Personality Matters: Predicting the Acceptance of Generative Artificial Intelligence Through Personality Traits and Job Insecurity

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Abstract

Generative artificial intelligence (GAI) has the potential to fundamentally change humans' lives, organizations, and industries by being able to create new content, expanding AI's capabilities to areas of production that were previously exclusively human. To ensure a successful implementation, human acceptance of GAI is crucial. This thesis aims to find out if personality traits predict acceptance of GAI in the workplace. As GAI may be used to automate processes and replace humans, this thesis also investigates the influence of job insecurity on the acceptance of GAI and the influence of personality traits on job insecurity.

This thesis' quantitative study revealed that highly neurotic participants perceive GAI as less useful and less easy to use, compared to participants who are low in neuroticism. Moreover, participants perceived job insecurity considering the potential applications of GAI as rather low. Considering the low perceived job insecurity and rather high number of participants who did not use GAI frequently, participants might lack awareness and knowledge of application possibilities.

These findings contribute to existing research on the relevance of personality traits in predicting the acceptance of intelligent technologies and provide guidance for recruitment and training of employees for positions where the use of GAI is crucial.

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Resumo

A inteligência artificial generativa (IAG) tem o potencial de mudar fundamentalmente a vida dos seres humanos, das organizações e das indústrias por ser capaz de criar novos conteúdos, expandindo as capacidades da IA para áreas de produção que anteriormente eram exclusivamente humanas. Para garantir uma implementação bem sucedida, a aceitação humana da IAG é crucial. Esta tese tem como objectivo descobrir se os traços de personalidade prevêem a aceitação da IAG no local de trabalho. Como a IAG pode ser utilizado para automatizar processos e substituir os seres humanos, esta tese também investiga a influência da insegurança no trabalho na aceitação da IAG e a influência dos traços de personalidade na insegurança no trabalho.

O estudo quantitativo desta tese revelou que os participantes altamente neuróticos consideram a IAG menos útil e menos fácil de utilizar, em comparação com os participantes com baixo nível de neuroticismo. Além disso, os participantes consideraram que a insegurança no emprego, tendo em conta as potenciais aplicações da IAG, era bastante baixa. Uma vez que as IAG podem ser utilizados para automatizar processos e substituir os seres humanos, esta tese também investiga a influência da insegurança no emprego na aceitação das IAG e a influência dos traços de personalidade na insegurança no emprego.

Estas conclusões contribuem para a investigação existente sobre a relevância dos traços de personalidade na previsão da aceitação de tecnologias inteligentes e fornecem orientações para o recrutamento e a formação de trabalhadores para cargos em que a utilização de IAG é crucial.

Título: A personalidade importa: Prever a aceitação da inteligência artificial generativa através de traços de personalidade e insegurança no trabalho

Autor: Debora Tassone

Palavras-chave: inteligência artificial, modelo de aceitação da tecnologia, modelo de cinco factores, insegurança no emprego.

Contents

List of abbreviations

Abbreviation	Meaning
α	Threshold for statistical significance
AI	Artificial Intelligence
b	Regression coefficient
GAI	Generative Artificial Intelligence
H	Hypothesis
FFM	Five-Factor Model
f^2	Cohen's f squared, effect size of ANOVAs
M	Sample Mean
Max	Maximum Value
Min	Minimum Value
N	Number of full sample
n	Number of part of sample
p	P-value
r	Correlation coefficient
RQ	Research Question
R^2	Coefficient of Determination
SD	Standard Deviation
SE	Standard Error
TAM	Technology Acceptance Model
US	United States of America

List of figures

List of tables

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1 Introduction

Within a week, ChatGPT reached its first million users, surpassing Instagram as the fastest application to do so (Dennean et al., 2023). The number of unique visitors reached 100 million in January 2023, two months after ChatGPT was launched to the public. In comparison, it took TikTok nine months and Instagram two years to reach this milestone (Milmo, 2023). Considering these numbers, questions arise as to what ChatGPT is and why the number of users has grown so rapidly.

ChatGPT is a tool based on generative artificial intelligence (GAI), which is a subtype of artificial intelligence (AI). AI is a technology that aims to mimic human intelligence with machines. "It is an umbrella term [… including] machine learning, computer vision, natural language understanding, natural language generation, natural language processing [,] and robotics" (Rouse, 2023, para. 2). In machine learning, a part of AI, machines independently learn from existing data without the continuous support of humans (McKinsey & Company, 2023). AI, more specifically machine learning, can be generative or non-generative. Non-generative AI can classify images or other forms of content. After the breakthrough development of GAI, it can create new images or other forms of content based on the available data (McKinsey & Company, 2023). ChatGPT is based on GAI because it creates new content in the form of text upon demand. It is one of the newest GAI tools for text-based outputs (McKinsey & Company, 2023). As the examples show, GAI's technology and applications are unique and make it clearly distinguishable from other types of AI.

The most obvious reason for the hype around ChatGPT is its accessibility for consumers. Besides ChatGPT, other tools based on GAI exist that can create images, programming code, videos, or audio upon demand (Davenport & Mittal, 2022). In this thesis, the term GAI includes tools based on GAI, such as ChatGPT, and does not refer solely to the technology of GAI itself. The same applies to AI.

GAI has the potential to substantially change the way organizations work, by providing numerous opportunities for application. Some possible applications are the creation of personalized marketing campaigns, automized customer support, and the development of new business ideas (Chui et al., 2022). The application of GAI could substantially increase employees' productivity and companies' innovativeness (Chui et al., 2022; Routley, 2023). Consulting firms like Boston Consulting Group, Inc. (n.d.) and McKinsey & Company (2023) recommend organizations to look at the opportunities for application now to prevent long-term disadvantages regarding costs and innovation capabilities, possibly leading to a competitive disadvantage.

The various applications of GAI in organizations are also reflected in the economy and the labor market. Goldman Sachs estimates that GAI will increase the annual global GDP by 7% (equivalent to almost $7 trillion) and expects an increase of productivity growth of 1.5% over a period of 10 years (Briggs et al., 2023).

Although GAI may seem like an autonomous robot that does not require any human interaction to create new content, this is not the case. So far, GAI only generates content after human interaction. For example, to generate content with ChatGPT, humans need to make a specific request regarding the content and type of text of the output (McKinsey & Company, 2023). Therefore, GAI depends on humans and the human's acceptance of GAI.

