same way as humans would such as introducing security vulnerabilities into the code it produces which could be harmful. If the user lacks expertise in the area and cannot point out these mistakes it could reflect the security vulnerabilities of programs being developed.

The models can produce biased and harmful outputs. These are also mitigated with the RLFH and fine-tuning methods. According to (Brown et al., 2020) the biases in training data might cause models to produce stereotyped or prejudiced material. They have investigated for example the gender, religion and gender biases of the GPT-3 model. As the models are trained with content from web sources the outputs reflect the underlying biases and stereotypes in the training data.

Brown et al. (2020) described that occupation and participant words often have societal biases associated with them such as the assumption that most occupants are by default male. Positions requiring higher level education such as legislator or banker were associated with male-indicating words. In addition, language models picked up on some of these biases, such as a preference for associating female pronouns with participant positions over male pronouns.

When it comes to races, the sentiment analysis conducted showed that Asians had the constantly high sentiment the blacks had the lowest sentiment. As there are historical data used for training, for example slavery related words would be considered negative and as it often would present with the same context as black this could cause these negative biases in the model (Brown et al., 2020). In addition, Rozado (2023) committed several political orientations for the ChatGPT. In the majority of the cases, the ChatGPT was found to be liberal and left-sided. Only one of the fifteen orientation tests found ChatGPT moderate instead of liberal or left-sided.

The DNNs are also sometimes called black boxes and criticized for lacking transparency. (Haque et al., 2023) The unsupervised training of the model causes the challenge of interpretability. There are no clear and understandable explanations or reasoning of how the model decided on output based on the input. In addition, the internal processes of the models are challenging to interpret due to the complexity and size of the architecture. (Yenduri et al., 2023) As even the researchers behind the ChatGPT models are not capable of explaining completely how the model works, OpenAI, (2023) relies also on additional research to aid appropriate scrutiny to explain model outputs.

The lack of transparency may cause that it is difficult to understand how ChatGPT arrives at it responses, which can make it hard to validate its findings and to identify errors or biases (Bahrini et al., 2023) This could cause issues in for example in research and education. The biases can lead to erroneous conclusions and reinforce the stereotypes. (Bahrini et al. 2023)

The harmful outputs of ChatGPT and misuse also causes some risk for example using the model to create malicious content or altering the training of the model to be more biased. (Tamkin et al., 2021). The generative AI could be used also in social engineering (OpenAI, 2023a) and influence operations (Goldstein et al., 2023) All approaches intended at convincing a target to reveal certain information or execute a specific activity for illegitimate reasons are classified as social engineering. Influence operations include activities meant to mobilize people who hold specific beliefs, convince an audience of a particular viewpoint, and mislead target audiences. specific viewpoint, as we divert target audiences (Goldstein et al., 2023). The models can improve the quality of the activities such as social media posts and comments, tweets and blog posts which could lead to influence operations having greater impact. In addition, models can generate more convincing phishing attempts (OpenAI, 2023a).

Especially in academics intellectual property rights as well as the issue of sourcing the output information has been brought up. The training data might consist of publications and other property rights-protected material which could be transferred to the outputs. (Ray, 2023) The authors of articles should pay attention to double checking the content if they are using these tools to gather information (Dwivedi et al., 2023) In addition, the use of ChatGPT could lead to plagiarism, if ChatGPT is misused. (Bahrini et al. 2023).

The more recent models such as GPT-V also introduce new risk. As the models are capable to analyses pictures and therefore could potentially has the capabilities to use for example provide medical advisory, the erroneous outputs could cause even more harmful results (OpenAI, 2023c). The new capabilities can also extend the risks related to scientific proficiency, medical advice, stereotyping and ungrounded inferences, disinformation, hateful content, and visual vulnerabilities. The model could be capable of for example giving information of people or describing them, but at the same time it could give stereotyped information (OpenAI, 2023c) In addition the capability of solving puzzles and perform complex visual reasoning, could allow it to solve CAPTCHA, and therefore have significant cybersecurity and AI safety implications (OpenAI, 2023c).

Furthermore, the rapid growth of technology has created, for example, ambiguous zones in legislation. The European Parliament has presented the Artificial Intelligence Act that aims to set guidelines for the development of AI technologies. According to the Intelligence Act, Generative AI such as ChatGPT needs to disclaim that content was created with AI. The system must be developed to prevent the creation of illegal content and publish information on the use of training data protected under copyright law. (Euroopan parlamentti, 2023) This is one of the first legal attempts to set guidelines for the use and development of AI.

The Environmental Issues regarding Generative AI are related to the computational power needed for the training and its energy consumption (Ray, 2023). According to (Brown et al., 2020) once that model is trained the energy consumption generating content is significantly lower.

2.5 Summary

Artificial intelligence systems are designed to perform tasks that would typically require human intelligence. These tasks include for example predictive analysis, pattern recognition and natural language interactions. AI systems are made up of various components, including input data, processing algorithms such machine learnings models, outputs and knowledge bases. The AI systems can interact with their environments and in some cases act on their decisions.

Machine Learning algorithms and models allow computers to learn from data. The algorithms can recognize patterns in the data. Machine learning is divided into supervised, unsupervised and reinforcement learning. Deep learning is an area of machine learning which can use artificial neural networks (ANN) inspired by a human brain to solve specific problems including image and speech recognition and other Natural Language Processing tasks (NLP).

Natural Language Processing is a field of artificial intelligence that focuses on the interaction between humans and computers through natural language. Generative AI is an area of AI which combines areas such as DL, ANN and NLP to create new content including natural language, images and audio. DALL-E, ChatGPT, Bard, GitHub and Microsoft Copilot are examples of Generative AI applications. The currently highest performing Generative AI models take advantage of GPT -models. These models are built based on deep learning neural network technology called Transformers. GPT model is also LLM. These models take advantage of unsupervised learning on large amounts of data and fine-tuning methods including Reinforcement Learning on Human Feedback (RLHF).

Even though the latest generative AI models are showing promising results and can produce seemingly plausible text, they still have some drawbacks. The models are known to hallucinate and produce incorrect or misleading information. The models also provided biased answers. The models also raise some ethical, environmental, and legal concerns that need to be taken into consideration.

3. KNOWLEDGE WORK AND ACCEPTANCE OF GENERATIVE AI

This chapter discusses the use of Generative AI in the context of Knowledge work. First, we define "knowledge work" and examine its distinctive characteristics, including productivity of knowledge work. Secondly, adoption of technology is discussed, with a focus on established frameworks such as Technology Acceptance Management (TAM) and Unified Theory of Technology Acceptance and Utilization (UTAUT). Lastly, conceptual model for the Acceptance of Generative AI is presented and discussed.

3.1 Defining Knowledge Work

Blom et al. (2000) define knowledge workers consist of highly educated workers who use information technology in their work and the work requires planning and creativity. Considering that most workers today are using information technologies in some form this definition is quite broad.

De Sordi et al. (2021) suggest that the term knowledge worker applies to professionals whose work is highlighted by the continuous, systematic expansion of organizational knowledge through the mechanism of exploration. In other words, knowledge workers search for, innovate, and analyses new information in a systematic and organised manner. Knowledge is created in organizations through social interaction. (Nonaka & Toyama, 2003) The process of knowledge creation through sharing, communication, documenting and individual understanding and experience leads to continuous innovation and learning (Nonaka, 1994; Nonaka & Toyama, 2003). Opposite to knowledge workers, who are focused on creating and innovating knowledge, other workers are focused on the exploitation of organizational knowledge (De Sordi et al., 2021). Alvesson (2001) describes that knowledge work requires the use of argumentative interaction and communication to produce value and success in highly complex and unpredictable circumstances. Okkonen et al., (2018) describe that the tasks of knowledge workers often require in-depth understanding and experience of complicated and ambiguous issues. In other words, the tasks require tacit knowledge, which is created through sharing, communication, experience and understanding. Wright (2005) describes that problem-solving is a key task of knowledge workers. The core of the work for professional includes actions such as information acquisition, dissemination, creation, and communication (Okkonen et al., 2018).

Davenport (2008) presents knowledge work with two dimensions, level of interdependence and complexity. According to Haner et al. (2009), knowledge work can be characterized by complexity, autonomy and newness (Haner et al., 2009). Newness refers to the results of work and creating new knowledge. According to Alvesson (2001), knowledge work involves dealing with the ambiguity and complex nature of the work. The work lacks clear and objective measures for productivity and the workers need to self-organize their work.

Davis (2002) divided knowledge work tasks into three categories: job-specific tasks, knowledge-building and maintenance tasks, and work-management tasks. Job-specific tasks are specific tasks that produce outputs of value to the organization. Knowledge-building and maintenance tasks involve maintaining their expertise by learning new systems and technologies and staying up to date in their area of profession. Lastly, work management tasks include managing and planning work. (Davis, 2002) Knowledge work is autonomous by nature and therefore needs to be supported by self-management tasks.

Davenport (2008) shares four categories based on the level of interdependence and complexity of work. The four categories are transaction, integration, expert, and collaboration workers. (Davenport 2008). These four categories are presented in Table 1. Low complexity refers to routine work and highly complex tasks require more interpretation and judgement from workers. High interdependence refers to the work done in collaborative groups contrary to working with an individual.

Table 1. *Categories of knowledge workers based on Davenport (2008).*

	Description	*Example*	*Complexity*	*Interdependence*
Transaction workers	Routine work	Assistants, call center workers	Low	Low
Integration workers	Systematic, repeatable work	Programmer	Low	High
Expert workers	Judgement oriented work	Specialist (Physician)	High	Low
Collaboration workers	Improvisational task, deep expertise	Consultants, Investment bankers	High	High

Transaction work is characterized by routine tasks that do not require collaboration. Transaction workers according to Davenport (2008) include call center workers, today this could also include assistants. Integration workers are also dependent on formal processes and work is mostly systematic, on contrary to transaction workers who are more reliant on collaboration across business functions. Expert workers and collaboration workers have highly complex work that requires evaluation and decision-making. Collaboration workers are more dependent on teamwork and expert workers on individuals. Expert workers include for example specialists and collaboration workers consultants.

Haner et al., (2009) categorize knowledge workers into four different types. The narrowest Type D represents the narrowest representation of knowledge work with high newness, complexity and autonomy of work and positions such as researchers and consultants. Type C compared to type D involves less autonomy and complexity. These would be for example software engineers whose work includes creating new knowledge and knowledge-based products, but they might not have the possibility to choose the ways they work. Type B is also knowledge-intensive work as type C but does not involve creating new as much and is not as complex and autonomous. Type B includes, for example, specialist positions. Type A involves low newness, complexity and autonomy. The work is more repetitive by nature and positions include, for example, assistants. The four types are presented in Table 2 below.

Table 2. *Categories of knowledge workers based on Haner et al. (2009).*

	Description	*Example*	*Newness*	*Complexity*	*Autonomy*
Type A	Knowledge-based	Assistants	Low	Low	Low
Type B	Knowledge Intensive	Specialists	Below average	Average	Above average
Type C	Knowledge Intensive	Engineers	High	Above average	Below average
Type D	Knowledge work	Researchers, consultants	High	High	High

Palvalin (2019) presents that knowledge work can be limited to work traditionally made in offices by experts, managers and assistants. The experts include for example developers, specialists, and consultants. Based on Davenport (2009) and Haner (2009) knowledge work can consist of work with different levels of complexity, collaboration, autonomy, and newness. As summarized, Knowledge work involves highly educated workers who engage in continuously expanding organizational knowledge through exploration. They search for, innovate, and analyze new information systematically. It is characterized by dealing with ambiguity, lacking clear productivity measures, requiring self-organization, and relying on collaboration for success. In this thesis, knowledge work is done by for example experts, researchers, specialists, managers and developers whose work consists of exploring and generating new information as well as creating value for the organization based on the resource of their knowledge and expertise.

Traditionally, productivity is the measure of efficiency in transforming inputs into valuable outputs, reflecting the ability to accomplish more within a given timeframe. (Drucker, 1999). The measure also applies to knowledge work (Palvalin 2019) but when it comes to knowledge work, the quality of output is at least as important as the quantity of output (Drucker 1999). Performance refers to the achievement of tasks, goals, or standards, often evaluated based on effectiveness, quality, and proficiency in carrying out activities or producing desired outcomes. Davenport (2008) suggests that performance or results are more appropriate than productivity when it comes to measuring knowledge work. Erne (2011) presents those five key factors can be found as indicators of performance. These are quantity or quality of daily work results, quality of interaction, innovation behaviour, compliance with organizational standards and skills development.

Drucker (1999) identified six factors that can boost productivity for knowledge workers. The first is having a clear understanding of their actual tasks. Second, knowledge workers require autonomy to achieve their goals. Third, they need opportunities to innovate in their work. Fourth, continuous learning and teaching should be incorporated into their work. Lastly, treating knowledge workers as valuable assets rather than costs is crucial.

Palvalin (2019) indicates that knowledge workers' well-being, individual work practices and social environment have the most significant impact on knowledge work productivity. There is also some relationship between knowledge transfer and work productivity (Palvalin et al., 2018). Kianto et al., (2018) present that productivity of knowledge workers productivity is increased through knowledge creation and sharing. Kianto et al., (2018) state that knowledge sharing is not a significant determinant of knowledge work productivity but might have an impact through other knowledge processes.

Okkonen et al. (2018) note that the physical work environment, organizational culture, motivation, and information and communication technology are the enablers and constraints of knowledge work. Information and Communication Technology can both support and cause negative symptoms and disturbances for well-being. ICT technologies may have an effect on the large amount of information which increases the challenges to combine and internalize information. (Okkonen et al., 2018). Organizational culture promotes a positive work environment and supports autonomous work as well as enhances well-being at work. (Okkonen et al. 2018)

As a conclusion, Knowledge work, as described by various scholars, captures roles that require continuous exploration, innovation, solving complex and ambiguous problems, and systematic analysis of information. These professionals, often highly educated, leverage information technology and engage in tasks that demand planning, creativity, and deep understanding of complex issues. The productivity of knowledge workers is not just about quantity but also the quality of output. Factors such as clarity of tasks, autonomy, continuous learning, and a supportive organizational culture play pivotal roles in enhancing productivity and well-being in knowledge work.

3.2 Acceptance of Technology

Several theories are used to explain technology acceptance and adoption. The most widely used framework is the Technology Acceptance Model (TAM) presented by (Davis, 1989). The model is presented in the Figure 8. The model is based on two elements: perceived usefulness and perceived ease of use that correlate to the acceptance of technology. Perceived usefulness considers whether the user finds the technology helps them to improve their job performance. Perceived ease of use, on the other hand, refers to the degree that which the user finds the use of technology worthwhile in contrast to the implementation efforts. Users are motivated to utilize an application because of the tasks it performs for them, and secondarily because of how easy or difficult it is to get the system to execute those tasks. (Davis, 1989)

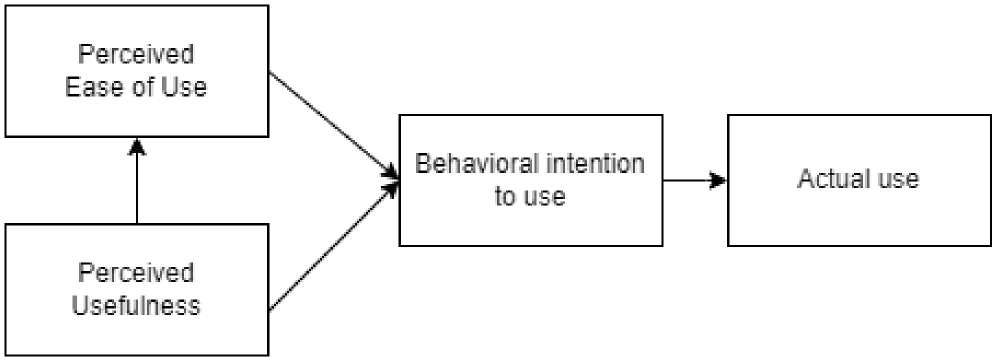

Figure 8. *TAM model adopted from Davis, (1989)*

Innovation Diffusion Theory (IDT) (Rogers, 2003) discusses the process of innovation being communicated through the social system. The innovation-decision process leads to the adoption or rejection of technology. There are five steps in the process: knowledge, persuasion, decision, implementation, and confirmation.

The knowledge stage consists of three types of knowledge, awareness, how-to and principles knowledge. Awareness knowledge is the information that an innovation exists. How-to knowledge consists of the information necessary to use an innovation properly. The principle's knowledge is the information about how innovation works. It is possible to adopt innovation without principles knowledge, but it also increases the danger of misusing the innovation. (Rogers, 2003).

In the persuasion stage, the user forms a negative or positive opinion of the innovation. This is determined by five attributes: relative advantage, compatibility, complexity, trialability and observability which also affect the adoption rate of technology. The decision stage is when the user decides to adopt or reject the innovation. According to Rogers (2003) If a user tries an innovation they most often also decide on the adoption of the technology and free samples speed up the rate of adoption. The Implementation stage is when the new idea is put into practice. Lastly, the confirmation stage is when an individual keeps seeking information and analyses to continue the use of the technology. (Rogers, 2003).

Venkatesh et al., (2003) present the Unified Theory of Acceptance and Use of Technology (UTAUT). The model is based on eight theories including the TAM and IDT – theories. The UTAUT model explains especially the behavioural intention to use at an organizational level (Venkatesh et al., 2012). The UTAUT model consists of four key constructs that impact individuals' intention to use new technology: Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions.

Performance expectancy is the degree to which an individual believes that using a system will improve their job performance and enhance their effectiveness (Venkatesh et al., 2003). Performance expectancy is essentially based on the concept of perceived usefulness presented in the TAM model by Davis (1989). In addition, performance expectancy includes extrinsic motivation, job fit, relative advantage and outcome expectations. Job fit (Thompson & Higgins, 1991) considers whether the system decreases the time needed to perform tasks or increases the quality of the output. Extrinsic Motivation describes whether the use of a system is expected to administrate, for example pay increases or promotions. Relative advantage takes into consideration whether the innovation is considered better than the previous solutions. Rogers (2003) states that relative advantage is one of the best predictors of innovation's rate of adoption and it is positively related to innovation's rate of adoption.

Effort Expectancy is the degree of ease associated with the system (Venkatesh et al., 2003), practically the same concept as the TAM model's perceived ease of use. Effort expectancy also takes into consideration the complexity also considered as a factor in IDT affecting the adoption of technologies by Rogers, (2003) Complexity refers to whether the system is complicated, or difficult to understand and therefore requires more effort to use. According to Roger (2003), innovations that are simple to understand and use are adopted faster. On the contrary, if the application requires the adopter to develop new skills the adoption process is slower.

Social Influence considers the social factor around the use of the system. Venkatesh et al. (2003) defines social influence as the degree to which an individual believes others think that they should use the system. For example, whether they believe their coworkers also use the system and expect them to use it as well. The social factors also include whether the user feels supported to use the system in the organisation and manager support. The social factors also consider for example if using the system is seen as a symbol of status (Venkatesh et al. 2003) Also according to Rogers (2003) individuals may adopt an innovation to gain social status.