Humans react differently to technological developments (Matthews et al., 2021). This may be due to differences in personality (typically described through personality traits), which is an important determinant of behavior (McCrae & John, 1992). This raises the question of whether personality traits can help to predict better or worse acceptance of GAI.

The impact of personality traits on the acceptance of GAI has not yet been studied, but there are several studies on the relationship between personality and acceptance of different kinds of technology. For example, researchers have studied the impact of personality traits on smartphones (Özbek et al., 2014), digital libraries (Nov & Ye, 2008b), social network use (Amichai-Hamburger & Vinitzky, 2010), collaborative technology (Devaraj et al., 2008), online gaming (Akbari et al., 2021), web based technological systems (Barnett et al., 2015), and storing of private data (Behrenbruch et al., 2013). These technologies do not involve the same challenges that intelligent technology might bring (Matthews et al., 2021). Matthews and collaborators (2021) emphasized the importance of research on the relationship of personality with AI, as the expected impact of this technology on humans' lives is huge. The authors continued that the study's results might change depending on the underlying technology, making it necessary to assess the individual relationship between personality traits and specific technologies, such as different types of AI. This shows that studies on the impact of personality on AI acceptance cannot necessarily be relied on to predict what will be the impact of personality on GAI acceptance. Considering that GAI has the potential to fundamentally change humans' lives, organizational processes, and industries (Chui et al., 2022), it is even more important to investigate the relationship between personality traits and GAI acceptance. Thus, this thesis aims to investigate the impact of personality traits on GAI acceptance.

As past technological developments have led to mass job losses due to automation (Fleming, 2020), people may fear losing their job to GAI (Goldman Sachs, 2023). Even though the potential impact of GAI is huge (Chui et al., 2022; Goldman Sachs, 2023), it is yet unverified how the adoption of GAI in organizations will change workplaces and employment rates around the globe. On the one hand, the adoption of GAI could lead to mass layoffs due to cost savings and quality improvements using technology instead of employing humans: Goldman Sachs estimates that GAI could substitute up to one-fourth of jobs in the US and Europe (that is 300 million jobs which could be automated globally by implementing GAI; Briggs et al., 2023). On the other hand, GAI could solve the problem of lack of skilled workers and increase productivity while some workers find employment in new positions (Dennean et al., 2023; Sowa et al., 2021). Thus, GAI may increase workers' job insecurity. This raises the question of whether GAI has an impact on job insecurity. Because previous research has shown that personality can influence job insecurity (Iliescu et al., 2017), the question also emerges if personality can be used to predict job insecurity in the scenario of introduction of GAI in the workplace. These questions are also investigated in this thesis.

1.1 Problem Statement and List of Research Questions

Due to the impact GAI is expected to have on humans' lives, organizations, and industries, an effective collaboration between humans and technology is crucial for both personal and organizational future success. As humans' behavior is rooted in their personality traits, these may help to predict humans' acceptance of GAI. This thesis aims to find out if personality traits predict GAI acceptance in the workplace. Also, this thesis investigates the influence of job insecurity on GAI acceptance and the influence of personality traits on job insecurity. To do so, the following research questions will be posed:

- RQ1: Do personality traits predict acceptance of GAI?
- RQ2: Does job insecurity influence acceptance of GAI?
- RQ3: Do personality traits influence perceived job insecurity?

To determine a potential difference between the acceptance of GAI and AI, as suggested by Matthews and collaborators (2021), the study asked participants to assess either AI or GAI, to allow comparison between the two.

1.2 Managerial and Academic Relevance

This thesis may contribute to the existing literature on personality traits' impact on technology acceptance. As previously mentioned, many studies exist on personality traits' impact on technology acceptance, yet little research exists on personality traits' impact on AI acceptance (and it focuses on facets like trust and fear; Riedl, 2022; Sindermann et al., 2022), and no study exists on personality traits' impact on GAI acceptance, making this a novel contribution to existing literature.

Moreover, this thesis may contribute to the existing literature on job insecurity's impact on technology acceptance. Previous research has linked job insecurity with technology acceptance (Eren et al., 2020), but not yet with GAI/AI, which makes this part a novel contribution to the existing literature. As GAI/AI can threaten many jobs (Briggs et al., 2023), it is important to assess how an increased job insecurity would influence GAI/AI acceptance.

Furthermore, limited research exists on personality traits' impact on job insecurity. Iliescu and collaborators (2017) found moderating effects of personality traits on the relation between job insecurity and mental health. As there is no research testing direct effects of personality traits on job insecurity in the context of GAI/AI, this is another novel contribution to the existing literature.

Finally, this thesis may support managers in the successful implementation of GAI. As previously mentioned, consulting firms recommend addressing implementation issues now to prevent competitive disadvantages (Boston Consulting Group Inc., n.d.; McKinsey & Company, 2023). As the successful implementation of GAI depends on the interaction between humans and GAI, this thesis' insights may thus be helpful. For example, when forming teams, managers can choose team members based on their personality traits and the impact these have been shown to have in GAI acceptance. Additionally, employees who have rather disadvantageous personality traits in dealing with GAI could be trained separately to simplify the handling of GAI (Devaraj et al., 2008).

1.3 Structure

This introduction is followed by a literature review on the topics of AI and GAI, the technology acceptance model, job insecurity and measurement scales for this concept, personality and personality traits, and the five-factor model (FFM). The hypotheses tested in this thesis are introduced in the literature review. To accomplish the thesis' objective, a quantitative study was conducted. Descriptions of the procedure, participants, and the variable measurement are provided thereafter. Next, the results of the study were presented, analyzed, and discussed. Then, academic and managerial implications as well as limitations and future research ideas are discussed. Finally, the main conclusions are presented.

2 Literature review

2.1 Generative Artificial Intelligence (GAI)

2.1.1 Definition of GAI

GAI is the latest breakthrough discovery in the broad field of AI. Using complex machine learning models, GAI-based tools like ChatGPT are able "to predict the next word based on previous word sequences" (Tanmay et al., 2023, p. 1). GAI identifies the underlying pattern of the input and uses this to create new content (Tanmay et al., 2023), such as text, images, programming code, videos, or audio (McKinsey & Company, 2023). "A generative AI system consists of several components such as input data, preprocessing modules, feature extraction layers, [a generative adversarial network], optimization algorithms and post-processing modules" (Ramos, 2023, How Does Generative AI Work? section).

The major transformation of GAI compared to AI is that GAI can create content that has not yet existed. In the past, only humans were able to do this, but the development of GAI is "taking technology into realms once thought to be reserved for humans" (Chui et al., 2022, para. 4). This technological development enables new possibilities for automation in various fields.

GAI has the potential to fundamentally change workspaces, organizations, industries, and people's lives in augmenting human capabilities in helping them to work faster, produce outputs of higher quality, and be more creative (Chui et al., 2022). Furthermore, GAI can be applied to automate repetitive tasks, giving employees more time to focus on value-adding work (Routley, 2023). This benefits companies whose employees use GAI tools to accomplish tasks.

On an organizational level, GAI can be applied to a greater extent, possibly cutting labor costs, increasing productivity, and streamlining processes (Chui et al., 2022). According to Chui and collaborators (2022), GAI could, for example, be used in marketing and sales (e.g., to create personalized content), in operations (e.g., to create chatbots for personalized customer support or to identify problems in the production process), in engineering (e.g., to write and review code), in law (e.g., to answer complex questions as well as draft and review contracts), in research and development (e.g., to discover new ideas and improve existing solutions), and in human resources (e.g., to create personalized interview questions; Chui et al., 2022). As these examples show, the possible use cases for GAI tools are highly diverse and continue to grow with the further development of the technology.

Despite the promising capabilities of GAI, there are some disadvantages that need to be considered when using it. First, since GAI tools are trained on large amounts of existing data, they replicate sexist, racist and biased content (McKinsey & Company, 2023). This makes it crucial to review the generated contents before use (McKinsey & Company, 2023; OpenAI, n.d.). Moreover, to prevent GAI from generating discriminatory content, the technology should be trained with non-biased data (McKinsey & Company, 2023) and one-size-fits-all solutions should be dismissed in favor of specialized tools, such as Google's specialized tools for biomedical and legal content (BioBERT and Legal-BERT; Davenport & Mittal, 2022; McKinsey & Company, 2023). Companies engaged in the development of GAI tools are aware of this problem of replicating social biases: According to OpenAI (n.d.), the newest version of its language model, ChatGPT-4, already has some improvements regarding the generation of prohibited or discriminatory content, compared to its previous version. Second, GAI facilitates the creation of fake images and videos, which could be used to spread misinformation (Davenport & Mittal, 2022). Third, there are intellectual property concerns, as it is yet unclear who owns the content generated through GAI tools (Davenport & Mittal, 2022). Fourth, organizations fear data loss or unwanted disclosures when employees use GAI to solve confidential problems (Boston Consulting Group Inc., n.d.). After an employee of Samsung Electronics Co. had uploaded confidential data to ChatGPT, the company has banned its employees from using openly accessible GAI tools and now develops their own GAI tool (Gurman, 2023). Lastly, even though the creativity of GAI is seen as an advantage, it is somewhat limited because the content generated is based on existing data. Thus, although the generated content is new, there is a danger that "it will be forever stuck in the zeitgeist of its training data" (Wayner, 2023, Intellectual stagnation section). Despite these disadvantages, the emerging market for GAI is promising.

Leading technology companies such as Google, Amazon, and Microsoft are investing heavily in GAI and related tools (Waters, 2023). Currently, some of the most popular tools are: ChatGPT-4 for all kinds of text-based output, DALL-E2 to create images, and Whisper for audio files (Davenport & Mittal, 2022). These tools have been developed by OpenAI, a nonprofit research laboratory which has a long-term partnership with Microsoft. The partnership aims to advance research on GAI and to make it more accessible to individuals and businesses (Official Microsoft Blog, 2023; OpenAI, 2023). Microsoft's financial investment in OpenAI is estimated to be $1 billion in 2019 (Feiner, 2019), an undetermined amount in 2021, and a multibillion-dollar investment in 2023, which is estimated to be $10 billion (Hoffman & Albergotti, 2023). In general, the market around GAI has great potential. According to Boston Consulting Group, Inc. (n.d.), GAI will reach a share of around 30% of the AI market by 2025 and, according to Goldman Sachs, GAI will cause a rise of the annual global GDP of 7%, which is equivalent to almost $7 trillion (Briggs et al., 2023).

As previously mentioned, GAI requires human interaction to serve its purpose. Since the quality of the output of GAI depends on the human's acceptance of GAI, it makes sense to investigate how humans accept GAI.

2.1.2 Main Theories and Measurements of Technology Acceptance

The most popular theories about technology acceptance and models to assess technology acceptance are as follows: the theory of reasoned action (Fishbein, 1967), the technology acceptance model (Davis, 1985, 1989) and modified versions thereof (Taylor & Todd, 1995; Venkatesh & Davis, 2000), and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). For this study, I will focus on the technology acceptance model (TAM) of Davis (1985, 1989). The TAM is the most applied theoretical model to assess the adoption of technology (Agarwal & Karahanna, 2000; Aladwani, 2002; Davis et al., 1989; Lee et al., 2003; Nov & Ye, 2008b; Schepers & Wetzels, 2007; Venkatesh & Morris, 2000). Next, I will explain the TAM and the reasons why I believe it is best suited for the purpose of this study.

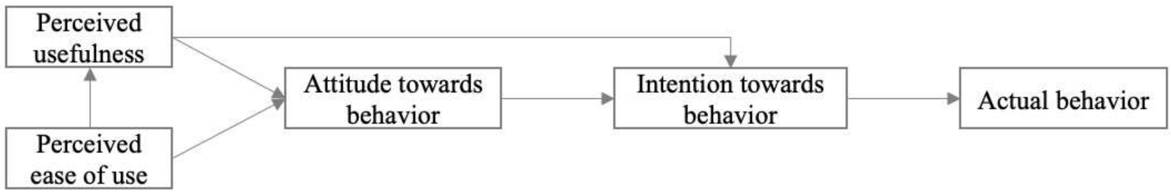
The TAM is based on the theory of reasoned action by Fishbein (1967). According to the theory of reasoned action, decision-making is a rational process. This theory has been used to predict and explain health behaviors but can be used to describe other kinds of human behavior, such as behavior in relation to technology (Fishbein, 1967).