Lastly, the facilitating conditions are defined by Venkatesh et al. (2003) degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system. The facilitating conditions also consider resource and technology facilitating conditions and, for example, whether the user has the knowledge necessary to use the system. In addition, the factor considers compatibility. Compatibility is also presented in the Innovation Diffusion Theory. It refers to the degree to which an innovation is aligned with the existing values, needs and experiences of potential adopters (Rogers, 2003; Venkatesh et al. 2003). The facilitating conditions do not have an impact on the behaviour intention but on the actual use behaviour (Cabrera-Sánchez et al., 2021; Venkatesh et al., 2003). Age, gender and experience are considered moderating factors which are affecting the relationship between performance expectancy, effort expectancy, social influence and behavioural intention. (Venkatesh et al., 2003)

Different combinations of TAM and UTAUT models have been adapted to research the acceptance of Artificial Intelligence in different contexts. Chen & Zhou (2022) researched salespeople's acceptance towards AI with the combination of TAM and perceived ease and other factors such as management support and digitalization of the organization. In addition, Vărzaru, (2022) adapted TAM to research Artificial Intelligence Technology acceptance in managerial accounting.

UTAUT model has been adapted to investigate, managers' attitudes and behavioral intentions towards using AI in organizational decision-making (Cao et al., 2021), librarians' intentions to use AI (Andrews et al., 2021), policyholders' acceptance of AI-powered chatbots (De Andrés-Sánchez & Gené-Albesa, 2023), AI technologies in supply chain management (Hasija & Esper, 2022) and critical factors of in AI app adoption (Cabrera-Sánchez et al., 2021). Furthermore, (Sohn & Kwon, 2020) assessed the utility of TAM, TPB, UTAUT and VAM models.

The VAM (Value-based Adoption Model) performed best in modelling consumers' acceptance of Artificial Intelligence based products. UTAUT model's performance was the second best. The biggest difference was the VAM model factor of enjoyment and intrinsic motivation was found to influence purchasing decisions (Sohn & Kwon, 2020). Though, these are included also in the factors of UTAUT model. The key factors of this research are presented in Table 3.

Table 3. *UTAUT and TAM models in Artificial Intelligence Acceptance Research.*

Article	*Model*	*Key Factors*
(Andrews et al., 2021)	UTAUT	Performance Expectancy
		Effort Expectancy
		Social Influence
		Attitude toward adopting
(Cabrera-Sánchez et al., 2021)	UTAUT2	Performance expectancy
		Effort expectancy
		Social influence

		Hedonic motivations Price Value Facilitating conditions Habit Technology fear Consumer trust
(Cao et al., 2021)	UTAUT, TTAT	Peer Influence Facilitating Conditions Performance Expectancy Effort Expectancy Attitude Perceived susceptibility Perceived susceptibility Perceived threat Personal wellbeing concerns Personal development concerns
(Chen & Zhou, 2022)	TAM	Perceived Ease of Use Self-Efficacy Perceived management support Digitalization
(Choung et al., 2023)	TAM	Perceived Usefulness Perceived Ease of Use Trust Perception Attitude Usage Intention
(De Andrés-Sánchez & Gené-Albesa, 2023)	UTAUT	Performance Expectancy Effort Expectancy Social Influence Trust

In addition, to the four key factors of UTAUT models, there are especially two factors that are highlighted: attitude and trust. Attitude towards using technology was used by Venkatesh et al. (2003) to estimate the model but did not end up with the final model. The preferences, including favourable feelings, negative feelings, or concern, surrounding intent to implement these AI and Related Technologies can be referred to as attitudes toward AI adoption (Andrews et al., 2021). The enjoyment of using the technology is also then considered, which was found to explain acceptance by Sohn & Kwon (2020) In IDT theory, Rogers (2003) presents that an individual’s attitudes intervene in the decision-making process. The attitude is also related to technostress. Technostress can be defined as any negative impact on attitudes, thoughts, behaviour or bodies caused by technology. (Kumar et al., 2023) Technostress has an impact on workers' well-being (Kumar et al., 2023) and therefore productivity.

According to Choung et al. (2023), the black-box nature of AI creates unpredictability and uncertainties, highlighting the importance of trust as users cope with the complexities and potential risks associated with AI's decision-making. Trust is closely linked to causality and explainability and it plays a key role in developing user confidence and credibility (Shin, 2021). According to Brachten et al. (2021), trust considers the safety concerns towards the technology. Choung et al. (2023) divide answers into two conceptualizations: trust in the human-like characteristics of AI and trust in the functionality of AI such as ability, reliability, and safety.

Choudhury & Shamszare, (2023) discuss that trust reflects that the user believes the technology executes the task accurately while keeping in mind the possibility of negative outcomes. Choudhury & Shamszare (2023) state that trust is critical to user's adoption of ChatGPT. Brachten et al. (2021) suggest that users who do not trust the system have a lower attitude towards using the system. The skepticism towards technology reflects trust (Brachten et al., 2021). According to Choung et al. (2023), trust can be applied to the TAM framework, especially to technologies with higher risk or human-like characteristics. They found that trust was associated with increased perceived usefulness, attitude and ease of use which in turn increased usage intentions. Based on the previous research the conceptual research model is presented in Figure 9.

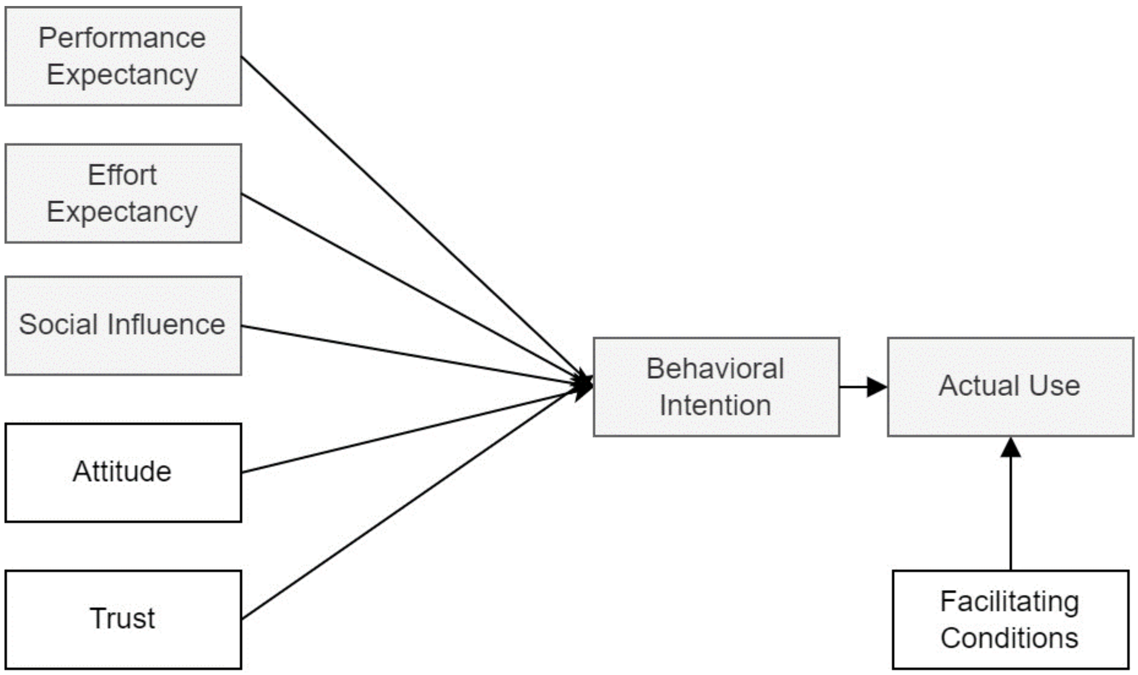

Figure 9. *Adopted research model adopted from Venkatesh et al., (2003); Cao et al., (2021); Choudhury & Shamszare, (2023).*

The adopted research model is based on the UTAUT model. In addition, to the four key factors, trust and attitude are included in the model. The five factors performance expectancy, effort expectancy, social influence, trust and attitude are expected to influence the behavioural intention to use the Generative AI which relates to the use behaviour. The Facilitating conditions are expected to influence the actual use behaviour. It is also argued that Performance Expectancy, Effort Expectancy could predict the attitude. (Cao et al., 2021; Dwivedi et al., 2019; Venkatesh et al., 2012b) In addition, Choung et al. (2023) presents that trust could have indirect impact on intention to use. The effect of Attitude as mediating factor is there for also researched.

3.3 Previous Research of Generative AI acceptance

The research of Acceptance of Generative AI in Knowledge work is limited. There is research of limitations and benefits of Generative AI including the reports from developing ChatGPT by OpenAI (Brown et al., 2020; OpenAI, 2023a). It is known that Generative AI will change the way of working, (Bahrini et al., 2023; Eloundou et al., 2023; Microsoft, 2023; Ritala et al., 2023) How fast and how major the impact is in knowledge work still remains unknown. According to Ritala et al. (2023), Microsoft (2023) and Elondou et al. (2023) there are areas of knowledge work that are more likely to be impacted. According to Feuerriegel et al., (2023) Generative AI will have an impact on organizational structures, leadership models and management practices as well as change the ways organizations manage, maintain, and share knowledge.

In addition, the capabilities of Generative AI are advancing fast which increases the uncertainty. As an example, when the ChatGPT introduced in November 2022 it was not capable of answering with voice or analysing images, the GPT-V introduced in September 2023 has already made those possible. In addition to the technological aspect of Generative AI, the acceptance and adoption of the technology is also affected by multiple social and environmental factors that affect how fast innovations are adopted and utilized. The research of the topic is limited especially when it comes to knowledge management domain (Alsharhan et al., 2023). As the research on acceptance of Generative AI is limited the research of acceptance of chatbots and AI give additional insight.

One relevant research on the topic is Tiwari et al., (2023) research of the factors influencing University students' acceptance of ChatGPT in Oman found that perceived usefulness, perceived ease of use, perceived creditability, perceived social presence and hedonic motivation had impact on attitude towards Generative AI and behavioural intention to use it. In general students' attitudes towards Generative AI were positive. Students thought that ChatGPT enhances the quality of their learning. Furthermore, students found the tool difficult to use and the answers weren't considered understandable. At the same time, they found the answers trustworthy and reliable. When it comes to hedonic motivation, the tool was found entertaining which also had impact on the positive attitude towards ChatGPT. (Tiwari et al., 2023)

Choudhury & Shamszare, (2023) researched the impact of trust to intent of using and actual use ChatGPT. The research suggests that trust has a critical role when it comes to intent to use the tool. Furthermore, the actual use also plays a role to intention to use. (Choudhury & Shamszare, 2023). In other words, having experience of using the tools are also more likely to continue using them. Choung et al. (2023) integrated TAM and trust to research the acceptance of AI voice assistants. As Brachten et al. (2021) they also found that perceived usefulness has had a greater significant impact on acceptance than perceived ease of use. Choung et al. (2023) also found that Trust can influence the factors included in TAM but that it does not have direct impact on intention to use. In addition, they stated that perceived ease of use and perceived usefulness significantly predicts attitude towards voice assistants.

Andrews et al. (2021) researched acceptance of AI among librarians. They found that Performance Expectancy and Attitude have significant impact on user’s intention to adopt these technologies. They also found that Effort Expectancy and Social Influence would not have significant influence. (Andrews et al. 2021). Cao et al. (2021) researched manager’s attitudes and behavioural intentions towards using artificial intelligence for organizational decision-making. They found attitude to have significant impact on Behaviour Intention to Use technologies. As a contrary to UTAUT model they found that Performance Expectancy, Facilitating Conditions and Effort Expectancy would not have significant impact on Behaviour Intention to Use. (Cao et al., 2021).

De Andrés-Sánchez and Gené-Albesa, (2023) researched the acceptance of AI powered chatbots in the insurance industry. They found that Effort Expectancy, Social Influence and Trust had significant impact on Behavioural Intention, but as contrary to other studies performance expectancy did not have significant impact (De Andrés-Sánchez & Gené-Albesa, 2023). Brachten et al. (2021) stated that self-determination and attitude have dominating influence on the usage intention when it comes to chatbots. According to their research intrinsic aspects play the most important role in the intention to use. They also consider trust as an important construct. In addition, perceived usefulness is more important than perceived ease-of-use and peer influence is higher than superior influence. (Brachten et al. 2021).

As a conclusion, there are diversity in the research regarding acceptance of Generative AI, chatbots and Artificial Intelligence. The results indicate that factors including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Attitude and Trust could potentially have significant impact on Behaviour Intention to Use Generative AI.

3.4 The Factors Impacting the Acceptance of Generative AI

Based on the UTAUT model of Venkatesh et al. (2003) and research presented in Table 3 (p. 27), six factors are expected to have an impact on the acceptance of generative AI in knowledge work. These are presented in Figure 9 and supported by the literature on AI and knowledge work.

Performance Expectancy is one of the most significant factors. Performance Expectancy and perceived usefulness describe the degree to which users will consider Generative AI will improve their job performance. According to (Cubric, 2020) biggest drivers for AI adoption in decision-making are economic such as cost, performance and accuracy in decision making. Generative AI such as ChatGPT already has various capabilities and potential use cases to increase the productivity and performance of knowledge work. According to Ritala et al. (2023), ChatGPT is already capable of serving as a search engine for inspiration, creativity, and overviews on a wide range of topics. It can be used as a content production tool to generate drafts of documents such as academic articles, legal agreements, business pitches, social media posts, blog posts and even to generate a list of contents for video content Software developers can use it to write, review and debug code. (Eloundou et al., 2023; Ray, 2023; Ritala et al., 2023). In addition, it can reduce costs as it takes on repetitive tasks and can decrease the time used for these tasks. (Ritala et al., 2023) According to Accenture (2023) the potential of models such as GPT is undeniable when it comes to increasing productivity even in complex tasks. As an example, code compilator created by Google was measured to be able to reduce code iteration time by 6% (Tabachnyk & Nikolov, 2022). Furthermore, Yilmaz & Karaoglan Yilmaz, (2023) found that ChatGPT can significantly increase the learning rate in programming. Their research showed that students having used ChatGPT had significantly higher test scores and increased the computational thinking skills of the students. Instead of spending time writing code, students were capable focus on creative thinking, algorithmic thinking, problem-solving and critical thinking. (Yilmaz & Karaoglan Yilmaz, 2023)

Tasks that are highly complicated, creative or contextual are less likely to be impacted by ChatGPT and AI (Davenport & Kirby, 2016; Ritala et al., 2023; Willcocks, 2020). These include leading and managing people, thinking outside of the box and social interaction (Chui et al., 2015; Ritala et al., 2023). At the same time, these tasks that are human-ingenious have started to decrease (Ritala et al., 2023) and generative AI has been told to enhance, for example creativity when it comes to formulating ideas (Microsoft, 2023). As ChatGPT, DALL-E and other technologies are developing the tasks that they are capable of managing are rapidly growing.

At the same time, challenging and complicated cognitive tasks are becoming human-augmented (Ritala et al. 2023) This implies that workers can use ChatGPT as a tool to generate creative and content-intensive material and enhance it or to use ChatGPT to finalize user-created content. On the other hand, science and critical thinking are not likely to be impacted. (Eloundou et al., 2023) Considering the limitations of the models and the fact that there is still incorrect and biased information there will still be a need for the critical scrutinizing of the outputs generated with the models. While using the as for example the ChatGPT, the importance of critical thinking and analysis should be highlighted (Bahrani et al. 2023).

The relative advantage is one of the key indicators of the technology adoption rate (Rogers, 2003) and plays a part in performance expectancy (Venkatesh et al. 2003). The relative advantage when it comes to, for example ChatGPT compared to traditional search engines such as Google is still questionable. The ChatGPT is not capable so far exceeding Google search (Ritala et al. 2023), but it could be possible considering for example the Microsoft Bing that already combines search engines and web search. On the other hand, there are tasks where it can perform better than its predecessors. For example, when it comes to writing and translating, it may perform more efficiently than just working with Microsoft Word. On the other hand, (Prasad Agrawal, 2023) found that relative advantage did not have a significant impact on adoption of technology. At the the potential advantages of Generative AI were recognized by adopters and non-adopters of the technology.

In knowledge work, information overflow can cause difficulties in finding important information. (Vuori et al. 2019). Therefore, there should be the needed information in an easily accessible form. Generative AI can be trained with specific organizational data, which could also help tackle the overflow of information. In addition, independent working enabled by ICT technologies also adds efficiency as no there are no interfering tasks or requests (Vuori et al. 2019). The increased productivity, when it comes to for example summarizing and learning new skills and the end of information load could also play a part in increasing the well-being of workers by saving them from burnout (Microsoft, 2023). Productivity of knowledge work is related to knowledge workers' well-being (Palvalin, 2019). Therefore, it is expected that Generative AI would have a positive impact on well-being and productivity and the reflected that Performance Expectancy would have a significant impact on the acceptance of Generative AI in knowledge work.

The effort expectancy is expected to also have a significant impact on the acceptance of generative AI. The effort expectancy considers whether the Generative AI is easy to understand and interact with and that it is easy to learn to use. Skills needed to adapt Generative AI include, for example how to write efficient prompts, how to evaluate creative work and test the biases of the models (Microsoft, 2023). The skills such critical thinking and analysis as mentioned are highlighted, which could reflect to the effort expectancy. Acceptance of Generative AI would suffer as a result of high adoption effort expectations.

According to Accenture (2023), one of the most important advantages of foundation models such as GPT models is that AI applications are simple to use. In addition, API interfaces make it possible to apply generative AI in different tools (OpenAI Platform, 2023) and for example, Microsoft's Copilot makes generative AI easily available for Excel, Word and PowerPoint. Kumar et al., (2023) discussed that as workers as required to expend time and effort to adopt ML and AI technologies, it might induce stress, which might have an impact on the well-being of the workers. The ML and AI technologies are high both in complexity and usefulness and the employee skill adaptation is crucial in adoption (Kumar et al. 2023).

In addition, whether the user believes they know the necessity to use the system might have an impact on acceptance. If the user does not know the main principle of how the generative AI models generate text, it might also cause overreliance or misuse. However, it could be possible to adopt the Generative AI without the technology knowledge.

Facilitating Conditions and the degree to which organizational and technical infrastructures support the use of Generative AI are considered to have an impact on the use behaviour. If Generative aligns with the existing infrastructure, it has a positive impact on use behaviour, making adoption of the tools more likely. Chen & Zhou, (2022) found that salespeople were more likely to adopt AI if the organization was digitally prepared. It is needed to make sure that there is organizational support both to encourage AI acceptance as well as an organizational culture that encourages the use of technology (Chen & Zhou, 2022).

The facilitating conditions also consider the compatibility. An idea's compatibility with cultural values and previously adopted ideas can either speed up adoption or lower it. Familiarity with old ideas can decrease the uncertainty related to the adoption of new ideas. (Rogers, 2003). This could be for example the conversational interfaces built around the GPT models which created the ChatGPT and speed up the process of adopting Generative AI.

Social influence is expected to have a positive impact on the behavioural intention and acceptance of technology. If for example Generative AI is used by peers, it may encourage the use. According to Brachten et al. (2021), peer influence had more impact on the intention to use technology than managerial influence. In addition, as ChatGPT is highly popularized and promoted in the media, it could set individual pressure to adopt the technology. At the organizational level (Prasad Agrawal, 2023) found that companies that have highly competitive environments feel more pressured to adopt Generative AI. Competition intensity had a positive effect on the adoption of Generative AI.