The TAM tailors the theory of reasoned action (Fishbein, 1967) to humans' behavior towards technology. Davis and collaborators (Davis, 1985; Davis et al., 1989) assume that the actual use of technology is influenced by the behavioral intention to use, which is, in turn, influenced by the attitude towards use and the perceived usefulness. The attitude towards using technology is influenced by two factors, the perceived usefulness and the perceived ease of use of technology (Davis, 1985; Davis et al., 1989). Perceived usefulness describes the user's belief to perform better when using the technology. Perceived ease of use describes the effort to use the technology, meaning the user's belief "that using a particular system would be free of effort" (Davis, 1989, p. 320). According to Davis (1989), perceived usefulness and perceived ease of use are "fundamental determinants of user acceptance" (Davis, 1989, p. 1). To measure technology acceptance, Davis (1989) developed and validated measurement scales for perceived usefulness and perceived ease of use. In this study, GAI acceptance was measured using the variables perceived usefulness, perceived ease of use, intention to use, and actual use.

The studies conducted to validate the TAM revealed that of two components of technology acceptance, perceived usefulness is more strongly linked to the actual use, compared to the perceived ease of use. People decide to use an application primarily because of its functionality and only secondarily for how easy it is to use (Davis, 1989). Based on this finding, Davis concluded that perceived ease of use is an antecedent of perceived usefulness, which then influences the attitude towards use and the behavioral intention to use the technology (Davis, 1989; Davis et al., 1989). See Figure 1 for the TAM.

Figure 1

Diagram Showing the Relationship Between Variables in the Technology Acceptance Model (TAM) by Davis (1989)



I consider TAM to be the most suitable model to assess the acceptance of GAI in this study. Alternative models to assess technology acceptance, including modifications of TAM and other models, are less suitable for this study. Modified versions of the TAM, for example, include variables that influence perceived ease of use, such as computer anxiety (Venkatesh, 2000), or other antecedents of TAM, such as perceived accessibility (Karahanna & Straub, 1999). The antecedents make the models more complex, which conflicts with the goal of conducting a compact study. Furthermore, some of the antecedents appear less applicable to the context of GAI, compared to the variables already included in TAM. For example, the factor perceived accessibility might not provide substantial value to this study as tools such as ChatGPT are currently freely accessible. Furthermore, the modified versions were not reviewed and used as frequently as the original TAM.

There are other models assessing technology acceptance that include the variables subjective norm or social influence, such as the theory of planned behavior (Ajzen, 1991), the combined model of TAM and theory of planned behavior (Taylor & Todd, 1995), and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). The variable subjective norm can also be combined with the TAM, as done by Devaraj and collaborators (2008). Since GAI has only been available to consumers for a relatively short time, I assume that other people's opinions are rather insignificant when deciding whether to use the technology. Thus, in my opinion, considering the factor subjective norm when assessing GAI acceptance is not useful.

Models like the motivational model of Davis and collaborators (1992), the model of PC utilization of Thompson and collaborators (1991), and the social cognitive theory by Compeau and Higgins (1995) are not as widely adopted as the TAM and include factors that are probably not relevant for this study or not measurable within the scope of this thesis. For example, the model of PC utilization analyzes long-term consequences, which cannot be assessed within the scope of this thesis. Considering this reasoning, the use of the TAM seems appropriate.

As discussed, TAM contains relevant factors that may influence the acceptance of GAI. Moreover, it does not contain any factors that I assume to be irrelevant in the context of GAI and increase the complexity of this study without contributing to the study's purpose. Therefore, I will assess the acceptance of GAI by measuring the variables perceived usefulness, perceived ease of use, intention to use, and actual use.

Nevertheless, the literature states limitations of TAM that need to be considered. First, TAM assumes that perceived usefulness and perceived ease of use are the only variables influencing the intention to use technology, although there could be other relevant influences (Mathieson, 1991). Since the scope of this study is limited and as I assume that perceived usefulness and perceived ease of use are important determinants of the acceptance of GAI, this limitation does not have a major impact on the validity of the study. Second, TAM only provides limited information that can be used in the development and implementation of technology. For example, TAM only gives information that a system is not easy to use but does not provide other reasons that prevent use (Mathieson, 1991). As the main aim of this thesis is to investigate a potential relationship between personality traits and GAI acceptance, and not to give recommendations regarding system development and design, TAM is still considered suitable for this study.

2.2 Job Insecurity

2.2.1 Definition of Job Insecurity

Job insecurity is defined as a subjective and involuntary experience about a possible job loss in the future and related worries (Vander Elst et al., 2014). In this study, job insecurity is seen as a stressor, creating negative emotions that are perceived differently by every individual (Sverke et al., 2006).

According to Burchell (1999), there are numerous reasons that increase perceived job insecurity: breakthrough technological discoveries, as GAI is commonly understood (Goldman Sachs, 2023; McKinsey & Company, 2023), could lead to the automation of jobs; globalization enables cost savings through outsourcing; and to cut costs, processes are optimized and jobs are eliminated. Global competition, economic downturns, and mergers further complicate the corporate environment (Greenhalgh & Rosenblatt, 1984). These and other factors increase the job insecurity of employees across industries and educational levels (Reisel, 2003). According to a report of Goldman Sachs, GAI could substitute up to one-fourth of jobs in the US and Europe, leading to 300 million jobs globally being at risk of being automated by GAI (Briggs et al., 2023).

Job insecurity is one of the most important stressors related to employment and negatively impacts employees' performance as well as physical and mental health (De Witte, 1999). This, in turn, has negative consequences for organizations, such as reduced commitment and satisfaction of employees (Ashford et al., 1989). Different measurements of job insecurity have been developed to anticipate job insecurity and prevent such negative consequences on an organizational level.

2.2.2 Main Theories and Measurements of Job Insecurity

There are two main possibilities to measure job insecurity: The first is based on the theory of Greenhalgh and Rosenblatt (1984). According to their theory, job insecurity is a multidimensional concept, including various dimensions of insecurity, such as the threat of job loss, the threat of losing single job features, and the person's perceived powerlessness to change the situation. The most widely used multidimensional measurement is the job insecurity scale by Ashford and collaborators (1989), which comprises 57 items. The scale has been criticized for its length and the inclusion of loss of job features and perceived powerlessness, aspects which are not part of the core concept of job insecurity (Reisel & Banai, 2002).