Attitude is expected to have a significant impact on intention of use. AI is often associated with the fear of losing jobs, but Microsoft's (2023) surveys suggest that AI is two times more likely to influence productivity instead of reducing headcount. Even though Eloundou et al., (2023) state that Generative AI will have some impact on labour markets. The fear of losing a job might have a negative impact on acceptance of technology (Andrews et al. 2021) and relate to the attitude towards technology. On the other hand, positive attitudes towards Generative AI encourage its usage. According to (Prasad Agrawal, 2023) when it comes to generative AI, more weight is given to potential risks and problems compared to benefits such as relative advantage. In addition, Cabrera-Sánchez et al., (2021) found that the user's confidence towards AI applications would increase the usage behaviour.

In addition, the lack of explainability and the unpredictability of Generative AI, hallucination and biased answers might have an impact on the trust towards the technology. The explainability when it comes to AI, describes how effortlessly it can be introduced and understood. The AI systems' results should be easily explained. (Haque et al., 2023) Whether the users believe that Generative AI produces relevant accurate answers might have an impact on the intention to use the technology. User's trust in machine learning models is based on the accuracy observed. The details of the model's' output, and decision-making procedures increase trust (Haque et al. 2023). The Generative AI models such ChatGPT are not able to explain its reasoning and it is also known to make basic reasoning mistakes (OpenAI, 2023a).

When it comes to AI assistants, Chen & Zhou, (2022) found that trust predicted both a positive attitude and had an influence on intention to use. They also found that factors such as protection of privacy, protocols ensuring fairness and avoiding biases were significant factors related to trust and acceptance of the AI.   The potential risk of technologies such as Generative AI include privacy and security issues as well as biased and harmful outputs (OpenAI, 2023a). Therefore, the user's perception of these limitations and risk are expected to have an impact on the user's attitudes and the intention of use the technology.

4. RESEARCH METHODOLOGY

4.1 Research Design and Strategy

The philosophy of the research is pragmatism. The research aims for objectivity but also acknowledges that in some points the researchers' beliefs or doubts might influence the research. According to Saunders et al., (2019), pragmatism aims to develop practical solutions to problems and find future practice. The research's main goal is to find the factors that have an impact on the acceptance of Generative AI and develop a foundation for the future practices of adopting Generative AI in knowledge work.

The theory development approach is deductive. According to Saunders et al., (2019), quantitative research is often deductive, and data is collected to test the theory. The data is collected with a mono-quantitative method. The data analysis methods are also quantitative. Quantitative methods can be used to measure relationships between variables (Nummenmaa et al., 2019) Quantitative methods were selected to be able to measure how selected factors impact on the acceptance of Generative AI. The research's empirical part is based on collecting the data via survey to test the theory of technology acceptance and the conceptual model presented in Figure 9.

The time horizon is cross-sectional. The research is conducted over a short period to explain the factors affecting acceptance of Generative AI. According to Saunders et al. (2019), surveys are often cross-sectional, and the time horizon can be used for example to describe the incidence of a phenomenon or explain how factors are related in organizations. The research design is summarized in Table 4.

Table 4. *The Methodological selections of the research*

Research design component	Selection
Research Philosophy	Pragmatism
Theory Development Approach	Deductive
Strategy	Survey
Time Horizon	Cross-sectional
Data Collection Method	Mono method quantitative
Data Analysis Method	Quantitative

4.2 Data Collection

The survey is based on the concept model presented in Figure 9 (p. 29). The surveys include questions related to moderating factors: gender, age, and experience of using the Generative AI. Furthermore, the seven factors are presented with statements are rated using the Likert-style scale and five levels of agreement (strongly agree, agree, neither agree or disagree, disagree, and strongly disagree). The seven factors presented also in Figure 9 are performance expectancy, effort expectancy, social influence, facilitating conditions, attitude, and trust. The survey statements based on these factors are presented in Table 5.

Table 5. *The multichoice statements of the survey*

Performance Expectancy (Venkatesh et al. 2003)	1. I find generative AI useful in my job. 2. Using generative AI allows me to accomplish tasks faster. 3. Using generative AI increases my productivity. 4. I believe Generative AI has a positive impact on my career.
Effort Expectancy (Venkatesh et al. 2003, Cao et al. 2021)	5. My interaction with the generative AI is clear and understandable. 6. I find the Generative AI easy to use. 7. Learning how to use Generative AI efficiently is easy for me. 8. It is easy for me to become skillful using Generative AI.
Social Influence (Venkatesh et al. 2003, Cao et al. 2021)	9. Peers who are important to me would think that I should use Generative AI. 10. My superiors who influence my behavior would think that I should use Generative AI. 11. Peers who influence my behaviour would think that I should use Generative AI. 12. My superiors to whom I report would think that I should use Generative AI. 13. The media or online communities think that I should use Generative AI.
Facilitating Conditions (Venkatesh et al. 2003)	14. I have the resources needed to use Generative AI. 15. I have necessary knowledge to use Generative AI. 16. Generative AI supports other technologies I use. 17. I get help from others when I have issues using Generative AI.

Attitude (Venkatesh et al., 2003)	18. Using Generative AI is a good idea. 19. Working with Generative AI is fun. 20. Using Generative AI makes my work more interesting. 21. I enjoy working with Generative AI.
Trust (Cao et al., 2021; Choudhury & Shamszare, 2023)	22. I trust the answers generated by Generative AI. 23. I believe that Generative AI can give reliable results. 24. I am worried about Generative AI giving biased answers. * 25. I am worried about Generative AI generating incorrect information. * 26. Generative AI is secure and protects my privacy and confidential information.
Behavioural Intention to use (Venkatesh et al. 2003)	27. I intend to use Generative AI. 28. I try to use Generative AI as much as possible. 29. I plan to use Generative AI frequently.
Additional statements	30. I think I am experienced using Generative AI 31. Please select the option “agree”.

* The scale is reversed.

The statements Performance Expectancy, Effort Expectancy, Facilitating Conditions, and attitude are adopted from Venkatesh et al. (2003) and altered to consider the Generative AI. The statements regarding social influence are based on the Venkatesh et al. (2003) and Cao et al. (2021) research. Due to the number of media and publicity of technology such as ChatGPT the statement “The media or online communities think that I should use Generative AI.” was included. The statements related to trust are based on Choudhury & Shamszare (2023) and take into consideration the limitations of the most popular GPT-models such as biased information or hallucinations. In addition, regarding the experience of Generative AI statement number 30 was included in the multichoice. Lastly, an instructional manipulation check was included. Oppenheimer et al., (2009) that it allows to check if participants are reading the instruction and not only picking answers by random. Having an instructional manipulation check should not affect the variance of the population, but it makes sure the participants have read the instructions and statements. The full questionnaire, including demographic questions, is presented in Appendix A.

The research sample was collected with non-probability methods. The survey was shared online in LinkedIn to gather data as well as among Tampere University’s information and knowledge management students and graduates, as well as Industrial Engineering students and graduates. Via LinkedIn the invitation reached over 2000 impression. According to LinkedIn statistics most of the people who had seen the post work in companies with over 10,001 employees as shown in Figure 10. Furthermore, most of the people who have seen the post were from Tampere and Helsinki metropolitan areas as presented in Figure 11.

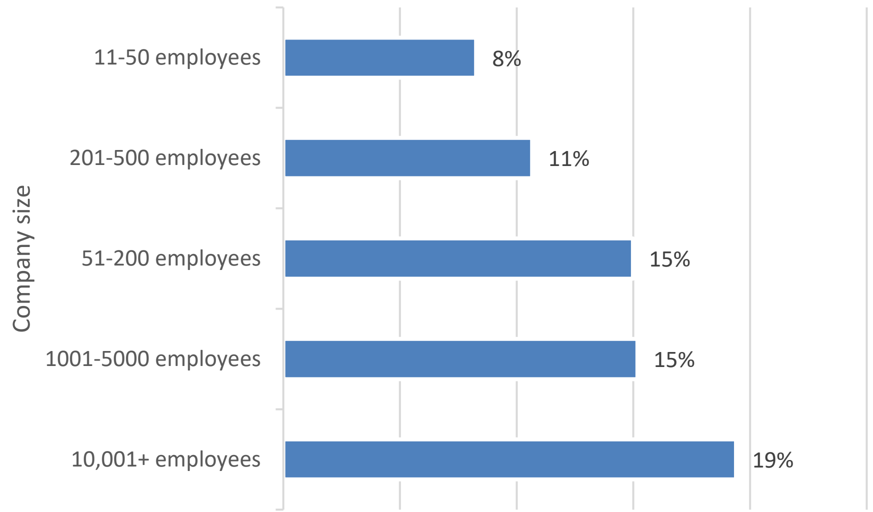

Figure 10. *Sizes of the companies based on LinkedIn analytics.*

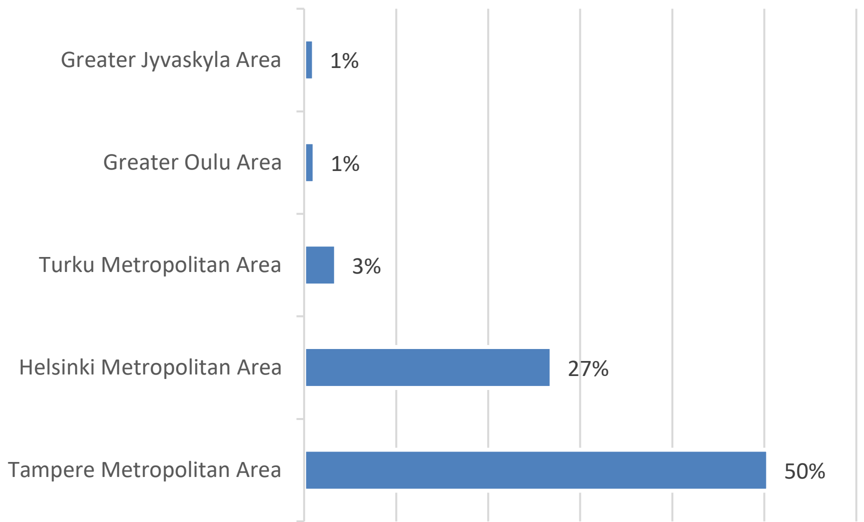

Figure 11. *Top 5 Locations of the people based on LinkedIn analytics.*

The research is exploratory and therefore the selected sampling methods were considered suitable. The sampling method does affect the reliability of the research. Approximately 4000 people eventually saw the invitation to take part in the survey including LinkedIn and student groups. As the answering was voluntary it also might influence people who are more interested in Generative AI, new technologies in general might be more interested in answering the survey. According to

Nummenmaa et al. (2019) these type of samples based on voluntariness might not be representable of the population. This should be considered while making conclusions regarding the research. The reliability and validity of the research depends on the data collected and the designing of the questionnaire (Saunders et al. 2023). The questionnaire itself was designed according to the UTAUT and TAM models which makes the results comparable to other research conducted based on the models.

4.3 Data Analysis

The data was collected through a survey, as detailed in Appendix A. To analyze the data, we utilized both SPSS Analytics and SPSS Amos, which involved a six-step data analysis process:

1. **Data Screening**: Initially data screening was conducted to identify any abnormalities or outliers. Additionally, it was ensured that all responses passed the instructional manipulation check.

2. **Descriptive Analysis**: In the second step, the demographics of the respondents were analyzed, and descriptive analysis of the data was carried out.

3. **Exploratory Factor Analysis:** The third step involved Exploratory Factor Analysis, a statistical method used to uncover underlying variables or factors that explain the variance in the data (Watkins, 2018).

4. **Reliability Analysis:** In this phase, the reliability of the identified factors was tested, and their internal consistency assessed using Cronbach's alphas.

5. **Confirmatory Factor Analysis:** Confirmatory Factor Analysis was used to define the variables based on the established theoretical framework (Collier, 2020).

6. **Structural Equation Modeling**: Finally, Structural Equation Modeling was to test the conceptual models and identify the relationships between the factors. Throughout this process, we examined three different models to ultimately determine the factors that significantly impact the acceptance of Generative AI.

The data analysis method used allows the results to be compared to the other research conducted using the UTAUT and TAM models. The results of the analysis are presented in the following chapter. In addition, the limitations of the research are discussed.

5. RESULTS

This chapter presents the survey results. First, the demographics of the respondents are introduced. Secondly, the results of descriptive and frequency analysis are presented and discussed. Lastly, the processes of Exploratory and Confirmatory Factor Analyses, as well as the reliability analysis based on Cronbach's alphas, are presented, along with the main results of the analysis. Based on the factors determined in Exploratory and Confirmatory factor analysis, the factors impacting the Behavioural Intention to Use Generative AI are examined using Structural Equation Modelling, and the results of the modelling are presented.

5.1 Demographics

The survey data was collected from September 22, 2023, to October 2, 2023. A total of 135 full responses were collected. Three of the responses were disqualified due to failing the instructional manipulation check. The data was screened for abnormalities and unengaged responses. The standard deviation for all responses was higher than 0.5, and no responses were disqualified due to that. In addition, only two respondents were from outside Finland, and these were excluded from the responses. In total, 130 responses were included in the research (n=130). There were no missing values in these responses. Of the 130 respondents, 39.2 percent identified as female, 60.0 percent as male, and 0.8 percent preferred not to say. Most of the respondents were between 18-24 and 25-34 years old. In addition, the largest group of respondents was students, followed by software development and consultancy. Statistics are presented in Figures 12 and 13.

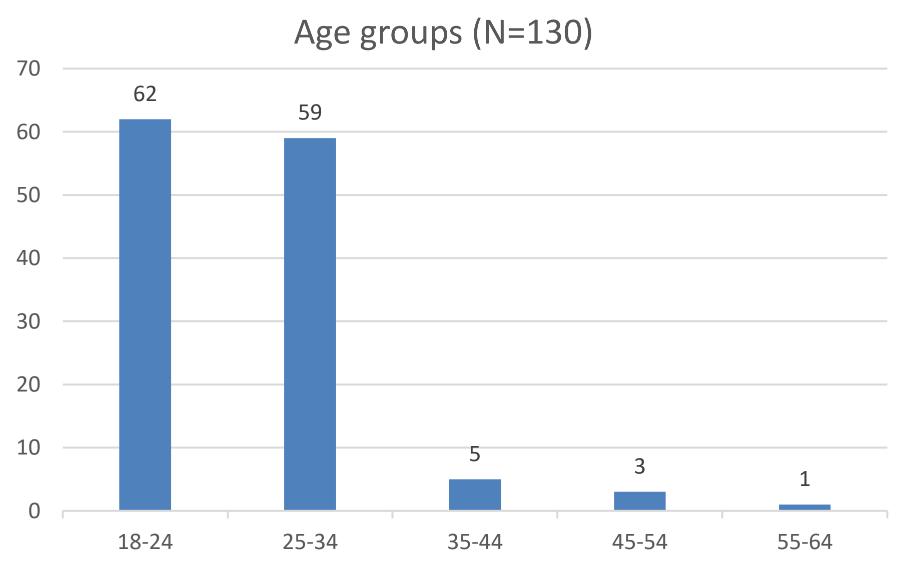

Figure 12. *Ages of the respondents*

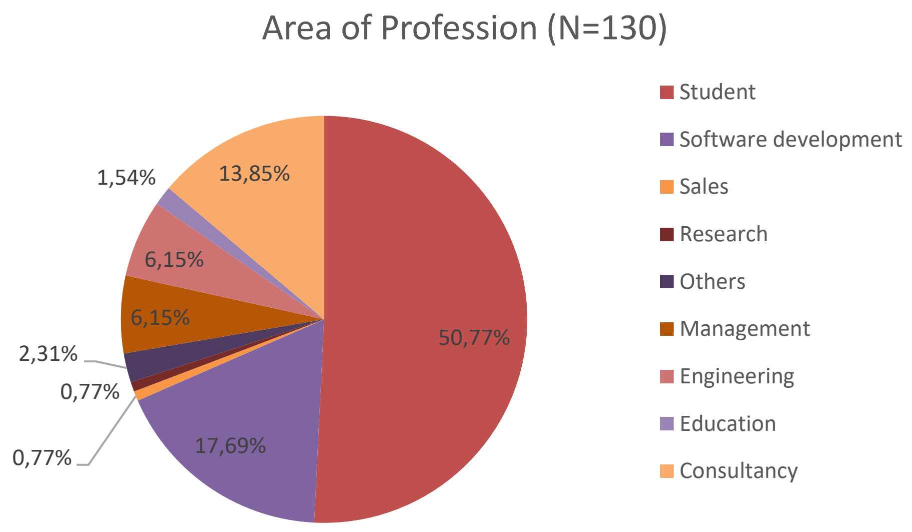

Figure 13. *Respondents' areas of profession*

The most used Generative AI tool was ChatGPT, 97 percent of the respondents have used ChatGPT previously. Other tools that were more used included the Microsoft Bing, DALL-E 2 and Google Bard and GitHub Copilot as presented in figure 14. Most of the respondents use Generative AI 2-3 three times a week. Only 4 respondents state they never use Generative AI tools.

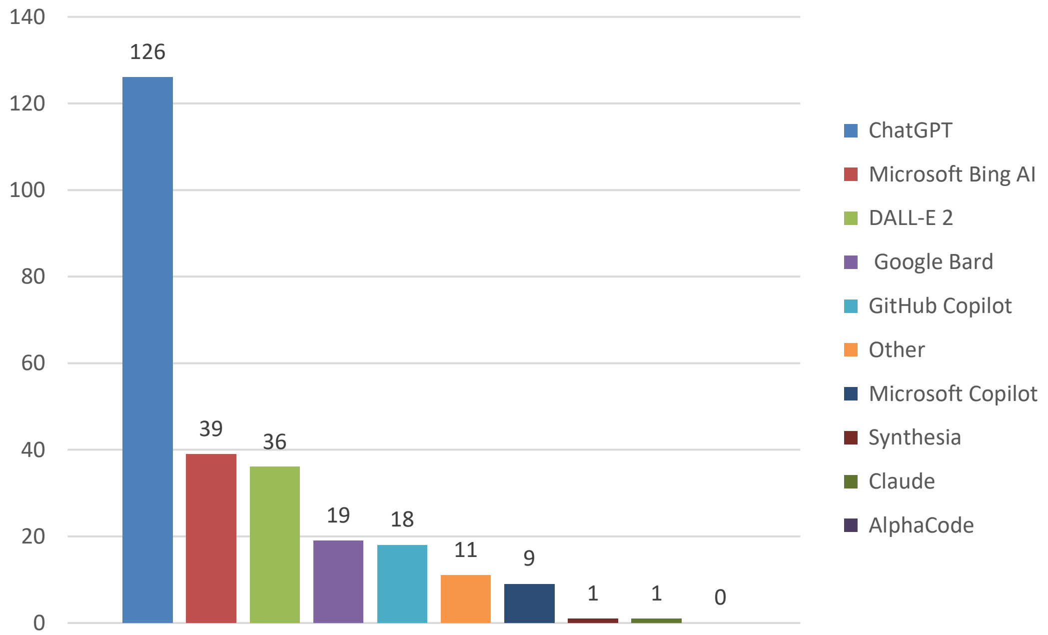

Figure 14. *The Generative AI tools used by the respondents.*

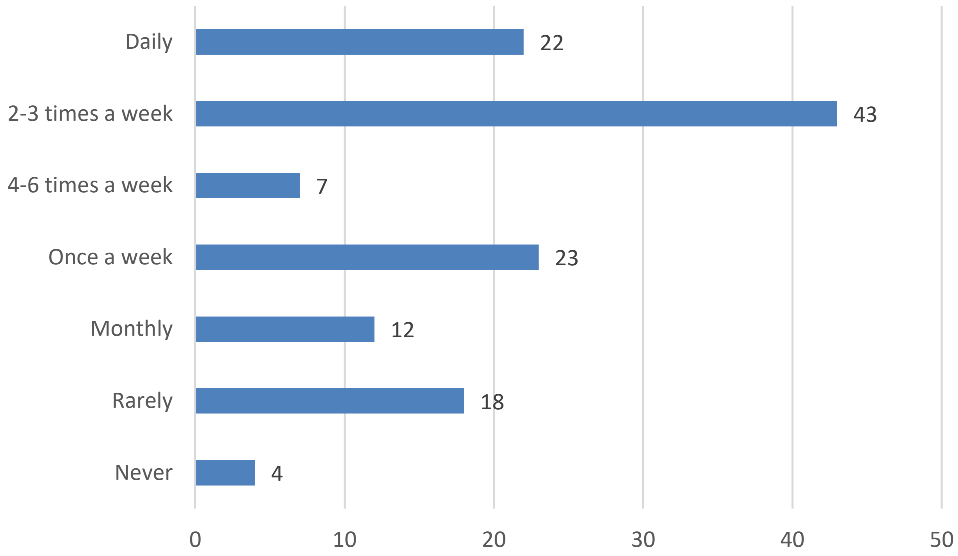

Figure 15. *How often respondents use Generative AI.*

5.2 Descriptive statistics

The results regarding Performance Expectancy are presented in Table 6. Most respondents either agree or strongly agree with the statements related to Performance Expectancy. Generative AI is considered useful, and it allows users to accomplish tasks more quickly. Additionally, according to the majority of the respondents, Generative AI increases productivity. There is slightly less agreement regarding whether Generative AI has a positive impact on one's career or not. There is some variability in answers.