The second possibility to measure job insecurity defines it as a unidimensional concept and uses a global scale with several items (Reisel & Banai, 2002). In contrast to the multidimensional concept, job insecurity in the unidimensional concept does not include the loss of job features nor the perceived powerlessness to influence the threat (Vander Elst et al., 2014). De Witte (2000) as well as Vander Elst and collaborators (2014) were the first researchers to develop and validate a global scale for perceived job insecurity across countries, which has been widely used since then. The scale is suitable for the purposes of the current study (in which job insecurity is not the main variable of the study), because it has been validated across countries and is short.

As job insecurity negatively affects employees' performance (Ashford et al., 1989; De Witte, 1999), I assume it negatively affects technology acceptance, which is part of their performance in a technological job. This assumption has been confirmed by Eren and collborators (2020), who found a negative correlation between job insecurity and TAM in a Turkish textile manufacturing company. As employees may perceive GAI as a threat, it could lead to increased job insecurity. This, in turn, could lead to a worse acceptance of GAI. Thus, people with a high level of job insecurity could perceive GAI as less useful, compared to people with a lower level of job insecurity.

H1a: Job insecurity will be negatively associated with the perceived usefulness of GAI.

To prevent their job from being automated by GAI, people might want to prevent the application of the technology. This might lead to a lower intention to use GAI.

H1b: Job insecurity will be negatively associated with the intention to use GAI.

2.3 Personality Traits

2.3.1 Definition of Personality and Personality Traits

In the *Dictionary of Psychology* of 1934, Warren defines the term personality as:

> "1. the integrated organization of all the cognitive, affective, conative, and physical characteristics of an individual as it manifests itself in focal distinctness to others; 2. the general characterization, or pattern, of an individual's total behavior; 3. the field property or form of the individual's total behavior-pattern; 4. those characteristics of an individual most important in determining his social adjustments; 5. (pop.) the physical and affective qualities of an individual as they synthetically attract or impress others." (H. C. Warren, 1934, p. 197).

Personality is usually described through personality traits (McCrae & John, 1992). Johnson (1997) defines personality traits as "consistent patterns of thoughts, feelings, or actions that distinguish people from one another." (Johnson, 1997, p. 74). According to Allport (1937), personality traits are not directly observable themselves but are inferred through individuals' behavior. This author further notes that, when observing humans' behavior to analyze personality traits, it is important to take into consideration the whole circumstances of the situation as well as the general level of stress on the nervous system, as they can influence human behavior (Allport, 1937).

Lewin, as cited in Allport (1937), distinguishes between two groups of personality traits: outer (behavioral/phenotypical) and inner (emotional and cognitive/genotypical) traits. Inner traits can lead to outer traits, which are observable as behavioral action. Related inner traits of outer traits cannot always be determined precisely, which makes it difficult to fully measure and analyze a person's personality traits (Johnson, 1997). Depending on the kind of trait and the person's awareness, it is more informative to conduct self or peer ratings (Luft & Ingham, 1961). As it is not possible to conduct peer ratings within the scope of this study, only measurement scales of self-ratings are discussed below.

2.3.2 Main Theories and Measurements of Personality Traits

Researchers have developed different methods to measure personality traits through questionnaires. For example, the Myers-Briggs type indicator is based on the theory of Jung (1923) and classifies people into one of 16 personality types (McCrae & Costa, 1989; Myers, 1962). Another method to assess personality traits is the different measurement scales based on the FFM (John et al., 2008; McCrae & Costa, 1992). For this study, I used the measurement scale of Donnellan and collaborators (2006), which is based on the FFM. Next, I will explain the FFM, introduce hypotheses related to this model, present alternative measurement scales of the FFM, and explain why I chose Donnellan and collaborators' measurement scale.

The FFM is based on the conclusions of Tupes and Christal (1961), who found that different personality models at the time were based on the same five factors (John et al., 2008; McCrae & John, 1992). The model distinguishes personalities using the factors extraversion, agreeableness, conscientiousness, openness, and neuroticism (McCrae & John, 1992).

In terms of what each factor of the FFM assesses, neuroticism assesses whether the person is "predisposed to emotional distress versus emotionally stable", extraversion whether the person is "energetic and thrill-seeking versus sober and solitary", agreeableness whether the person is "kind and trusting versus competitive and arrogant", conscientiousness whether the person is "disciplined and fastidious versus laidback and careless", and openness whether the person is "curious [,] unconventional [, and imaginative] versus traditional and pragmatic" (McCrae & Costa, 1992, all p. 226). Using these five factors, every personality can be described individually.

The FFM is a thoroughly tested and widely used model to assess personality traits (Akbari et al., 2021; Devaraj et al., 2008; Marengo et al., 2020; Rıfat et al., 2016). It has been officially translated to over 40 languages (McCrae & Costa, 1992), and the personality traits have been tested using both self-report and peer rating data (McCrae & John, 1992). Thus, the completeness and reliability of the FFM can be assumed (McCrae & John, 1992).

Nevertheless, the model has some limitations, such as allowing only a restricted level of individuality and not replacing a comprehensive psychological analysis (McCrae & Costa, 1992; McCrae & John, 1992). Since only a limited depth of analysis of personality traits is required for the current study, these limitations do not diminish the validity of the measurement scale.

I consider the FFM to be the most suitable model to assess personality traits in this study. It is a thoroughly tested and frequently used model to assess personality traits, allowing enough detail without being too complex.

In addition to the reasons in favor of using the FFM to assess personality traits, there are reasons against using the Myers-Briggs type indicator. The Myers-Briggs type indicator is criticized for the loss of valuable information due to the high number of classifications and the non-inclusion of the personality trait neuroticism (McCrae & Costa, 1989). Due to the importance of the personality trait neuroticism to assess the acceptance of technology in this study, as previous studies on personality traits and technology acceptance show (Akbari et al., 2021; Devaraj et al., 2008), I considered the Myers-Briggs type indicator not appropriate for this study.

Considering other personality traits that have been previously linked to technology acceptance, it is possible to include the person's resistance to change (Markus, 1983; Nov & Ye, 2008b) and personal innovativeness (Nov & Ye, 2008a) in the conceptual model. Yet, as the person's resistance to change is already assessed by the personality traits neuroticism and openness, the variable resistance to change was not added in this study. As personal innovativeness is influenced by the person's resistance to change and the personality trait openness (Agarwal & Prasad, 1998), this variable was also not added to this study.

As discussed, the FFM is the best suited model to assess personality traits in this study, as it contains all the relevant traits that may influence GAI acceptance. Moreover, it is reduced to the essential personality traits that describe humans' behavior without being too complex. There are various measurement scales of the FFM.

The measurements scales differ, for example, regarding length and self or peer rating. Since only self-ratings are relevant for this study, measurement scales with different lengths are analyzed hereafter. Comprehensive measurement scales of the FFM have been developed, such as the NEO-PI-R, which comprises a 240-item questionnaire that takes about 45 minutes to complete (Gosling et al., 2003). Besides that, there are 20 (Donnellan et al., 2006), ten (Gosling et al., 2003; Rammstedt & John, 2007), and five (Gosling et al., 2003) item measurement scales of the FFM. Such short measurements are needed in case the time is limited or "personality is not the primary topic of interest" (Gosling et al., 2003, p. 1). Although the reliability and validity of the ten-item model is comparable to the 44-item big five inventory of John and collaborators (1991; Rammstedt & John, 2007), on which the ten-item model is based, valuable information gets lost with the short scale, as there are only two items per personality trait (Gosling et al., 2003; Rammstedt & John, 2007).

To address this limitation, Donnellan and collaborators (2006) developed a 20-item measure of the FFM. The goal was to develop a short measure with low correlations among the factors to optimize prediction research. Misinterpretations due to multicollinearity are prevented by empirically separated scales and the items can be assigned relatively clearly to one distinct factor (Donnellan et al., 2006). The 20-item measure, so-called mini-IPIP, is based on the 50-item IPIP-FFM by Goldberg (1999), which is frequently used (Donnellan et al., 2006). The mini-IPIP has four items per factor, of which two are positively and two negatively keyed, except for openness, which has three negatively keyed items. The mini-IPIP is comparable to the IPIP-FFM in terms of long and short-term retest reliability, content coverage, and criterion-related validity (Donnellan et al., 2006). A limitation of the measure is that its development and validation were based only on student populations, although the same results are expected for other populations (Donnellan et al., 2006). I decided to use the measure of Donnellan and collaborators (2006) for this study, because it is a thoroughly validated and short measurement scale of the FFM. As also other variables will be measured besides personality traits in the questionnaire, the chosen scales should not be too long to achieve a convenient length of the whole questionnaire.

As personality traits influence a person's behavior (Allport, 1937), it can be assumed that personality traits have an influence on the acceptance of technology. Regarding GAI, some of the five personality traits may influence GAI acceptance positively or negatively.

The personality trait conscientiousness describes people who are intrinsically motivated to perform well (McCrae & Costa, 1992). Thus, different researchers (Barnett et al., 2015; Özbek et al., 2014) assume that conscientious people perceive technology as helpful to perform better and easy to use, compared to less conscientious people. Also, the researchers assume that conscientious people are more willing to use such technology. I assume that the positive influence of conscientiousness on the acceptance of technology applies to GAI. As such:

H2a: Conscientiousness will be positively associated with the perceived usefulness of GAI.

H2b: Conscientiousness will be positively associated with the perceived ease of use of GAI.

H2c: Conscientiousness will be positively associated with the intention to use GAI.

Moreover, as conscientious people highly value the quality of their work, I assume that they evaluate a potential benefit of using GAI thoroughly before using it. In case conscientious people determine a benefit in using GAI, they might be more motivated than non-conscientious people to use GAI. Devaraj and collaborators (2008) found that conscientiousness moderates the relationship between perceived usefulness and the intention to use technology, thus:

H3: Conscientiousness will moderate the relationship between perceived usefulness of GAI and intention to use GAI such that the relationship is stronger for individuals with higher conscientiousness.

The personality trait neuroticism describes the way a person copes with distress. A person who is low in neuroticism is calm and self-satisfied, whereas a person who is high in neuroticism is anxious and insecure (McCrae & John, 1992; Özbek et al., 2014). According to different studies (Barrick & Mount, 2000; Devaraj et al., 2008; Özbek et al., 2014), neuroticism is negatively associated with performance and satisfaction in the workplace. In addition, neurotic people might feel stressed and threatened by new technologies at the workspace, especially because of the possible impact GAI might have on their lives, such as the increased job insecurity. This might trigger negative emotions. As a result, neurotic people might struggle using new technologies, compared to people who are low in neuroticism and see such changes more calmly. Researchers found a significant negative association between neuroticism and the perceived usefulness of technology (Devaraj et al., 2008; Özbek et al., 2014). Thus:

H4a: Neuroticism will be negatively associated with the perceived usefulness of GAI.

H4b: Neuroticism will be negatively associated with the perceived ease of use of GAI.

H4c: Neuroticism will be negatively associated with the intention to use GAI.

Given the nature of the personality trait neuroticism, people who are high in neuroticism may feel more threatened by GAI and thus the perceived job threat might be higher (Iliescu et al., 2017), compared to people who are low in neuroticism, thus:

H5: Neuroticism will be positively associated with job insecurity.

People who are open to new experiences are more comfortable with change and using new technologies. On the contrary, people who are not open to new experiences are challenged by changes and struggle adapting to new technologies (McCrae & Costa, 1992). Thus, the personality trait openness may be beneficial when adapting to GAI (Özbek et al., 2014). Özbek and collaborators (2014) found a significant positive relation between openness and perceived ease of use of smartphones. Other researchers assumed relationships between openness and perceived usefulness (Devaraj et al., 2008) and intention to use (Barnett et al., 2015). Thus:

H6a: Openness will be positively associated with the perceived usefulness of GAI.

H6b: Openness will be positively associated with perceived ease of use of GAI.

H6c: Openness will be positively associated with the intention to use GAI.

Behrenbruch and collaborators (2013) assumed a moderating relationship with perceived usefulness and the intention to use, which was not significant, thus:

H7: Openness will moderate the relationship between perceived usefulness and intention to use GAI such that the relationship is stronger for individuals with higher openness.