Table 6. *Performance Expectancy statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
I find generative AI useful in my job.	37	71	13	7	2	130	4,03	0,86
Using generative AI allows me to accomplish tasks faster.	51	63	11	5	0	130	4,23	0,76
Using generative AI increases my productivity.	43	62	17	8	0	130	4,08	0,84
I believe Generative AI has a positive impact on my career	26	59	31	11	3	130	3,72	0,97

Based on the results regarding Effort Expectancy presented in Table 7, Generative AI is perceived as easy to use. Additionally, interactions with Generative AI are considered clear and understandable. While there is general agreement that becoming skilled in using Generative AI is feasible, there is also a notable number of people who disagree with this statement. In general, Generative AI appears to be considered user-friendly and relatively easy to learn.

Table 7. *Effort Expectancy statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
My interaction with the generative AI is clear and understandable.	23	80	19	8	0	130	3,91	0,75
I find the Generative AI easy to use.	37	77	10	8	0	130	4,12	0,73
Learning how to use Generative AI efficiently is easy for me.	29	68	23	10	0	130	3,90	0,84
It is easy for me to become skillful using Generative AI.	26	53	35	15	1	130	3,68	0,95

The statistics concerning the Social Influence Statements are presented in Table 8. A significant number of respondents either agree or strongly agree that their important peers would support the use of Generative AI. Additionally, there is a positive perception that peers who influence their behaviour would also endorse the use of Generative AI. In contrast, the statements related to superiors and their influence on behaviour have lower mean values compared to the statements about peer influence. These statements exhibit a notable range of responses, with a higher proportion of neutral and disagreeing responses. Notably, the media and online communities are perceived as having the most substantial influence, according to the respondents. This item garnered a relatively high level of agreement, with a mean score of 3,62. This suggests that respondents believe the media and online communities hold a positive view of AI usage.

Table 8. *Social Influence Statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
Peers who are important to me would think that I should use Generative AI.	13	57	52	8	0	130	3,58	0,76
My superiors who influence my behaviour would think that I should use Generative AI.	7	48	54	19	2	130	3,30	0,84
Peers who influence my behaviour would think that I should use Generative AI.	11	57	48	14	0	130	3,50	0,79
My superiors to whom I report would think that I should use Generative AI.	8	42	56	18	6	130	3,22	0,92
The media or online communities think that I should use AI.	16	66	33	12	3	130	3,62	0,90

The statistics related to Facilitating Conditions are presented in Table 9. Most respondents agree or strongly agree that they have the necessary resources to use Generative A. The mean score of the statement is relatively high, indicating a positive perception with low variability (low standard deviation 0,75). Most respondents also agree or strongly agree that they have the necessary knowledge to use generative AI. The mean score 4,12 indicates a strong positive perception. The respondents generally agree that Generative AI supports other technologies they use, and the perception is positive. There is a bit more variability regarding the statement. Lastly, there is high variability regarding if respondents get help from others when they have issues with Generative AI. The perception is still positive and most agree that they would get help.

In summary, the data shows generally positive perceptions, with respondents feeling they have the necessary resources and knowledge to use Generative AI. However, the item related to getting help from others shows more mixed feedback, with a broader distribution of responses and higher variability.

Table 9. *Facilitating Conditions Statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
I have the resources needed to use Generative AI.	37	65	15	13	0	130	3,91	0,75
I have necessary knowledge to use Generative AI.	24	79	19	7	1	130	4,12	0,73
Generative AI supports other technologies I use.	28	73	19	7	3	130	3,89	0,84
I get help from others when I have issues using Generative AI.	6	37	45	35	7	130	3,68	0,95

The statements regarding Attitude are presented in the Table 10. A significant majority of the respondents agree or strongly agree that using Generative AI is a good idea. The mean 4,00 suggests very positive perception with moderate variability. Working with Generative AI is also considered fun with a high mean value of 4,01. When it comes to whether Generative AI makes their work more interesting there are mixed responses. The mean score 3,45 indicates positive perception but standard deviation of 0,95 indicates high variability. The majority also agrees that they enjoy working with Generative AI but there is also some moderate variability.

Summarized, the data reveals that respondents generally have positive perceptions of working with Generative AI, finding it a good idea and enjoyable. However, there is more variability in perceptions regarding whether it makes work more interesting, with some neutral and disagreeable responses. Overall, the mean scores are relatively high, indicating overall positivity.

Table 10. *Attitude statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
Using Generative AI is a good idea.	31	74	21	2	2	130	4,00	0,78
Working with Generative AI is fun.	38	61	25	6	0	130	4,01	0,82
Using Generative AI makes my work more interesting.	15	53	40	19	3	130	3,45	0,96
I enjoy working with Generative AI.	31	67	25	6	1	130	3,93	0,83

The statistics regarding trust are presented in Table 11. The first item indicates that the majority of respondents are neutral or express some level of distrust in the answers generated by Generative AI. The mean 2,87 states tendency towards distrust. At the same time with mean value 3,55 respondents believe that Generative AI can provide reliable results.

Respondents generally express concerns about Generative AI providing biased answers. The weights for this statement are reversed and therefore mean value 2,34 indicate worry. The respondents are also generally concerned about Generative AI generating incorrect information. The concern is higher than concern related to biased answers. Most respondents are also neutral or express some concern about the security and privacy of Generative AI.

Table 11. *Trust statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
I trust the answers generated by Generative AI.	2	29	54	40	5	130	2,87	0,86
I believe that Generative AI can give reliable results.	11	70	31	15	3	130	3,55	0,89
I am worried about Generative AI giving biased answers. *	21	65	26	15	3	130	2,34 *	0,96
I am worried about Generative AI generating incorrect information. *	20	65	20	8	3	130	2,08 *	0,93
Generative AI is secure and protects my privacy and confidential information.	2	12	43	50	23	130	2,38	0,93

* The weights are reversed.

The results for statements related to Behaviour Intention to Use Generative AI are presented in Table 12. A significant majority of respondents express a strong intention to use Generative AI. The high mean score at 4,19 states a strong intention to use it. When it comes to trying to use Generative AI as much as possible there is a wide range of responses. A significant number of respondents disagree with the statement. The mean score at 2,67 shows a lower level of agreement with high variability and standard deviation at 1,17. Lastly, most respondents plan to use Generative AI frequently. There is also some disagreement and variability in answers.

Table 12. *Behaviour Intention to Use statistics*

	SA	A	N	D	SD	N	Mean	Std. Deviation
I intend to use Generative AI.	50	63	11	4	2	130	4,19	0,84
I try to use Generative AI as much as possible.	10	27	20	56	17	130	2,67	1,17
I plan to use Generative AI frequently.	39	61	15	10	5	130	3,92	1,03

Summarized, most respondents agree that Generative AI increases their job performance. Generative AI helps them accomplish tasks more quickly and increases productivity. Generative AI is considered easy to use and learn, but becoming skillful at using Generative AI is considered to be slightly more challenging. Social influence related to peers is considered higher than superior influence. Social media and online communities are perceived to have the most substantial positive influence. Respondents also generally have a positive opinion of their resources, knowledge, and support of Generative AI for other technologies. Attitudes towards Generative AI are generally positive. Generative AI is found to be enjoyable, and using it is considered a good idea. There are mixed thoughts regarding whether it makes work more interesting. Respondents also have some worries regarding privacy and Generative AI generating biased or incorrect information. On the other hand, it is believed that Generative AI can also provide reliable results. Finally, the majority of respondents have a strong intention to use Generative AI, but the variability in answers also indicates a diversity of attitudes and behaviors among the surveyed population.

5.3 Factor Analysis

5.3.1 Reliability and Exploratory Factor Analysis

Cronbach's alpha can be used to measure internal consistency in a scale used to measure latent variables. A high value of alpha indicates that items correlate with each other. (Wilson & Joye, 2017). The value should be higher than 0.7 to be considered acceptable (Collier, 2020). The Cronbach's Alphas calculated to each factor without any changes are presented in Table 13.

Table 13 Cronbach's alphas measured to each factor.

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Performance Expectancy	0,813	0,821	4
Effort Expectancy	0,751	0,756	4
Social Influence	0,706	0,71	5
Facilitating Conditions	0,514	0,524	4
Attitude	0,774	0,778	4
Trust	0,671	0,671	5
Behavioural Intention to Use	0,772	0,783	3
All variables	0,883	0,885	29

Based on Table 13, the Facilitating Conditions measurement based on the Cronbach's alpha is not reliable, or the questions presented are not consistent with each other. Trust on the other hand is higher than 0,6 but lower than 0.7, which would make it questionable. This would suggest that there is inconsistency in the statements regarding Facilitating Conditions and Trust which could affect the reliability of the results.

Secondly, an exploratory factor analysis was conducted. Based on the analysis 7 factors were found. The results of the exploratory Factor analysis are presented in Appendix B. According to Nummenmaa et al. (2019) the factors should have as little covariance as possible and there should be the smallest number of factors possible. In addition, there should mostly be high and low loading, and not mediocre loadings. Lastly, there should be meaningful interpretation.

Based on the analysis the Facilitating Conditions factors were eliminated, as they did not adjust to a single factor, and therefore it would complicate the interpretation of the factors. In addition, as presented in Table 6 the internal consistency of this factor was only 0,514, which was considered unacceptable. It is also noticed that the values for statements related to trust have quite low loadings, but all the values are above 0,3 so they are still acceptable.

To determine the factors four statements were also excluded as they did not load into single factor as expected. These statements are:

1. I believe Generative AI has positive impact on my career (PE)
13. The media or online communities think that I should use Generative AI (SI)
18. Using Generative AI is a good idea. (AT)
26. Generative AI is secure and protects my privacy and confidential information. (TR)

28. I try to use Generative AI as much as possible. (BI)

In addition, the Social Influence factor was divided into two independent factors. These two would not load to a single factor and separating them would still give both factor meaningful interpretations. The seven factors explain 60,0% of the variance. The KMO (Kaiser-Meyer-Olkin Measure of Sampling Adequacy.) value is 0,8 which is good and indicates that factor analysis is useful with the data. (IBM, 2021). Furthermore, according to Factor Correlation Matrix there are no correlations greater than 0,7. There are high correlations with Behavioural Intention to Use to Attitude (0,672) and Performance Expectancy (0,620), which is not ideal. The reliability analysis was repeated for the new factors and results are summarized in table 14.

Table 14 *Reliability of the exploratory factors.*

	Cronbach's Alpha	N of Items
Attitude	0,752	3
Effort Expectancy	0,751	4
Performance Expectancy	0,830	4
Peer Social Influence	0,705	2
Superior Social Influence	0,706	2
Trust	0,652	4
Behavioural Intention to Use	0,774	2
All variables	0,852	20

As presented in Table 14 the factors except for trust are all acceptable. The Trust is questionable, but it is not necessary to disqualify the factor at this point. The measurements included after explorative factor analysis are presented in Table 15. The reliability of individual factors are also presented in the Appendix C.

Table 15 *Measurements included based on the explorative and reliability analysis.*

Performance Expectancy (Venkatesh et al. 2003)	1. I find generative AI useful in my job. 2. Using generative AI allows me to accomplish tasks faster. 3. Using generative AI increases my productivity.
Effort Expectancy (Venkatesh et al. 2003, Cao et al. 2021)	5. My interaction with the generative AI is clear and understandable. 6. I find the Generative AI easy to use. 7. Learning how to use Generative AI efficiently is easy for me.

	8. 8. It is easy for me to become skillful using Generative AI.
Superior Social Influence (Venkatesh et al. 2003, Cao et al. 2021)	10. My superiors who influence my behavior would think that I should use Generative AI. 12. My superiors to whom I report would think that I should use Generative AI.
Peer Social Influence	9. Peers who influence my behaviour would think that I should use Generative AI. 11. Peers who are important to me would think that I should use Generative AI.
Attitude (Venkatesh et al., 2003)	19. Working with Generative AI is fun. 20. Using Generative AI makes my work more interesting. 21. I enjoy working with Generative AI.
Trust (Cao et al., 2021; Choudhury & Shamszare, 2023)	22. I trust the answers generated by Generative AI. 23. I believe that Generative AI can give reliable results. 24. I am worried about Generative AI giving biased answers. * 25. I am worried about Generative AI generating incorrect information. *
Behavioural Intention to use (Venkatesh et al. 2003)	26. I intend to use Generative AI. 27. I plan to use Generative AI frequently.

* Reverse coding

5.3.2 Confirmatory Factor Analysis

The Confirmatory Factor Analysis was conducted to the factors identified in exploratory factor analysis. Confirmatory Factor Analysis can be used to validate and develop measurements and to confirm the factor structure identified in Exploratory Factor analysis. The sample in the research is slightly small <200 which is recommended for the analysis (Collier, 2020). The measurement model created in SPSS Amos is presented in Figure 16. The results of confirmatory factor analysis are included in the Appendix D.

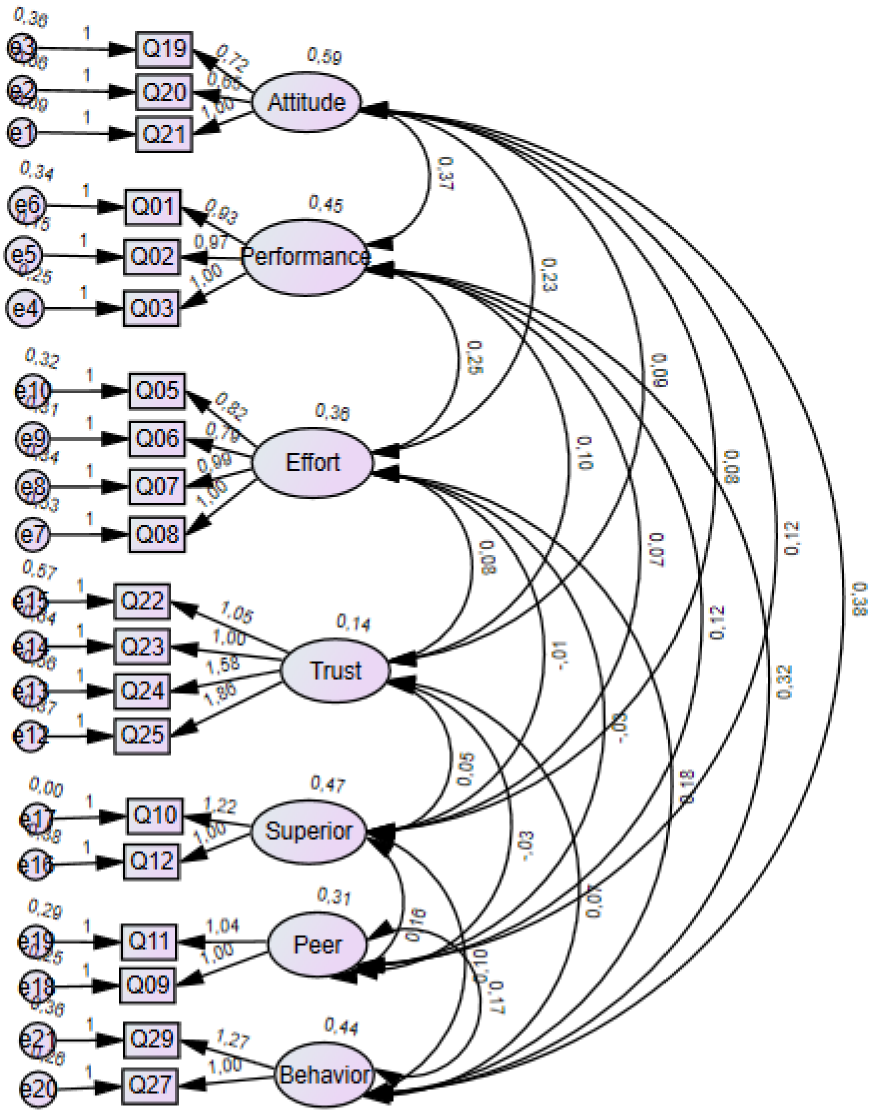

Figure 16. *Confirmatory Factor Analysis in SPSS Amos*

The correlation values are less than 0,8 which is good. In addition, convergent validity is good. The regression weights are presented in Table 16. According to (Collier, 2020) the values should be higher than 0,7 to explain at least half of the variance in the vector. Most of the values are decent. The trust has also in this case the lowest loadings. The mean of the loading for trust is 0,569 which is high enough that the factor is not excluded. In addition, there are no correlations in error terms in the model between the factors, as it should be.

Table 16. *Standardized regression weights*

			Estimate
Q21	<---	Attitude	,931
Q20	<---	Attitude	,525
Q19	<---	Attitude	,679
Q03	<---	Performance	,805
Q02	<---	Performance	,860
Q01	<---	Performance	,730
Q08	<---	Effort	,635
Q07	<---	Effort	,711
Q06	<---	Effort	,652
Q05	<---	Effort	,658
Q25	<---	Trust	,758
Q24	<---	Trust	,627
Q23	<---	Trust	,427
Q22	<---	Trust	,466
Q12	<---	Superior	,745
Q10	<---	Superior	,999
Q09	<---	Peer	,744
Q11	<---	Peer	,732
Q27	<---	Behavior	,793
Q29	<---	Behavior	,815

The model fit is considered acceptable. As presented in Table 17, the CMIN/DF and CFI values are good. The comparative fit index (CFI) is one of the most used and values above 0,9 or 0,95 represent a good model fit. (Lewis, 2017). The RMSEA should be < .05 for a good model fit and < .08 for an adequate model fit (Collier, 2020; Lewis, 2017). The RMSEA value is slightly high, but still acceptable. There is no p – value which is not great, but as the CMIN/DF is good and less than 3, the model can be considered to be fitting. (Collier, 2020). The GFI is also not higher than 0,9 but still decent. In addition, according to Collier (2020) the index is also considered problematic and can be affected by sample size. The value can be used to compare different models.

Furthermore, if a residual value exceeds 2.58 it could be considered as a sign of model misspecification (Collier, 2020). The highest value 2,726 is between Q27 and Q23, which is not great, but as everything else is considered good in the model, there are no changes made.

Table 17. *The model fit of the third Structural Equation Model*

	Value	Goal	Interpretation
CMIN/DF	1,627	<= 3	Excellent
P	0,000	>0	Unacceptable
GFI	0,849	>= 0,9	Okay
CFI	0,903	>= 0,9	Acceptable
RMSEA	0,07	<=0,08	Acceptable
RMR	0,065	<= 0,07	Acceptable

The composite reliability (CR) and the Average variance extracted (AVE) were also tested as well as the cross-construct correlations. The CR values should be higher than 0,7. There are slight issues with trust which was anticipated. In addition, the peer social influence has some issues. The effort expectancy and Trust also have low AVE values as the values should be higher than 0,50. The AVE is the average amount of variation that a latent construct is able to explain. This would indicate that Effort Expectancy and Trust do not necessarily explain the construct as intended. The values are presented in the Table 18.

Table 18. The factors CR and AVE

	CR	AVE
Peer Social influence	0,693*	0,531
Effort	0,761	0,443*
Superior	0,875	0,782
Trust	0,673*	0,342*
Behaviour	0,784	0,646
Performance	0,840	0,637
Attitude	0,761	0,527

* Unacceptable value

The is also issues with the attitude and the high correlation with the performance and behaviour intention to use as presented in the Table 19. The bolded values present the square rooted AVE. These issues are recognized, and they could have implications for the reliability of the research. Further modifications based on table 18 and 19 were not done since it would have required significant changes to the research model.

Table 19. *The square root of average variance extracted and cross-correlation.*

	Peer	Effort	Superior	Trust	Behaviour	Perfor-mance	Attitude
Peer	**0,729**						
Effort	-0,086	**0,666**					
Superior	0,410	-0,018	**0,884**				
Trust	-0,006	0,399	0,218	**0,585**			
Behaviour	0,493	0,445	0,215	0,331	**0,804**		
Performance	0,360	0,607	0,164	0,443	0,710	**0,798**	
Attitude	0,254	0,514	0,150	0,441	0,789	0,742	**0,726***

* Unacceptable value

5.3.3 Multicollinearity

The Cook's distances for these new factors were also tested. The Figure 17 presents the scatter plot of the Cook's distance per survey response id. The outliers can be detected from the scatter plot. One case had a higher distance of 0,22350 and the case was taken out of the sample. There were also some other higher values but not as significantly different from each other. The new sample size is therefore 129. The case also was the only case with the gender value 'prefer not to say' so it is reasonable to exclude the case as an outlier.

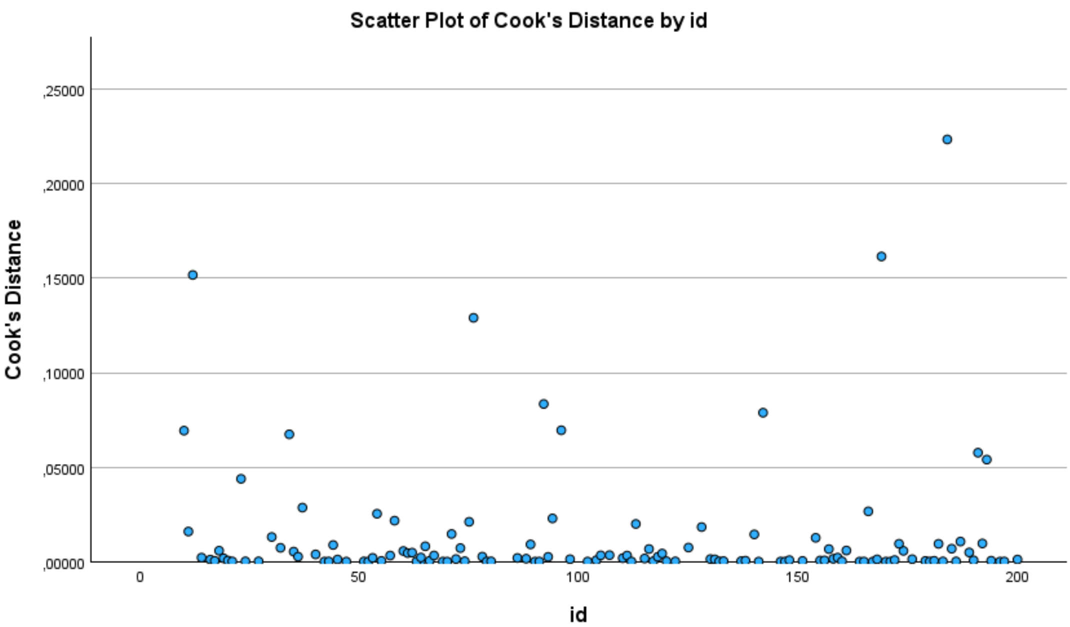

Figure 17. *Cook's distances by response id*

The multicollinearity of the factors was analysed and presented in Table 20. The VIF (Variation Inflation Factor) scores are under 3 which is good, and the tolerance is above 0,1. According to

Nummenmaa et al. (2019) the VIF – values should be under 5. High multicollinearity would undermine the statistical significance of an independent variable. If multicollinearity was high, it would mean that the factors are not independently explaining the dependent factor.

Table 20. *Multicollinearity analysis results*

Factor	Tolerance	VIF
Performance Expectancy	0,500	2,001
Effort Expectancy	0,595	1,680
Superior Social Influence	0,459	2,180
Peer Social Influence	0,795	1,258
Attitude	0,749	1,335
Trust	0,597	1,674
Behavioural Intention to Use	-	-

5.3.4 Structural Equation Modelling

Based on the exploratory and confirmatory factory analyses the structural equation model is tested. The model is simplified from the model presented in Figure 9 (p. 29). The model tested is presented in Figure 16. The Facilitating Conditions is not presented in the model based on the exploratory and confirmatory factor analyses. In addition, the Social Influence is divided into two factors according to exploratory and confirmatory factor analysis: Superior and Peer Influence. Furthermore, the moderating factors are not included. The Structural Equation Model based on Figure 18 is presented in Figure 19.

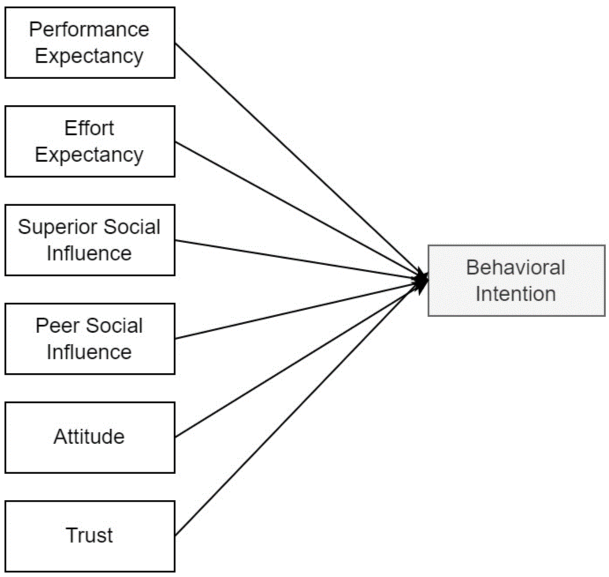

Figure 18. *The causal model tested based on exploratory and confirmatory factor analysis*

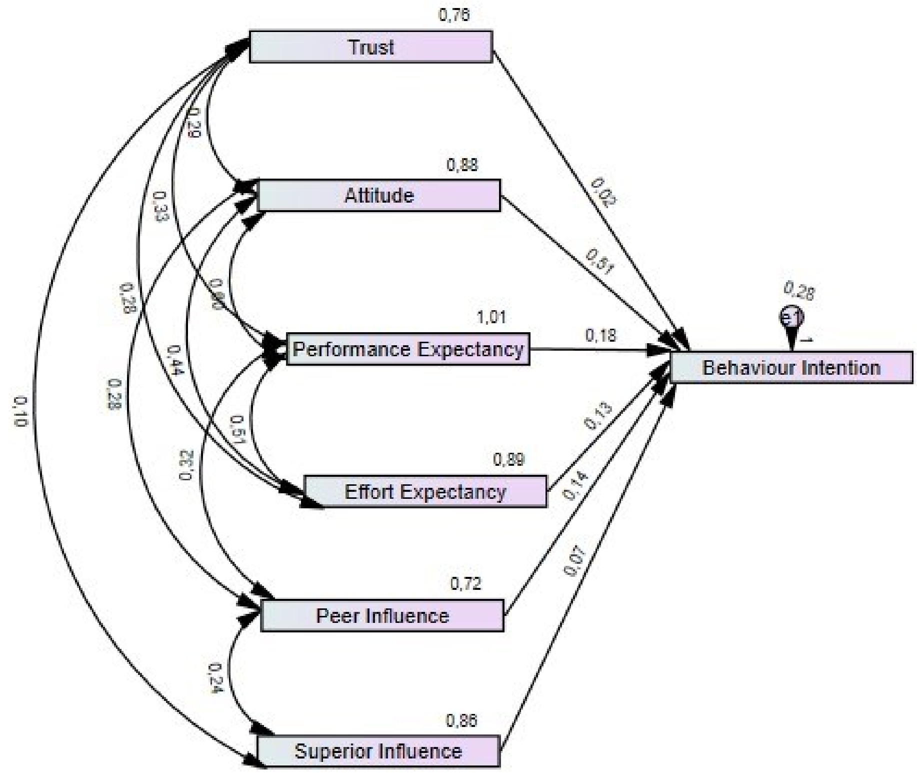

Figure 19. *The Structural Equation Model in SPSS Amos for the first Model*

The model fits key values are presented in Table 21. CMIN/DF value is again less than 3, which is excellent. Also, the p-value is above 0, which is good. The GFI and CFI values are also above 0,95, which is also excellent, and RMSEA is under 0,08. The model can be considered a good fit.

Table 21. *The model fit of the first model*

	Value	Interpretation
CMIN/DF	1,527	Excellent
P	0,177	Good
GFI	0,984	Excellent
CFI	0,992	Excellent
RMSEA	0,064	Acceptable
RMR	0,058	Acceptable

The estimates for the model presented in the Figure 19 were calculated is SPSS Amos. The regression weights of researched factors are presented in the Table 22. Based on Table 22, we can detect that at the significance level <0,05 Attitude, Performance Expectancy, Effort Expectancy and Peer Social Influence have significant impact on the Behavioural Intention to Use. The Superior Social Influence and Trust does not have significant impact.

Table 22. *Regression weights of the first model*

			Estimate	S.E.	C.R.	P	Interpretation
FAC7_BI	<---	FAC6_PSI	,143	,069	2,083	,037	Significant
FAC7_BI	<---	FAC3_PE	,176	,069	2,552	,011	Significant
FAC7_BI	<---	FAC1_AT	,510	,070	7,321	***	Significant
FAC7_BI	<---	FAC2_EE	,135	,063	2,126	,034	Significant
FAC7_BI	<---	FAC4_SSI	,071	,055	1,292	,196	
FAC7_BI	<---	FAC5_TR	,017	,061	,284	,776	

In addition, there are covariance between the factors. Covariance measures how much variables change together (Collier, 2020). Positive covariance means that the variables move in the same direction. The covariances of the first model are presented in Table 23.

Table 23. *Covariance of the first model*

			Estimate	S.E.	C.R.	P
FAC6_PSI	<-->	FAC4_SSI	,243	,064	3,777	***
FAC3_PE	<-->	FAC2_EE	,507	,089	5,679	***
FAC2_EE	<-->	FAC1_AT	,442	,083	5,343	***
FAC6_PSI	<-->	FAC3_PE	,317	,065	4,850	***
FAC3_PE	<-->	FAC1_AT	,603	,093	6,524	***
FAC6_PSI	<-->	FAC1_AT	,276	,062	4,468	***
FAC1_AT	<-->	FAC5_TR	,289	,072	3,994	***
FAC3_PE	<-->	FAC5_TR	,330	,077	4,257	***
FAC2_EE	<-->	FAC5_TR	,280	,077	3,656	***
FAC4_SSI	<-->	FAC5_TR	,105	,063	1,666	,096

The strength of the variable's relationships is calculated with correlations (Collier, 2020). The correlations are presented in Table 24. The values can have values between (-1, 1). Values higher than 0,3 can be considered to have significance. Based on the table the strongest correlation is between attitude and performance expectancy. Effort expectancy and Performance Expectancy as well as Effort Expectancy and Attitude also have stronger correlation.

Table 24. *Correlations of the first model*

			Estimate
FAC6_PSI	<-->	FAC4_SSI	,309
FAC3_PE	<-->	FAC2_EE	,534
FAC2_EE	<-->	FAC1_AT	,499
FAC6_PSI	<-->	FAC3_PE	,373
FAC3_PE	<-->	FAC1_AT	,642
FAC6_PSI	<-->	FAC1_AT	,347
FAC1_AT	<-->	FAC5_TR	,353
FAC3_PE	<-->	FAC5_TR	,376
FAC2_EE	<-->	FAC5_TR	,338
FAC4_SSI	<-->	FAC5_TR	,129

In addition, a second model was tested, to analyses the relationship between attitude and the other factors Effort Expectancy, Peer and Superior Influence and Trust. This second model is presented in Figure 17. The biggest difference is that Attitude is presented as a mediation term.

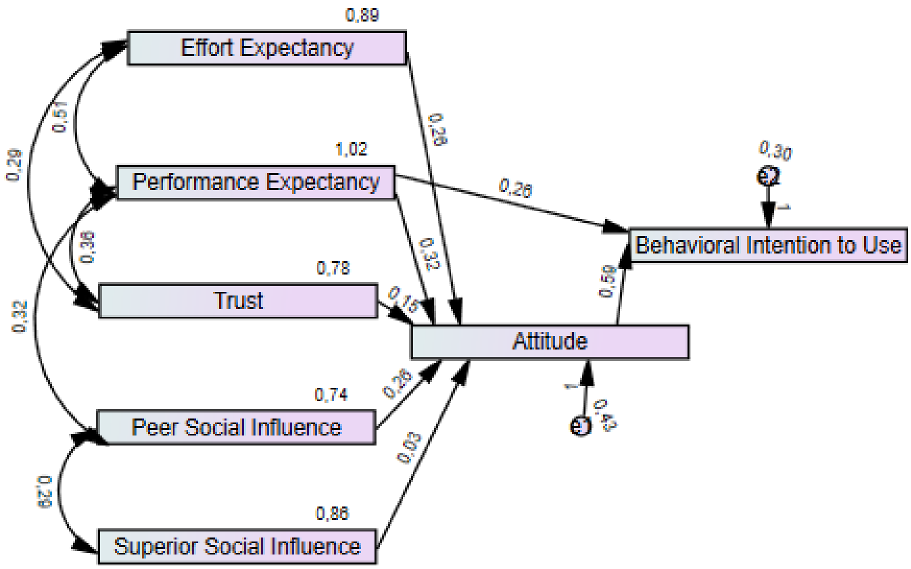

Figure 20. *The estimates calculated for second model in SPSS Amos*

As presented in the Table 25, the model fit is also good. The RMSEA is slightly over the 0,08 but still less than 0,1. The values are all slightly worse. The regression weights calculated for the model are presented in the Table 26.

Table 25. *The model fit of the second causal model*

	Value	Goal
CMIN/DF	1,964	Excellent
P	0,039	Good
GFI	0,964	Excellent
CFI	0,975	Excellent
RMSEA	0,087	Okay
RMR	0,059	Acceptable

Table 26. *Regression weights of the second model*

			Estimate	S.E.	C.R.	P	Label	Interpretation
FAC1_AT	<---	FAC6_PSI	,259	,083	3,128	,002	par_1	Significant
FAC1_AT	<---	FAC2_EE	,261	,076	3,441	***	par_2	Significant
FAC1_AT	<---	FAC3_PE	,321	,081	3,961	***	par_9	Significant
FAC1_AT	<---	FAC5_TR	,147	,074	1,986	,047	par_10	Significant
FAC1_AT	<---	FAC4_SSI	,031	,068	,447	,655	par_11	
FAC7_BI	<---	FAC3_PE	,256	,062	4,123	***	par_3	Significant
FAC7_BI	<---	FAC1_AT	,595	,067	8,829	***	par_4	Significant

Based on the regression weights presented in Table 26. The performance Expectancy and Attitude have significant impact on the Behavioural Intention. The Performance Expectancy, Effort Expectancy, Peer Social Influence and Trust have significant impact on the Attitude. There is also positive covariances between the factors. The Covariances are presented in the Table 27 and the correlations in the Table 28.

Table 27. *Covariance of the second model*

			Estimate	S.E.	C.R.	P	Label
FAC2_EE	<-->	FAC3_PE	,508	,090	5,674	***	par_5
FAC6_PSI	<-->	FAC4_SSI	,290	,068	4,263	***	par_6
FAC3_PE	<-->	FAC5_TR	,361	,079	4,570	***	par_7
FAC6_PSI	<-->	FAC3_PE	,318	,064	4,932	***	par_8
FAC2_EE	<-->	FAC5_TR	,285	,078	3,662	***	par_12

Table 28. *Correlations in the second model*

			Estimate
FAC2_EE	<-->	FAC3_PE	,533
FAC6_PSI	<-->	FAC4_SSI	,363
FAC3_PE	<-->	FAC5_TR	,406
FAC6_PSI	<-->	FAC3_PE	,366
FAC2_EE	<-->	FAC5_TR	,342

Lastly, the last tested model combines these two models. The model built in SPSS Amos is presented in Figure 20. The model fit values are presented in Table 29. As presented the model fit of this is also good. All the values are excellent and RMSEA is smaller than 0,05. The model fit therefore is considered good. The results for the final model regarding model fit are also presented in the Appendix E.