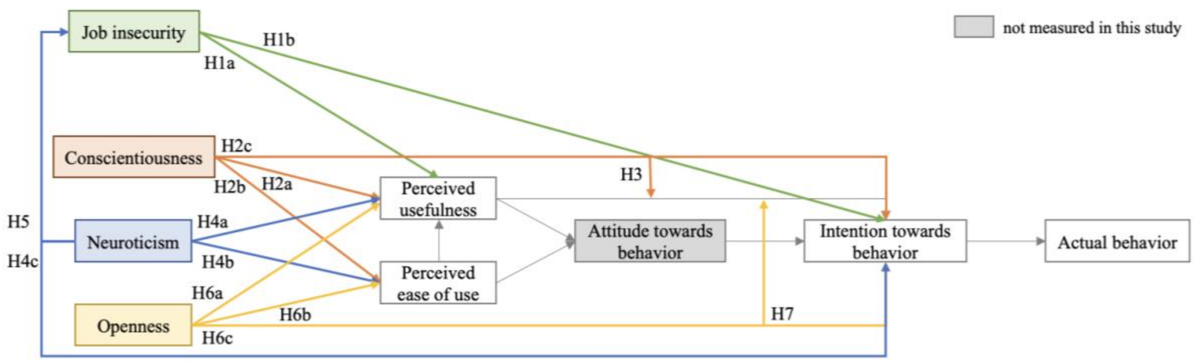
The personality traits agreeableness and extraversion were not included in this study because the expected impact on the acceptance of GAI is rather low. Extraversion and agreeableness are assumed to be more relevant when assessing the acceptance of collaborative technologies, as it is the technologies' purpose to interact with other people (Devaraj et al., 2008). As GAI is not a collaborative technology and it does not require interaction between people to fulfill its purpose, the personality traits extraversion and agreeableness were not assessed.

2.4 Conceptual Model

The current study makes two main contributions. First, it applies two known models, TAM and FFM, to a novel technology, GAI. As GAI is different to previously studied technologies, existing studies on the impact of personality traits on the acceptance of technology can only give guidance for this study. Nevertheless, this thesis might lead to new findings (Matthews et al., 2021; Özbek et al., 2014). Second, this study is different from existing research because the factor job insecurity was added to the conceptual model (see Figure 2). Considering the potential impact of GAI on people's lives and organizations, GAI has a rather high threat potential. Thus, job insecurity might be an important determinant of the acceptance of GAI.

Figure 2

Conceptual Model of the Thesis' Study, Relating Personality and Job Insecurity with TAM Variables



3 Method

3.1 Variable Measurement

To assess personality traits, the mini-IPIP scale by Donnellan and collaborators (2006) was used. The mini-IPIP is a short measure of the FFM with good reliability and viability compared to other measurement scales of the FFM (Donnellan et al., 2006). As not all five personality traits are relevant for this study, only the statements about conscientiousness, neuroticism, and openness were included in the questionnaire. No further adjustments were made. Participants were asked to rate how well the 12 statements described them on a 5-point Likert scale from very inaccurate to very accurate (Goldberg, 1999).

To compare the results regarding the acceptance of GAI, participants were randomly assigned into two groups to measure the acceptance of either GAI or AI. To measure the acceptance of GAI/AI, the variables perceived usefulness and perceived ease of use were measured using the original scale of the TAM by Davis (1989). In the initial study, perceived usefulness had a Cronbach's α of .98 and perceived ease of use of .94 (Davis, 1989). Participants were asked to rate how strongly they agree with the 12 statements on a 7-point Likert scale from extremely unlikely to extremely likely. No adjustments were made to the scale.

Furthermore, I developed and included two questions about the current use of GAI/AI and the intention to use GAI/AI in the future. Participants were asked to report the frequency of their current use of GAI/AI on a scale from never to daily and indicate their intention to use GAI/AI in the future. The question about intention to use is similar to questions asked in other studies (Šumak et al., 2011; Teo, 2011; Teo & Zhou, 2014). I included two single item scales in the survey because they are short, easy to understand, and appropriate to measure the variables (Elo et al., 2003; Wanous et al., 1997).

The variable job insecurity was measured using the scale developed by De Witte (2000) and translated by Vander Elst and collaborators (2014). The scale has good reliability and criterion and construct validity (Vander Elst et al., 2014). Participants were asked to rate how strongly they agree with the four statements on a 5-point Likert scale from strongly disagree to strongly agree. No adjustments were made to the scale.

Lastly, demographic questions on age, gender, location of residence, highest level of education, and the current employment status were asked. I included a short and simple instructional manipulation check (Oppenheimer et al., 2009) to measure participants' attention ("What is your favorite fruit? This is an attention check, please write computer in the text box.").

The order of the scales for the different variables was carefully chosen to avoid distortions in the measurement of the subsequent instruments. Thus, the scale on job insecurity was placed after the TAM to prevent a negative perception of GAI/AI, which could influence the rating of the TAM statements. Besides the random assignment to the group of GAI or AI, no further randomization between questions/statements or scales was implemented.

3.2 Procedure

Building on previous research that studied whether personality traits predict a better acceptance of technology (Behrenbruch et al., 2013; Devaraj et al., 2008), I used a quantitative approach to answer the research questions using an online study on the survey platform Qualtrics.

After agreeing with the informed consent, participants were asked to indicate whether the statements about personality traits described them accurately or not. Then, participants were randomly assigned to one of two groups. One group was given a description and possible use cases of GAI in the workplace, while the other group was given a description and possible use cases of AI. Afterwards, participants were asked to indicate their agreement with statements about their perceived usefulness and perceived ease of use of GAI/AI. Then, participants were asked about their current and future intended use of the technology. Next, participants were asked to indicate their agreement with statements about job insecurity, considering the potential impact of GAI/AI. Lastly, participants answered demographic questions and an attention check question. See Appendix 1 for both versions of the survey.

3.3 Participants

The required sample size was determined as $N = 172$ using G*Power (Faul et al., 2009) and calculating the required sample for the most complex hypothesized relationship between variables, a moderation, of a size between medium and small ($f^2 = .065$), power = 80%, $\alpha = .05$. This sample size seems reasonable because Devaraj and collaborators (2008) have the same sample size and tested for moderating effects between conscientiousness and the relationship between perceived usefulness and the intention to use.