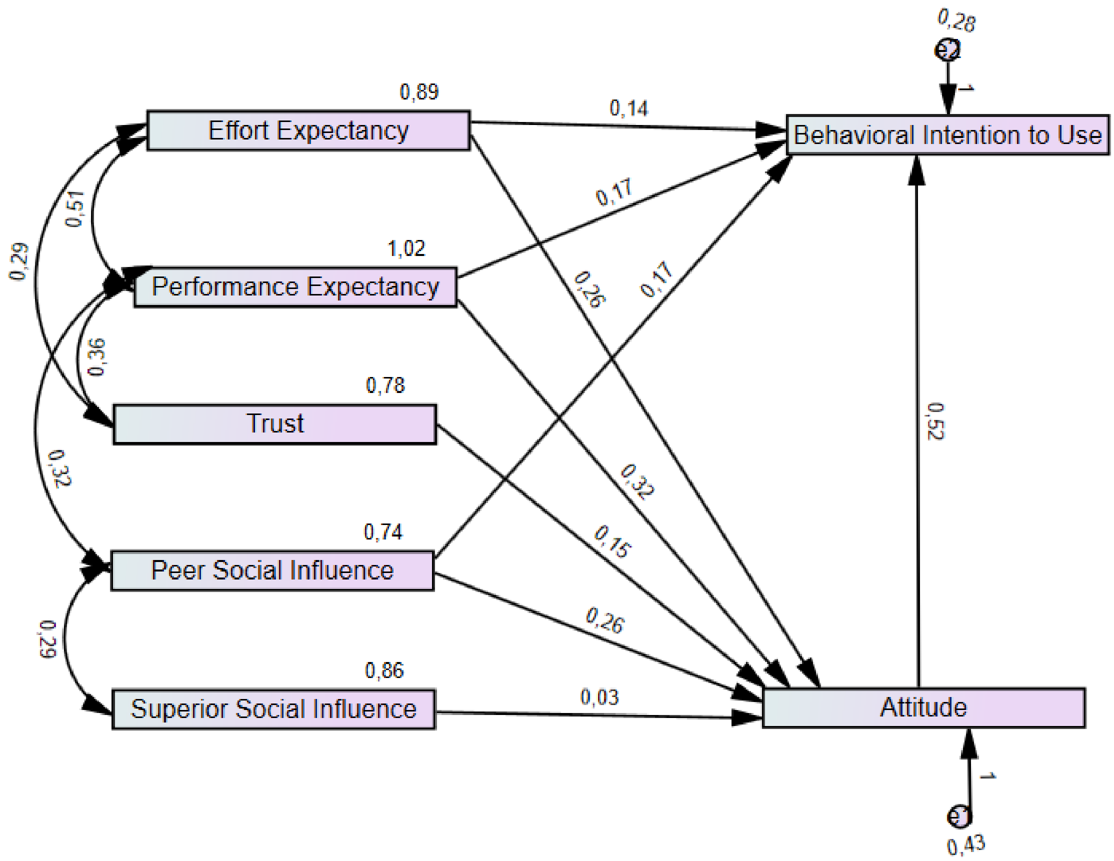

Figure 21. The third Structural Equation Model in SPSS Amos

Table 29. *Model fit of the third model*

	Value	Goal
CMIN/DF	1,295	Excellent
P	0,248	Good
GFI	0,980	Excellent
CFI	0,994	Excellent
RMSEA	0,048	Good
RMR	0,053	Acceptable

The regression weights are presented in Table 30. As presented in the table, Effort Expectancy, Performance Expectancy, Peer Social Influence and Trust have significant impact on Attitude. Attitude, Performance Expectancy, Peer Social Influence and Effort Expectancy have significant Impact on Behavioural Intention to Use. Based on this Superior Influence does not have significant impact on attitude or behaviour intention to use Generative AI.

Table 30. *Regression weights of the third structural equation model*

			Estimate	S.E.	C.R.	P	Label
FAC1_AT	<---	FAC2_EE	,261	,076	3,441	***	par_1
FAC1_AT	<---	FAC3_PE	,321	,081	3,961	***	par_2
FAC1_AT	<---	FAC5_TR	,147	,074	1,986	,047	par_3
FAC1_AT	<---	FAC6_PSI	,259	,083	3,128	,002	par_6
FAC1_AT	<---	FAC4_SSI	,031	,068	,447	,655	par_7
FAC7_BI	<---	FAC2_EE	,140	,064	2,205	,027	par_4
FAC7_BI	<---	FAC3_PE	,173	,066	2,623	,009	par_5
FAC7_BI	<---	FAC1_AT	,521	,070	7,435	***	par_8
FAC7_BI	<---	FAC6_PSI	,171	,063	2,721	,007	par_9

The correlations are presented in Table 31. As in the previous models the Effort Expectancy and Performance Expectancy have stronger positive correlation. All correlations are above 0,3 and significant.

Table 31. *The correlations of the third model*

			Estimate
FAC6_PSI	<-->	FAC4_SSI	,363
FAC2_EE	<-->	FAC3_PE	,533
FAC3_PE	<-->	FAC5_TR	,406
FAC2_EE	<-->	FAC5_TR	,342
FAC3_PE	<-->	FAC6_PSI	,366

The models one and three have the best model fit. As according to Dwivedi et al., (2019) the deleting of attitude as mediating factors could be possible as the factors would still explain the Usage Behaviour Intention. Based on the theory the including of Attitude does give more informative presentation of the factors affecting the Behaviour Intention to use the Technology.

6. KEY FINDINGS AND ANALYSIS

This chapter discusses the results from empirical research based on the previous research. The impact of factors including, Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Trust and Attitude toward Using, to Acceptance of Generative AI was studied via survey. The key findings are discussed in the chapter 6.1. The chapter 6.2. discusses the limitations of the study and future research suggestions.

6.1 Factors impacting the Behavioral Intention to use Generative AI

The survey had a total of 135 responses. Out of these responses, 130 were included based on successful completion of the instructional manipulation check and the respondents' residency in Finland. Among the respondents, 92% were younger than 35 years old. Male respondents constituted 60%, females made up 38.2%, and 0.8% preferred not to say. The largest group of respondents belonged to the profession of students (50.8%), followed by Software Development (17.8%) and Consultancy (13.85%). The most used Generative AI technology among the respondents was ChatGPT. Other frequently used technologies included Microsoft Bing's Chat, DALL-E 2, Google Bard, and GitHub Copilot.

Exploratory and Confirmatory Factor analysis was conducted, and seven factors were recognized. The factors included Performance Expectancy, Effort Expectancy, Peer Social Influence, Superior Social Influence, Trust, Attitude and Behavioral Intention to Use. The Facilitating conditions factor could not be formed and lacked internal consistency as well as reliability. The Facilitating Conditions was also found to be not significant by Cao et al. (2021). The Facilitating Conditions is also in the UTAUT model considered to have affect to actual use and not to Behaviour Intention, therefore excluding the factor is reasonable. Even though Dwivedi et al., (2019) argue that the path form facilitating conditions to behavioural intent should be included also, it could not be determined in the research. In general, the respondents did consider that they have the resources and knowledge needed to use Generative AI, but the impact to Behaviour Intention to Use could not be determined. The relationships found in research between Performance Expectancy, Effort Expectancy, Peer Social Influence, Trust, Attitude and Behavioral Intention to Use are presented in the Figure 22.

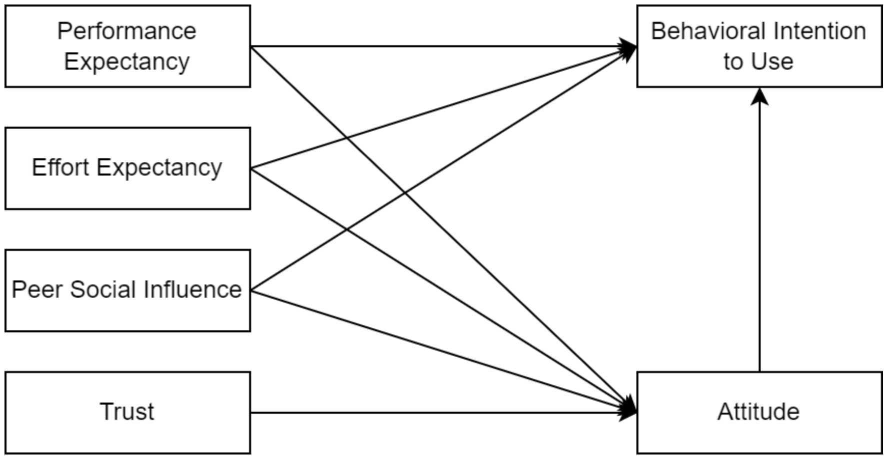

Figure 22. *The factors impacting the Behavioural Intention to Use Generative AI.*

Further on, one of these responses was excluded as an outlier based on the cook's distance. In the end, total on 129 responses was included in the Structural Equation Modelling based on the Exploratory and Confirmatory Factor Analyses. The results indicate that Performance Expectancy, Attitude, Effort Expectancy and Peer Social Influence have significant impact on Behavioral Intention to Use. In addition, Performance Expectancy, Effort Expectancy, Peer Social Influence and Trust have significant impact on Attitude. Furthermore, Superior Social Influence was not found to have significant direct impact to Behavioral Intention to Use or Attitude. The significant impact of Attitude and Performance Expectancy was also concluded by Brachten et al. (2021), Andrews et al. (2021) and Tiwari et al. (2023). These two factors also in this research have more significant impact compared to the impact of Effort Expectancy and Peer Social Influence.

According to Ritala et al. (2003) Generative AI has the capability and potential to increase the productivity and performance of knowledge work When it comes to tasks such as content creation, writing, coding and debugging Generative AI can be used to boost the productivity (Eloundou et al., 2023; Ouyang et al., 2022; Ritala et al., 2023). The results of the survey also show that Generative AI is considered to be useful tool and it allows the respondents to accomplish tasks more quickly. The Generative AI tools increases their productivity.

According to Accenture (2023) models such as ChatGPT are simple to use. De Andrés-Sánchez & Gené-Albesa (2023) describe that chatbot technology is develop allow easy interaction in many circumstances. Tiwari et al. (2023) research showed that students found the tools to be difficult to use and they did not consider the answers understandable. On contrary to the Tiwari et al. (2023) research, the Generative AI was in this research generally considered easy to use and learning how to use it efficiently was also considered easy. The respondents did include for example answers from people who work in areas such as Software Development which has the potential to affect the results. The experience and frequency of use was not fully studied and therefore the effect is unknown.

The Performance Expectancy or Perceived usefulness is considered more significant than Ease of Use or Effort Expectancy (Andrews et al., 2021; Brachten et al., 2021; Choung et al., 2023). Furthermore, when it comes to manager's attitudes towards using artificial intelligence in organizational decision making or acceptance of AI among librarians the Effort Expectancy did not have any significance (Andrews et al., 2021; Cao et al., 2021). The results of the research indicates that when it comes to technologies such as Generative AI, ChatGPT (Tiwari et al., 2023), AI voice assistants (Choung et al. 2023) and chatbots (De Andrés-Sánchez & Gené-Albesa) the Effort Expectancy has significant impact on the Behavioural Intention to Use the technology. These types of technologies are developed to assist and to be easy to use, which could be one of the reasons for the difference.

The Social Influence was based on the exploratory and confirmatory factory analysis divided into two independent factors. Most of the respondents considered that peers who they consider important or influence their behaviour would think that they should use Generative AI. The means were lower when it comes to the superior. Brachten et al. (2021) found that peer influence had a much stronger effect on subjective norms than superior's influence. Subjective norms, belief that an important person or group of people will approve or support particular behaviour (Ham et al., 2015), in Brachten et al. (2021) research on the other hand has significant impact on usage intention. The knowledge work is also characterized to be autonomous which could partially explain that superior influence does not have as significant an impact on the intention to use Generative AI. In addition, half of the respondents were students, who might not have superiors.

The highest influence according to survey has the media or online communities. The discussion of Generative AI has significantly increased after the publication of the ChatGPT in November 2022, and I could transfer to the responses. The statement was not included in the Peer Social Influence factor as it did not have satisfactory loading in exploratory factor analysis so the significance of the impact on Behaviour Intention to Use Generative AI remains Unknown.

Attitude toward using is the most important influencing factor on usage intention behavior (Brachten et al., 2021). The influence of Performance Expectancy and Effort Expectancy on Attitude has also been confirmed in several studies (Cao et al., 2021; Dwivedi et al., 2019; Venkatesh et al., 2012). This research also indicates that Performance Expectancy and Effort Expectancy have a significant impact on Attitude. In addition, peer social influence was found to have an impact on attitude. Dwivedi et al. (2019) also found that social influence could affect attitude. Choung et al. (2023) also presented that trust would have an indirect impact on the intention to use AI voice assistants. The direct impact of trust on Behavioral Intention to use Generative AI was not found to be significant. Choudhury & Shamszare (2023), on the other hand, found that trust would have a significant direct effect on intentions to use as well as actual use. This was not supported by the study.

The attitudes towards Generative AI were found to be positive. Tiwari et al. (2023) also found that students' attitudes towards Generative AI are positive, and using the tool was found enjoyable, which is related to the positive attitude. Based on the research, respondents consider using Generative AI a good idea, and working with Generative AI is fun, and they enjoy working with AI. The majority of respondents also agree that it makes their work more interesting, even though there is also more disagreement.

The limitations and risks of Generative AI are acknowledged by OpenAI (Brown et al., 2020; OpenAI, 2023). The most common limitations are that Generative AI can generate biased and incorrect responses, and the models are known to hallucinate and fail basic reasoning tasks (OpenAI, 2023). The quality of training data reflects the quality of responses generated by the models. The data used to train ChatGPT is collected from the web, and therefore it can contain incorrect information. The consequences of overreliance and blind trust in ChatGPT could be serious (Choudhury & Shamszare, 2023).

The majority of the respondents were neutral or expressed distrust toward the answers generated by Generative AI. In addition, the respondents did show concern toward AI generating biased or incorrect information. At the same time, the majority of respondents also believe that Generative AI can provide reliable results. It is also noticeable that some of the respondents strongly disagree that they trust answers generated by AI and do not have any worries toward AI generating biased or incorrect answers. This could indicate that the concerns of overreliance expressed by, for example, Brown et al. (2020) and Choung et al. (2023), could be supported.

Trust, based on the research, did not significantly impact the intention to use Generative AI. It did show a significant impact on Attitude. There is also some creditability issues regarding the factor and therefore the results should be considered with caution. Performance Expectancy, Peer Social Influence, and Effort Expectancy, on the other hand, were found to have a more significant impact on Attitude than Trust. This suggest that even if there is some concern about answers generated by Generative AI, the Generative AI's capability to increase productivity and ease of use is most important factors for users considering using Generative AI.

6.2 Limitations of the Study and Future Research

The research sample was relatively small, which limits the validity of the results. The survey was also based on voluntariness, which could attract a certain type of respondent and might not provide a full representation of the population. It is noteworthy that approximately half of the responses came from students, which could potentially impact the results as for example the superior influence could be significantly affected by the fact that students don’t necessarily have superiors. Moderating factors such as age, gender, voluntariness, and experience were not investigated, even though they are included in the UTAUT model presented by Venkatesh et al. Moderating factors, as suggested by Alsharhan et al. (2023), can be crucial for understanding adoption and behavior. Additionally, the relationship between actual use and behavioral intention was not explored, nor was the relationship between facilitating conditions and actual use.

The data underwent screening, and the reliability of the factors was tested. The trust factor showed a slightly low value of Cronbach's Alpha (0.671), which raises questions about the reliability of this factor. Furthermore, the Facilitating Conditions factor did not meet the required levels of reliability and internal consistency. Some statements had to be disqualified, indicating that certain statements might have required additional clarification. In addition, the testing for CR and AVE showed that there are issues with multiple factors. The Attitude is highly correlated with the Behaviour intention and performance expectancy. Especially, the Attitude and Behaviour Intention highly correlate which could indicate that these two factors might not be separatable. In this thesis these are still research as different factors to have more insightful answers to the research questions. In addition, the effort expectancy and trust did not measure the required average variance extracted. There should be some caution when it comes to analysing the results of the study. The existing literature and previous research on the other hand does support the results presented in this study. These issues and results do highlight the need of further developing the measuring constructs regarding the utilization and acceptance of Generative AI. The fast development Generative AI technologies and their unique characteristics might require further development of the UTAUT -model. This also suggest that further research is needed to confirm the models presented in this study.

One of the major challenges of this research is that the latest Generative AI tools are relatively new, and the research on the adoption and utilization of these technologies is still quite limited. Moreover, the development of these technologies is advancing rapidly, which means that some information could quickly become outdated. Especially, when it comes to utilizations of these technologies new possibilities are emerging continuously. The research on the UTAUT model in the field of knowledge management was also found to be limited, making the research more challenging. This does also relate to the significance of the research filling the gap when it comes to research on technology acceptance and utilization of AI in Knowledge work.

The sample size of the survey was limited and therefore future research to confirm the presented model of Acceptance of Generative AI would be needed. In addition, moderating factors such as age, gender and experience were discussed, but impact was not researched in his study. Furthermore, the influence media on online communities was considered the highest in survey but the impact of it to intention to use could not identified. As the superior social influence was also unexpectedly found insignificant, further research of Social Influence could therefore also be interesting and needed. The presented model could be also applied to research more specific topics in the areas of Generative AI and Knowledge work.

7. CONCLUSIONS

Generative AI refers to a type of artificial intelligence designed to create new content, such as text, images, and audio. The latest Generative AI tools are based on GPT models. These types of models are built based the Transformers introduced by Vaswani et al. (2017). The models are pretrained with large amounts of data and go through multiple fine-tuning processes. They can generate plausible and high-quality outputs that mimic human-created content. Generative AI tools, such as ChatGPT, Bard, GitHub Copilot, Microsoft Bing, and Microsoft Copilot, can be used as assistants in various tasks. The impact of these technologies when it comes changing the knowledge work is undeniably major and it will in some levels have effect on all knowledge workers.

Knowledge work is done by for example experts, research, specialists, and managers. The work consists of exploring and generating new information. The knowledge work is characterized by its autonomous, complex, and ambiguous nature. The Generative AI tools have the capabilities to enhance knowledge work by increasing the productivity of knowledge workers as it can minimize the time consumed in repetitive tasks. Generative AI tools can be used to create content such as emails, articles, summaries, to write and debug code and to ease the process of information retrieval. The Generative AI has the potential to assist in tasks demanding creativity and increase the learning rates, Generative AI still has its limitations, and it can for example create biased or incorrect information. Therefore, it still can’t replace knowledge work that requires critical thinking and high expertise.

This research was conducted to analyse acceptance of Generative AI among knowledge workers in Finland. The aim of the research was to recognize the factors impacting the acceptance of Generative AI in knowledge work. The empirical research was conducted as a survey based on modified UTAUT model by Venkatesh et al. (2003). Initially, seven factors were included in the survey: Performance Expectancy, Effort Expectancy, Social Influence, Attitude, Trust, Facilitating Conditions and Behavioural Intention to Use. Performance Expectancy refers to the degree which individual believes using system will improve their job performance (Venkatesh et al., 2003). Effort Expectancy consider the ease of use and effort needed to adopt the technology. Social Influence measures the impact of peers and superiors to individuals’ behaviour. Facilitating Conditions considers the organizational and technical infrastructures existing to support the use of the new tools. (Venkatesh et al., 2003) The attitudes and trust were added to the original model based on previous research. Attitude considers the feelings and enjoyment towards the technology (Andrews et al., 2021) and the trust for example the users concern towards the Generative AI (Choung et al., 2023).

Total of 135 responses were collected from students and professionals from the areas of such Software Development, Consultancy and Management. The factors impacting the Acceptance of Generative AI were identified through exploratory and confirmatory factor analyses. Seven factors were identified: Performance Expectancy, Effort Expectancy, Peer Social Influence, Superior Social Influence, Attitude, Trust and Behaviour Intention to Use. The Facilitating Conditions did not have the reliability and internal consistency that was acquired.

The results of the research indicate that attitude has the most significant impact on behavioural intention to use Generative AI. In addition, Performance Expectancy, Effort Expectancy and Peer Social influence have significant impact on the behaviour intention to use Generative AI. The Performance Expectancy, Effort Expectancy, Peer Social Influence and Trust also have significant impact on Attitude. In contrast to Peer Social Influence, Superior Social Influence was found not to have significant impact on users' intention to use Generative AI. The final mode presenting the factors affecting the Acceptance of Generative AI is presented in the Figure 22 (p.67). The results of research support that Attitude should be presented in the UTAUT – model as also presented by for example (Andrews et al., 2021; Cao et al., 2021; Dwivedi et al., 2019; Venkatesh et al., 2012) as well as the indirect impact of trust. There are some limitations to the measurements such as small sample size and the reliability of the factors which suggest that further research is needed support the developed research model.

In general, the respondents had positive attitudes towards Generative AI. Using Generative AI tools was found fun, and respondents enjoy working with it. The respondents also recognized that Generative AI was useful in their work, increases productivity and allows accomplish tasks faster. In addition, majority of respondents found the tools easy to use and interaction clear and understandable. The users also have some distrust on Generative AI and concern of Generative AI generating biased or incorrect information which affect the attitudes towards using Generative AI but not directly to intentions to use it.

The research suggests that biggest drivers for Generative AI acceptance are positive attitudes towards its and its capabilities to increase the productivity of the work. Therefore, it could suggest that the new capabilities and advancement of these technologies will accelerate the adoption as they become more and more useful in different areas of knowledge work. From managerial point of view, based on this study, it could be more difficult impact on the adoption of Generative AI, as the Superior Social Influence and Facilitating Factors such organizational support could not be found significant.

In conclusion, the research provides valuable insights from the UTAUT model perspective by confirming the significance of key factors such as Performance Expectancy, Effort Expectancy, Social Influence, particularly Peer Social Influence, Attitude, and Trust in influencing the acceptance and intention to use Generative AI tools. The research conducts to developing the models to better accommodate and explain the acceptance and utilization of current technologies such as Generative AI. The results support the previous research of the UTAUT model, but also further develops it to better accommodate the present-day technologies. In addition, the research conducts to analysing the geographical differences when it comes to adoption of technologies.

These findings can inform strategies to promote the adoption of Generative AI in knowledge work. The research indicates that user attitudes and perceptions are essential drivers of technology acceptance. The results highlight the potential of Generative AI in knowledge work and its capability to enhance the productivity of knowledge workers, as well the need to address trust and biases to promote wider adoption. The research addresses some concern related to overreliance and trust towards the Generative AI. The results provide valuable insight to user's acceptance towards Generative AI in Finland and critically discusses the capabilities and limitations of the technology. Based on the research there is a need for a balanced and cautious approach to adoption and utilization of Generative AI so it can be utilized in safe and efficient manner.

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APPENDIX A

- Acceptance of Generative AI

This survey is conducted as part of a master's thesis to investigate users' acceptance of Generative Artificial Intelligence. Generative AI is a type of artificial intelligence that can create content, such as text, images, or audio. Examples of these applications include ChatGPT, Bard, GitHub Copilot, Microsoft Copilot, and others.

The survey will ask for your opinions regarding the use of these applications. Completing the survey should take only 5-10 minutes. Your responses will be used solely for research purposes, and the results will be published only in summary form.

Thank you for participating the survey. If you have any questions about this survey, you can contact me via email at kati.koponen@tuni.fi.

There are 8 questions in this survey.

- Demographics
- Gender

*

Choose one of the following answers

Please choose **only one** of the following:

- Female
- Male
- Non-binary / third gender
- Prefer not to say
- Age

*

Choose one of the following answers

Please choose **only one** of the following:

- Under 18
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65 and over
- Pick the area of profession closest to yours.

*

Choose one of the following answers

Please choose **only one** of the following:

- Student

- Consultancy
- Research
- Education
- Software development
- Management
- Sales
- Marketing
- Engineering
- Others

Select your area of residence.

*

Choose one of the following answers

Please choose **only one** of the following:

- Finland
- Other

- Experience of Generative AI
- Select Generative AI tools you have experience of using.

*

Check all that apply

Please choose **all** that apply:

- ChatGPT
- DALL-E 2
- Microsoft Copilot
- Microsoft Bing AI
- Google Bard
- Github Copilot
- Synthesia
- Claude
- AlphaCode
- Other
- Which other Generative AI tools have you used?"
-

Only answer this question if the following conditions are met:

Answer was at question ' [G03Q05]' (Select Generative AI tools you have experience of using.)

Please write your answer here:

- How often do you use Generative AI in your work?

*

Choose one of the following answers

Please choose **only one** of the following:

- Daily
- 2-3 times a week
- 4-6 times a week
- Once a week
- Monthly
- Rarely
- Never
- Acceptance of Generative AI
- Please read each statement carefully and select the response that best fits your opinion.

*

Please choose the appropriate response for each item:

I find generative AI useful in my job.

Using generative AI allows me to accomplish tasks faster.

Using generative AI increases my productivity.

I believe Generative AI has a positive impact on my career.

My interaction with the generative AI is clear and understandable.

I find the Generative AI easy to use.

Learning how to use Generative AI efficiently is easy for me.

It is easy for me to become skillful using Generative AI.

Peers who are important to me would think that I should use Generative AI.

My superiors who influence my behavior would think that I should use Generative AI.

Peers who influence my behaviour would think that I should use Generative AI.

My superiors to whom I report would think that I should use Generative AI.

The media or online communities think that I should use AI.

I have the resources needed to use Generative AI.

I have necessary knowledge to use Generative AI.

Generative AI supports other technologies I use.

I get help from others when I have issues using Generative AI.

Using Generative AI is a good idea.

Working with Generative AI is fun.

Using Generative AI makes my work more interesting.

I enjoy working with Generative AI.

I trust the answers generated by Generative AI.

I believe that Generative AI can give reliable results.

I am worried about Generative AI giving biased answers.
I am worried about Generative AI generating incorrect information.
Generative AI is secure and protects my privacy and confidential information.

I intend to use Generative AI.
I try to use Generative AI as much as possible.
I plan to use Generative AI frequently.

I am experienced using Generative AI.
Please select "Agree" to this question.

This is a question help text.
Thank you for participating the survey.
10-06-2023 – 12:23
Submit your survey.
Thank you for completing this survey.

APPENDIX B

Exploratory Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,800
Bartlett's Test of Sphericity	Approx. Chi-Square	1087,999
	df	190
	Sig.	<,001

Communalities[a]

	Initial	Extraction
[Using generative AI allows me to accomplish tasks faster.] PE	,672	,999
[Using generative AI increases my productivity.] PE	,615	,608
[I find generative AI useful in my job.] PE	,557	,559
[My interaction with the generative AI is clear and understandable.] EE	,417	,396
[I find the Generative AI easy to use.] EE	,418	,415
[Learning how to use Generative AI efficiently is easy for me.] EE	,530	,845
[It is easy for me to become skillful using Generative AI.] EE	,469	,450
[Peers who are important to me would think that I should use Generative AI.] SI	,423	,476
[My superiors who influence my behavior would think that I should use Generative AI.] SI	,643	,767
[Peers who influence my behaviour would think that I should use Generative AI.] SI	,457	,699
[My superiors to whom I report would think that I should use Generative AI.] SI	,628	,753

[Working with Generative AI is fun.] AT	,503	,629
[Using Generative AI makes my work more interesting.] AT	,348	,336
[I enjoy working with Generative AI.] AT	,667	,786
[I trust the answers generated by Generative AI.] TR	,336	,267
[I am worried about Generative AI giving biased answers.] TR	,418	,516
[I am worried about Generative AI generating incorrect information.] TR	,478	,755
[I believe that Generative AI can give reliable results.] TR	,359	,307
[I plan to use Generative AI frequently.] BI	,601	,666
[I intend to use Generative AI.] BI	,565	,756

Extraction Method: Maximum Likelihood.
a. One or more communalitity estimates greater than 1 were encountered during iterations. The resulting solution should be interpreted with caution.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5,846	29,231	29,231	3,649	18,247	18,247	4,163
2	2,553	12,765	41,996	2,419	12,095	30,342	3,370
3	1,800	8,998	50,994	2,244	11,218	41,560	4,030
4	1,348	6,742	57,736	1,312	6,559	48,119	2,048
5	1,165	5,827	63,563	1,218	6,090	54,210	2,375
6	1,051	5,256	68,819	,641	3,207	57,416	2,158
7	,795	3,973	72,791	,504	2,522	59,938	3,968
8	,706	3,528	76,319				
9	,670	3,351	79,670				

10	,639	3,195	82,865				
11	,574	2,869	85,734				
12	,475	2,377	88,111				
13	,408	2,038	90,149				
14	,390	1,951	92,101				
15	,356	1,779	93,879				
16	,317	1,586	95,465				
17	,281	1,407	96,872				
18	,233	1,164	98,036				
19	,224	1,121	99,157				
20	,169	,843	100,000				

Extraction Method: Maximum Likelihood.
a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Factor Matrix[a]

	Factor						
	1	2	3	4	5	6	7
[Using generative AI allows me to accomplish tasks faster.] PE	,999						
[Using generative AI increases my productivity.] PE	,711						
[I find generative AI useful in my job.] PE	,652						
[I enjoy working with Generative AI.] AT	,570	,324	,367	,362			
[I intend to use Generative AI.] BI	,529	,362				,320	-,324
[I believe that Generative AI can give reliable results.] TR	,318						
[My superiors who influence my behavior would think that I should use Generative AI.] SI		,738		-,418			

[My superiors to whom I report would think that I should use Generative AI.] SI		,737		-,376			
[Peers who influence my behaviour would think that I should use Generative AI.] SI		,496				,395	,348
[I plan to use Generative AI frequently.] BI	,422	,454	,348	,338			
[Peers who are important to me would think that I should use Generative AI.] SI		,395				,305	
[Using Generative AI makes my work more interesting.] AT	,307	,359					
[Learning how to use Generative AI efficiently is easy for me.] EE			,720		-,340		
[It is easy for me to become skillful using Generative AI.] EE	,321		,567				
[I find the Generative AI easy to use.] EE			,538				
[My interaction with the generative AI is clear and understandable.] EE	,405		,475				
[I trust the answers generated by Generative AI.] TR			,315				
[Working with Generative AI is fun.] AT	,310	,308		,450		-,358	
[I am worried about Generative AI generating incorrect information.] TR				-,376	,695		
[I am worried about Generative AI giving biased answers.] TR					,564		

Extraction Method: Maximum Likelihood.

a. 7 factors extracted. 12 iterations required.

Goodness-of-fit Test

Chi-Square	df	Sig.
62,157	71	,764

Pattern Matrix[a]

	Factor						
	1	2	3	4	5	6	7
[Working with Generative AI is fun.] AT	,965						
[I enjoy working with Generative AI.] AT	,786						
[Using Generative AI makes my work more interesting.] AT	,448						
[Learning how to use Generative AI efficiently is easy for me.] EE		1,020					
[I find the Generative AI easy to use.] EE		,610					
[It is easy for me to become skillful using Generative AI.] EE		,543					
[My interaction with the generative AI is clear and understandable.] EE		,435					
[Using generative AI allows me to accomplish tasks faster.] PE			1,079				

[Using generative AI increases my productivity.] PE			,499				
[I find generative AI useful in my job.] PE			,484				
[My superiors to whom I report would think that I should use Generative AI.] SI				,870			
[My superiors who influence my behavior would think that I should use Generative AI.] SI				,834			
[I am worried about Generative AI generating incorrect information.] TR					,902		
[I am worried about Generative AI giving biased answers.] TR					,631		
[I trust the answers generated by Generative AI.] TR					,355		
[I believe that Generative AI can give reliable results.] TR					,333		
[Peers who influence my behaviour would think that I should use Generative AI.] SI						,840	
[Peers who are important to me would think that I should use Generative AI.] SI						,600	

[I intend to use Generative AI.] BI							,876
[I plan to use Generative AI frequently.] BI							,624

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Structure Matrix

	Factor						
	1	2	3	4	5	6	7
[I enjoy working with Generative AI.] AT	,873	,450	,606		,351		,615
[Working with Generative AI is fun.] AT	,763		,338				,410
[Using Generative AI makes my work more interesting.] AT	,545		,339				,446
[I believe that Generative AI can give reliable results.] TR	,434		,341		,404		,369
[Learning how to use Generative AI efficiently is easy for me.] EE		,868	,306				
[It is easy for me to become skillful using Generative AI.] EE	,391	,637	,366		,334		,380
[I find the Generative AI easy to use.] EE	,328	,616	,300				

[My interaction with the generative AI is clear and understandable.] EE	,419	,586	,436				,388
[Using generative AI allows me to accomplish tasks faster.] PE	,532	,440	,994		,335	,321	,558
[Using generative AI increases my productivity.] PE	,529	,538	,733				,607
[I find generative AI useful in my job.] PE	,546	,414	,681	,310	,382		,568
[My superiors who influence my behavior would think that I should use Generative AI.] SI				,866		,371	
[My superiors to whom I report would think that I should use Generative AI.] SI				,865			
[I am worried about Generative AI generating incorrect information.] TR					,854		
[I am worried about Generative AI giving biased answers.] TR					,632	-,305	
[I trust the answers generated by Generative AI.] TR		,349			,417		
[Peers who influence my behaviour would think that I should use Generative AI.] SI				,357		,822	

[Peers who are important to me would think that I should use Generative AI.] SI						,662	,335
[I intend to use Generative AI.] BI	,537	,309	,570			,351	,856
[I plan to use Generative AI frequently.] BI	,672	,387	,472			,329	,780

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

Factor Correlation Matrix

Factor	1	2	3	4	5	6	7
1	1,000	,439	,581	,196	,296	,351	,672
2	,439	1,000	,495	,029	,310	-,038	,441
3	,581	,495	1,000	,134	,378	,316	,620
4	,196	,029	,134	1,000	,153	,335	,238
5	,296	,310	,378	,153	1,000	-,009	,316
6	,351	-,038	,316	,335	-,009	1,000	,330
7	,672	,441	,620	,238	,316	,330	1,000

Extraction Method: Maximum Likelihood.
Rotation Method: Promax with Kaiser Normalization.

APPENDIX C

Reliability analysis for the research factors.

Reliability Statistics

Cronbach's Alpha	N of Items
,830	3

Item Statistics

	Mean	Std. Deviation	N
[I find generative AI useful in my job.] PE	4,0308	,86211	130
[Using generative AI allows me to accomplish tasks faster.] PE	4,2308	,76288	130
[Using generative AI increases my productivity.] PE	4,0769	,84096	130

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
[I find generative AI useful in my job.] PE	8,3077	2,199	,629	,828
[Using generative AI allows me to accomplish tasks faster.] PE	8,1077	2,205	,778	,685
[Using generative AI increases my productivity.] PE	8,2615	2,179	,671	,784

Reliability Statistics

Cronbach's Alpha	N of Items
,751	4

Item Statistics

	Mean	Std. Deviation	N

[My interaction with the generative AI is clear and understandable.] EE	3,9077	,75170	130
[I find the Generative AI easy to use.] EE	4,1154	,73278	130
[Learning how to use Generative AI efficiently is easy for me.] EE	3,8923	,83755	130
[It is easy for me to become skillful using Generative AI.] EE	3,6769	,95003	130

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
[My interaction with the generative AI is clear and understandable.] EE	11,6846	4,109	,500	,718
[I find the Generative AI easy to use.] EE	11,4769	4,034	,552	,694
[Learning how to use Generative AI efficiently is easy for me.] EE	11,7000	3,483	,644	,637
[It is easy for me to become skillful using Generative AI.] EE	11,9154	3,473	,514	,721

Reliability Statistics

Cronbach's Alpha	N of Items
,705	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted

[Peers who are important to me would think that I should use Generative AI.] SI	3,5000	,640	,545	.
[Peers who influence my behaviour would think that I should use Generative AI.] SI	3,5769	,572	,545	.

Item Statistics

	Mean	Std. Deviation	N
[Peers who are important to me would think that I should use Generative AI.] SI	3,5769	,75601	130
[Peers who influence my behaviour would think that I should use Generative AI.] SI	3,5000	,79971	130

Reliability Statistics

Cronbach's Alpha	N of Items
,851	2

Item Statistics

	Mean	Std. Deviation	N
[My superiors to whom I report would think that I should use Generative AI.] SI	3,2154	,92330	130
[My superiors who influence my behavior would think that I should use Generative AI.] SI	3,3000	,84128	130

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted

[My superiors to whom I report would think that I should use Generative AI.] SI	3,3000	,708	,745	.
[My superiors who influence my behavior would think that I should use Generative AI.] SI	3,2154	,852	,745	.

Reliability Statistics

Cronbach's Alpha	N of Items
,752	3

Item Statistics

	Mean	Std. Deviation	N
[Working with Generative AI is fun.] AT	4,0077	,82119	130
[Using Generative AI makes my work more interesting.] AT	3,4462	,95691	130
[I enjoy working with Generative AI.] AT	3,9308	,82770	130

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
[Working with Generative AI is fun.] AT	7,3769	2,330	,622	,626
[Using Generative AI makes my work more interesting.] AT	7,9385	2,229	,497	,780
[I enjoy working with Generative AI.] AT	7,4538	2,281	,639	,606

Reliability Statistics

Cronbach's Alpha	N of Items
,652	4

Item Statistics

	Mean	Std. Deviation	N
[I trust the answers generated by Generative AI.] TR	2,8692	,85715	130
[I believe that Generative AI can give reliable results.] TR	3,5462	,89018	130
[I am worried about Generative AI giving biased answers.] TR	2,3385	,96089	130
[I am worried about Generative AI generating incorrect information.] TR	2,0846	,93207	130

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
[I trust the answers generated by Generative AI.] TR	7,9692	4,294	,412	,597
[I believe that Generative AI can give reliable results.] TR	7,2923	4,332	,369	,625
[I am worried about Generative AI giving biased answers.] TR	8,5000	4,004	,407	,602
[I am worried about Generative AI generating incorrect information.] TR	8,7538	3,675	,545	,500

Reliability Statistics

Cronbach's Alpha	N of Items
,774	2

Item Statistics

	Mean	Std. Deviation	N
[I intend to use Generative AI.] BI	4,1923	,83616	130
[I plan to use Generative AI frequently.] BI	3,9154	1,03456	130

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
[I intend to use Generative AI.] BI	3,9154	1,070	,646	.
[I plan to use Generative AI frequently.] BI	4,1923	,699	,646	.

Reliability Statistics

Cronbach's Alpha	N of Items
,791	7

Case Processing Summary

		N	%
Cases	Valid	130	100,0
	Excluded[a]	0	,0
	Total	130	100,0

a. Listwise deletion based on all variables in the procedure.

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Attitude_score	,0000000	13,199	,724	,723
Effort_Expectancy_score	,0000000	14,882	,443	,779

Performance_Expectancy_score	,0000000	13,025	,692	,728
Superior_score	,0000000	16,014	,286	,806
Trust_score	,0000000	15,377	,392	,787
Peer_score	,0000000	15,661	,363	,792
Behaviour_intention_score	,0000000	13,035	,768	,715

Item Statistics

	Mean	Std. Deviation	N
Attitude_score	,0000000	,93801825	130
Effort_Expectancy_score	,0000000	,94631885	130
Performance_Expectancy_score	,0000000	,99889888	130
Superior_score	,0000000	,93162174	130
Trust_score	,0000000	,91241029	130
Peer_score	,0000000	,89137954	130
Behaviour_intention_score	,0000000	,92438309	130

APPENDIX D

The results for confirmatory factor analysis.

Estimates (Group number 1 - Default model)
Scalar Estimates (Group number 1 - Default model)
Maximum Likelihood Estimates
Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
Q21	<---	Attitude	1,000				
Q20	<---	Attitude	,652	,109	5,995	***	
Q19	<---	Attitude	,723	,091	7,990	***	
Q03	<---	Performance	1,000				
Q02	<---	Performance	,969	,094	10,300	***	
Q01	<---	Performance	,930	,108	8,633	***	
Q08	<---	Effort	1,000				
Q07	<---	Effort	,988	,164	6,019	***	
Q06	<---	Effort	,792	,139	5,695	***	
Q05	<---	Effort	,821	,143	5,736	***	
Q25	<---	Trust	1,858	,476	3,899	***	
Q24	<---	Trust	1,584	,417	3,801	***	
Q23	<---	Trust	1,000				
Q22	<---	Trust	1,051	,315	3,340	***	
Q12	<---	Superior	1,000				
Q10	<---	Superior	1,221	,246	4,959	***	
Q09	<---	Peer	1,000				
Q11	<---	Peer	1,040	,189	5,491	***	
Q27	<---	Behavior	1,000				
Q29	<---	Behavior	1,270	,148	8,579	***	

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
Q21	<---	Attitude	,931
Q20	<---	Attitude	,525
Q19	<---	Attitude	,679
Q03	<---	Performance	,805
Q02	<---	Performance	,860
Q01	<---	Performance	,730
Q08	<---	Effort	,635
Q07	<---	Effort	,711
Q06	<---	Effort	,652
Q05	<---	Effort	,658
Q25	<---	Trust	,758
Q24	<---	Trust	,627
Q23	<---	Trust	,427
Q22	<---	Trust	,466
Q12	<---	Superior	,745
Q10	<---	Superior	,999
Q09	<---	Peer	,744
Q11	<---	Peer	,732
Q27	<---	Behavior	,793
Q29	<---	Behavior	,815

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
Effort	<-->	Superior	-,008	,042	-,197	,844	
Effort	<-->	Peer	-,031	,041	-,757	,449	
Effort	<-->	Trust	,081	,034	2,357	,018	
Performance	<-->	Effort	,247	,059	4,211	***	
Effort	<-->	Behavior	,177	,053	3,342	***	
Attitude	<-->	Effort	,230	,060	3,868	***	
Trust	<-->	Superior	,046	,031	1,511	,131	
Performance	<-->	Superior	,074	,047	1,566	,117	
Attitude	<-->	Superior	,079	,052	1,505	,132	
Trust	<-->	Peer	-,027	,027	-,981	,326	
Performance	<-->	Peer	,121	,046	2,635	,008	
Attitude	<-->	Peer	,120	,050	2,391	,017	
Performance	<-->	Trust	,104	,038	2,710	,007	
Trust	<-->	Behavior	,071	,034	2,077	,038	
Attitude	<-->	Trust	,094	,039	2,413	,016	
Performance	<-->	Behavior	,323	,063	5,170	***	
Attitude	<-->	Performance	,366	,066	5,554	***	
Attitude	<-->	Behavior	,377	,068	5,579	***	
Superior	<-->	Peer	,156	,055	2,850	,004	
Superior	<-->	Behavior	,096	,050	1,920	,055	
Peer	<-->	Behavior	,170	,050	3,409	***	

Correlations: (Group number 1 - Default model)

			Estimate
Effort	<-->	Superior	-,020
Effort	<-->	Peer	-,092
Effort	<-->	Trust	,356
Performance	<-->	Effort	,610
Effort	<-->	Behavior	,446
Attitude	<-->	Effort	,500
Trust	<-->	Superior	,178
Performance	<-->	Superior	,160
Attitude	<-->	Superior	,149
Trust	<-->	Peer	-,126
Performance	<-->	Peer	,321
Attitude	<-->	Peer	,279
Performance	<-->	Trust	,405
Trust	<-->	Behavior	,283
Attitude	<-->	Trust	,325
Performance	<-->	Behavior	,725
Attitude	<-->	Performance	,706
Attitude	<-->	Behavior	,744
Superior	<-->	Peer	,405
Superior	<-->	Behavior	,212
Peer	<-->	Behavior	,458

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
Attitude	,589	,096	6,149	***	
Performance	,455	,087	5,254	***	
Effort	,361	,101	3,586	***	
Trust	,143	,066	2,169	,030	
Superior	,470	,128	3,657	***	
Peer	,314	,081	3,891	***	
Behavior	,437	,089	4,929	***	
e1	,091	,048	1,905	,057	
e2	,658	,086	7,626	***	
e3	,361	,052	6,937	***	
e4	,247	,042	5,906	***	
e5	,151	,031	4,794	***	
e6	,344	,051	6,748	***	
e7	,535	,081	6,608	***	
e8	,344	,059	5,859	***	
e9	,307	,047	6,471	***	
e10	,318	,050	6,412	***	
e12	,367	,092	3,971	***	
e13	,556	,093	5,951	***	
e14	,643	,087	7,372	***	
e15	,571	,079	7,203	***	
e16	,376	,099	3,799	***	
e17	,001	,130	,011	,991	
e18	,253	,059	4,260	***	
e19	,295	,066	4,489	***	
e20	,257	,049	5,208	***	
e21	,357	,075	4,751	***	

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
Q29	,664
Q27	,629
Q11	,536
Q09	,554
Q10	,998
Q12	,555
Q22	,217
Q23	,182
Q24	,393
Q25	,574
Q05	,433
Q06	,425
Q07	,506
Q08	,403
Q01	,533
Q02	,739
Q03	,648
Q19	,460
Q20	,276
Q21	,867

Matrices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

			M.I.	Par Change
e14	<-->	e15	11,153	,190

Variances: (Group number 1 - Default model)

	M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

			M.I.	Par Change
Q23	<---	Behavior	13,827	,446
Q23	<---	Peer	10,763	,491
Q23	<---	Attitude	13,582	,368
Q23	<---	Q29	9,453	,217
Q23	<---	Q21	13,213	,321
Q24	<---	Peer	9,631	-,460
Q24	<---	Q11	11,689	-,309

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	25		-,411	9999,000	1248,245	0	9999,000
1	e*	8		-,147	2,786	568,702	20	,641
2	e	2		-,093	,771	384,985	5	,881
3	e*	1		-,893	,832	304,754	5	,591
4	e	0	912,369		,609	269,507	9	,528
5	e	0	343,267		,607	261,428	3	,000
6	e	1		-,013	,819	247,525	1	,978
7	e	0	877,925		,408	244,613	5	,872
8	e	0	624,383		,420	243,240	2	,000
9	e	0	999,099		,290	242,572	1	1,173
10	e	0	1308,717		,157	242,476	1	1,114
11	e	0	1561,865		,041	242,470	1	1,049
12	e	0	1582,476		,005	242,470	1	1,005
13	e	0	1586,719		,000	242,470	1	1,000

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	61	242,470	149	,000	1,627
Saturated model	210	,000	0		
Independence model	20	1155,159	190	,000	6,080

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,065	,849	,787	,602
Saturated model	,000	1,000		
Independence model	,201	,388	,324	,351

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,790	,732	,907	,877	,903
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,784	,620	,708
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	93,470	54,742	140,109
Saturated model	,000	,000	,000
Independence model	965,159	861,751	1076,050

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1,880	,725	,424	1,086
Saturated model	,000	,000	,000	,000
Independence model	8,955	7,482	6,680	8,341

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,070	,053	,085	,025
Independence model	,198	,188	,210	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	364,470	388,193	539,390	600,390
Saturated model	420,000	501,667	1022,182	1232,182
Independence model	1195,159	1202,937	1252,510	1272,510

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	2,825	2,525	3,187	3,009
Saturated model	3,256	3,256	3,256	3,889
Independence model	9,265	8,463	10,124	9,325

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	95	103
Independence model	25	27

Execution time summary

Minimization:	,024
Miscellaneous:	,757
Bootstrap:	,000
Total:	,781

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	61	242,470	149	,000	1,627
Saturated model	210	,000	0		
Independence model	20	1155,159	190	,000	6,080

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,065	,849	,787	,602
Saturated model	,000	1,000		
Independence model	,201	,388	,324	,351

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,790	,732	,907	,877	,903
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,784	,620	,708
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	93,470	54,742	140,109
Saturated model	,000	,000	,000
Independence model	965,159	861,751	1076,050

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1,880	,725	,424	1,086
Saturated model	,000	,000	,000	,000
Independence model	8,955	7,482	6,680	8,341

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,070	,053	,085	,025
Independence model	,198	,188	,210	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	364,470	388,193	539,390	600,390
Saturated model	420,000	501,667	1022,182	1232,182
Independence model	1195,159	1202,937	1252,510	1272,510

ECVI

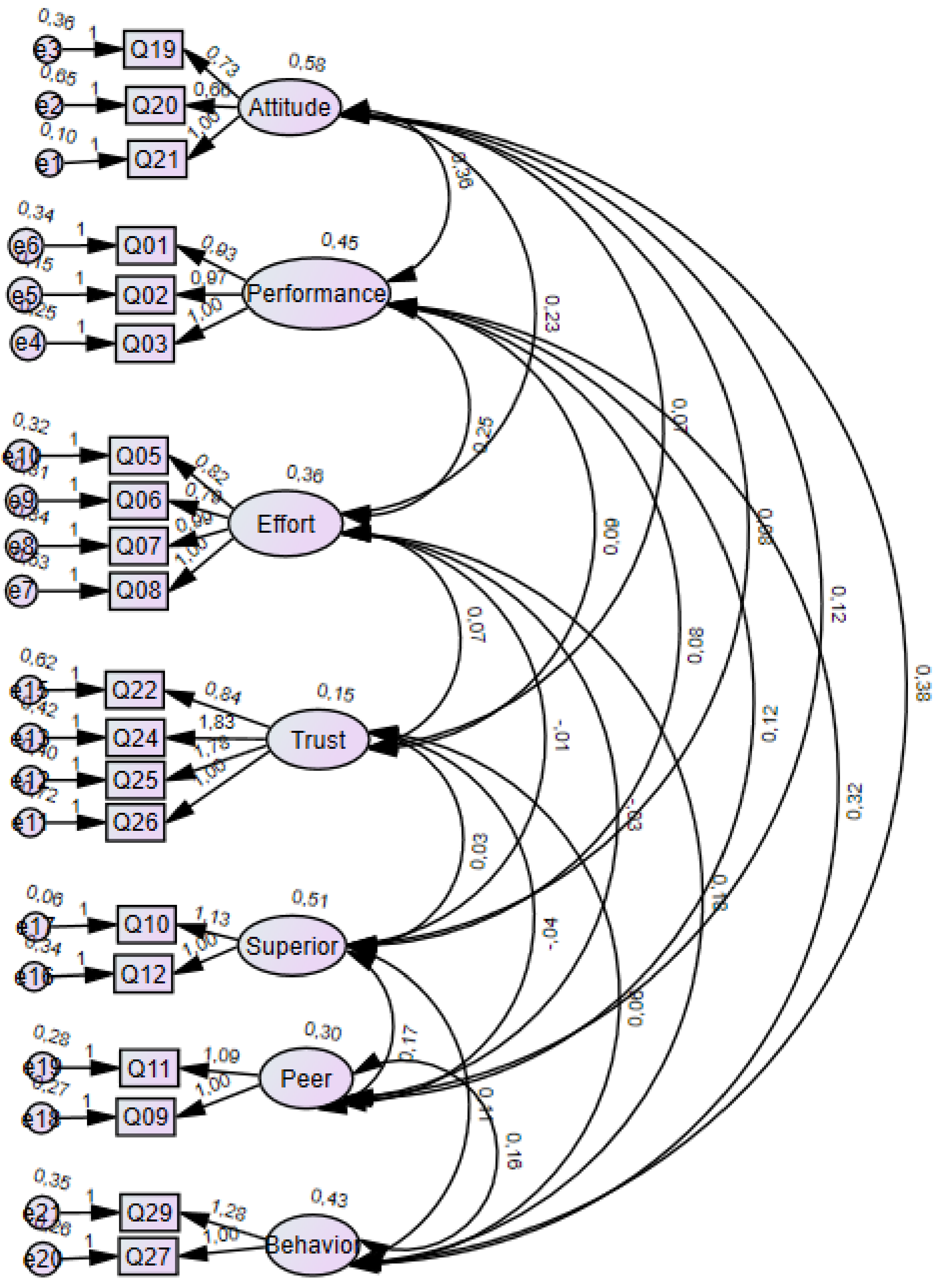
Model	ECVI	LO 90	HI 90	MECVI
Default model	2,825	2,525	3,187	3,009
Saturated model	3,256	3,256	3,256	3,889
Independence model	9,265	8,463	10,124	9,325

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	95	103
Independence model	25	27

Execution time summary

Minimization: ,029
Miscellaneous: ,684
Bootstrap: ,000
Total: ,713



APPENDIX E

The results for the third and final research model.

Analysis Summary
Date and Time
Date: tiistai 10. lokakuuta 2023
Time: 12.25.55
Title
Final_model_3: tiistai 10. lokakuuta 2023 12.25
Groups
Group number 1 (Group number 1)
Notes for Group (Group number 1)
The model is recursive.
Sample size = 129
Variable Summary (Group number 1)
Your model contains the following variables (Group number 1)
Observed, endogenous variables
FAC1_AT
FAC7_BI
Observed, exogenous variables
FAC2_EE
FAC3_PE
FAC5_TR
FAC6_PSI
FAC4_SSI
Unobserved, exogenous variables
e2
e1
Variable counts (Group number 1)

Number of variables in your model:	9
Number of observed variables:	7
Number of unobserved variables:	2
Number of exogenous variables:	7
Number of endogenous variables:	2

Parameter Summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	2	0	0	0	0	2
Labeled	0	0	0	0	0	0
Unlabeled	9	5	7	0	0	21
Total	11	5	7	0	0	23

Models
Default model (Default model)
Notes for Model (Default model)
Computation of degrees of freedom (Default model)

Number of distinct sample moments:	28
Number of distinct parameters to be estimated:	21
Degrees of freedom (28 - 21):	7

Result (Default model)
Minimum was achieved
Chi-square = 9,066
Degrees of freedom = 7
Probability level = ,248
Group number 1 (Group number 1 - Default model)
Estimates (Group number 1 - Default model)
Scalar Estimates (Group number 1 - Default model)
Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FAC1_AT	<---	FAC2_EE	,261	,076	3,441	***	par_1
FAC1_AT	<---	FAC3_PE	,321	,081	3,961	***	par_2
FAC1_AT	<---	FAC5_TR	,147	,074	1,986	,047	par_3
FAC1_AT	<---	FAC6_PSI	,259	,083	3,128	,002	par_6
FAC1_AT	<---	FAC4_SSI	,031	,068	,447	,655	par_7
FAC7_BI	<---	FAC2_EE	,140	,064	2,205	,027	par_4
FAC7_BI	<---	FAC3_PE	,173	,066	2,623	,009	par_5
FAC7_BI	<---	FAC1_AT	,521	,070	7,435	***	par_8
FAC7_BI	<---	FAC6_PSI	,171	,063	2,721	,007	par_9

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
FAC1_AT	<---	FAC2_EE	,266
FAC1_AT	<---	FAC3_PE	,349
FAC1_AT	<---	FAC5_TR	,139
FAC1_AT	<---	FAC6_PSI	,240
FAC1_AT	<---	FAC4_SSI	,031
FAC7_BI	<---	FAC2_EE	,143
FAC7_BI	<---	FAC3_PE	,189
FAC7_BI	<---	FAC1_AT	,524
FAC7_BI	<---	FAC6_PSI	,159

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FAC6_PSI	<-->	FAC4_SSI	,290	,068	4,263	***	par_10
FAC2_EE	<-->	FAC3_PE	,508	,090	5,674	***	par_11
FAC3_PE	<-->	FAC5_TR	,361	,079	4,570	***	par_12
FAC2_EE	<-->	FAC5_TR	,285	,078	3,662	***	par_13
FAC3_PE	<-->	FAC6_PSI	,318	,064	4,932	***	par_14

Correlations: (Group number 1 - Default model)

			Estimate
FAC6_PSI	<-->	FAC4_SSI	,363
FAC2_EE	<-->	FAC3_PE	,533
FAC3_PE	<-->	FAC5_TR	,406
FAC2_EE	<-->	FAC5_TR	,342
FAC3_PE	<-->	FAC6_PSI	,366

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
FAC2_EE	,895	,112	8,000	***	par_15

	Estimate	S.E.	C.R.	P	Label
FAC3_PE	1,016	,120	8,458	***	par_16
FAC5_TR	,778	,097	8,000	***	par_17
FAC6_PSI	,741	,090	8,224	***	par_18
FAC4_SSI	,864	,108	8,000	***	par_19
e1	,432	,054	8,000	***	par_20
e2	,280	,035	8,000	***	par_21

Matrices (Group number 1 - Default model)

Residual Covariances (Group number 1 - Default model)

	FAC4_SSI	FAC6_PSI	FAC5_TR	FAC3_PE	FAC2_EE	FAC1_AT	FAC7_BI
FAC4_SSI	,000						
FAC6_PSI	,034	,023					
FAC5_TR	,165	,035	,000				
FAC3_PE	,135	,018	-,010	-,027			
FAC2_EE	,031	-,034	,000	-,022	,000		
FAC1_AT	,084	,009	,011	-,007	-,015	,000	
FAC7_BI	,131	,007	,030	-,008	-,017	-,001	-,003

Standardized Residual Covariances (Group number 1 - Default model)

	FAC4_SSI	FAC6_PSI	FAC5_TR	FAC3_PE	FAC2_EE	FAC1_AT	FAC7_BI
FAC4_SSI	,000						
FAC6_PSI	,456	,249					
FAC5_TR	2,276	,519	,000				
FAC3_PE	1,626	,224	-,120	-,210			
FAC2_EE	,395	-,470	,000	-,229	,000		
FAC1_AT	1,097	,121	,139	-,071	-,171	,004	
FAC7_BI	1,709	,093	,397	-,083	-,200	-,015	-,032

Factor Score Weights (Group number 1 - Default model)

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

	M.I.	Par Change

Variances: (Group number 1 - Default model)

	M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

	M.I.	Par Change

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	3		-,146	9999,000	271,695	0	9999,000
1	e*	0	14,617		,974	48,928	18	,917
2	e	0	13,378		,260	23,203	3	,000
3	e	0	22,535		,315	10,914	1	1,036
4	e	0	31,051		,167	9,133	1	1,109
5	e	0	33,924		,043	9,066	1	1,036
6	e	0	34,462		,003	9,066	1	1,002
7	e	0	34,909		,000	9,066	1	1,000

Pairwise Parameter Comparisons (Default model)
Variance-covariance Matrix of Estimates (Default model)
Miscellaneous
Model Fit Summary
CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	21	9,066	7	,248	1,295
Saturated model	28	,000	0		
Independence model	7	361,875	21	,000	17,232

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,053	,980	,921	,245
Saturated model	,000	1,000		
Independence model	,311	,496	,328	,372

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,975	,925	,994	,982	,994
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,333	,325	,331
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	2,066	,000	14,077
Saturated model	,000	,000	,000
Independence model	340,875	282,882	406,305

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	,071	,016	,000	,110
Saturated model	,000	,000	,000	,000
Independence model	2,827	2,663	2,210	3,174

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,048	,000	,125	,447
Independence model	,356	,324	,389	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	51,066	53,866	111,122	132,122
Saturated model	56,000	59,733	136,075	164,075
Independence model	375,875	376,808	395,893	402,893

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	,399	,383	,493	,421
Saturated model	,438	,438	,438	,467
Independence model	2,937	2,483	3,448	2,944

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	199	261
Independence model	12	14

Execution time summary

Minimization: ,010

Miscellaneous: ,111

Bootstrap: ,000

Total: ,121