Between April 7 and 28, 2023, a total of 247 surveys were completed. However, 74 surveys were excluded from the analysis because the participants did not answer all questions of the survey. Furthermore, 42 participants did not answer the attention check question correctly. Feedback of some participants made clear that the attention check question was misunderstood and that some attentive participants answered the question incorrectly. The bivariate correlation showed a significant negative correlation between the attention check question and neuroticism ($r(171) = -.17$, $p < .030$). Besides that, no other variable showed a significant correlation with the attention check question (all $p > .05$). Therefore, I included the

42 participants in all analyses and removed only those participants whose responses had no relationship to the question asked. To control for the attention check question in the regressions including neuroticism, I included the respective dummy variable. This led to a final valid sample of 173 participants, of which 83 participants answered the questions regarding GAI and 90 participants regarding AI.

Participants were recruited on social media platforms, namely LinkedIn and Instagram, to reach a diverse sample. Furthermore, the survey link was shared in the intranet of two companies, one multinational company developing management software based in Portugal and a global consulting company.

The participants' ages ranged from 17 to 62 years (M = 30.15, SD = 9.56). In terms of gender, 55.49% of the participants identified as female and 42.77% as male. Most of the respondents had an academic degree (n = 149), of which 74 participants had a master's degree, 70 a bachelor's degree, and 5 a Ph.D. Regarding employment, 37.57% of the participants were employed full-time, 35.26% were students, 10.40% were self-employed, and 8.09% worked part-time. Most respondents lived in Europe at the time (n = 162). See Appendix 2 for more detailed descriptive statistics.

4 Results

4.1 Data Cleaning and Transformation

The following steps were taken to prepare the data for analysis. First, dummy variables for the demographic variables were created. To make the analysis of the data concise, the following simplifications were made in coding of the dummy variables: the location of residence was assigned to Europe (n = 162) or other (n = 11), gender was assigned to female (n = 96) or male (n = 77), education was divided into bachelor's degree (n = 70), master's degree (n = 74), and other (high school, apprenticeship, Ph.D., other, prefer not to say; n = 29), students who worked were assigned to the categories full-time employment (n = 66), part-time employment (n = 21), or self-employed (n = 21), accordingly, leading to n = 61 students and n = 4 other educations (other, prefer not to say). Second, numerical scales were created, and the dataset was adjusted accordingly, considering if the scale item was normally or reverse coded. Lastly, the scale items were summed up to scale scores.

4.2 Descriptive Statistics

See Table 1 for an overview of the descriptive statistics of the variables of the FFM, TAM, actual use, intention to use, and job insecurity for GAI and AI.

Table 1

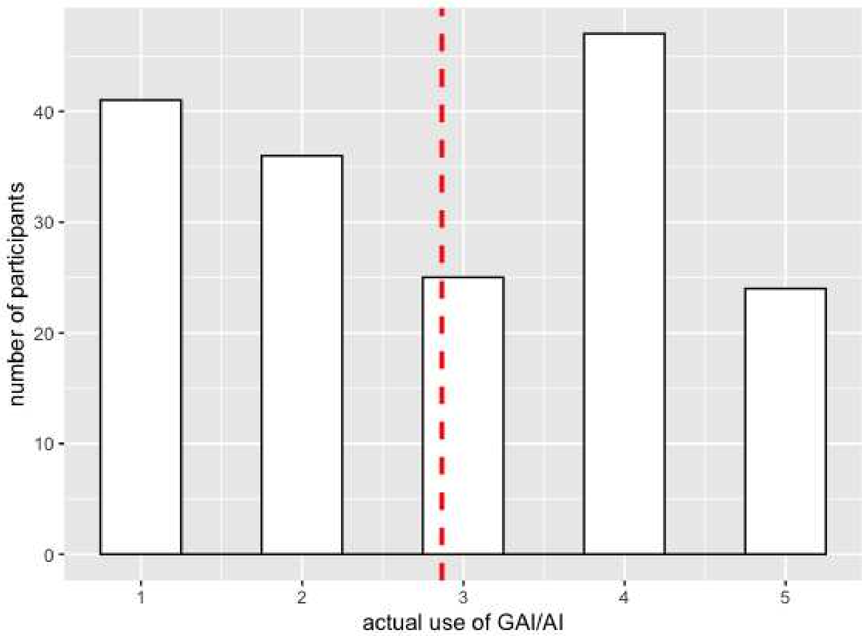
Descriptive Statistics

Variable	*M*	*SD*	Min	Max
Conscientiousness	14.89	3.32	4	20
Neuroticism	11.12	2.90	4	19
Openness	15.00	2.96	6	20
Perceived usefulness (GAI)	33.11	6.87	11	42
Perceived usefulness (AI)	31.37	8.29	7	42
Perceived usefulness (both)	32.20	7.67	7	42
Perceived ease of use (GAI)	32.61	6.17	16	42
Perceived ease of use (AI)	31.46	6.54	16	42
Perceived ease of use (both)	32.01	6.38	16	42
Actual use (GAI)	2.81	1.48	1	5
Actual use (AI)	2.92	1.34	1	5
Actual use (both)	2.87	1.41	1	5
Intention to use (GAI)	2.75	0.46	1	3
Intention to use (AI)	2.72	0.52	1	3
Intention to use (both)	2.73	0.49	1	3
Job insecurity (GAI)	7.05	3.49	4	19
Job insecurity (AI)	7.53	3.45	4	17
Job insecurity (both)	7.30	3.47	4	19

See Figure 3 for the distribution and mean of actual use of GAI/AI.

Figure 3

Histogram of Actual Use of GAI/AI With Red Dashed Vertical Line Indicating Mean



Note: 1 = Daily, 2 = Several times a week, 3 = Once a week, 4 = Less than once a week, 5 = Never; red dashed vertical line indicates the mean ($M = 2.87$).

4.2.1 Bivariate Correlations

The bivariate correlations showed a significant correlation between the dependent and some control variables. With perceived usefulness as dependent variable, gender, $r(171) = -.15$, $p = .045$, location of residence, $r(171) = -.15$, $p = .043$, master's degree, $r(171) = .21$, $p = .005$, and other education, $r(171) = -.45$, $p < .001$, correlated significantly. With perceived ease of use as dependent variable, age, $r(171) = -.16$, $p = .037$, location of residence, $r(171) = -.16$, $p = .036$, bachelor's degree, $r(171) = .21$, $p = .007$, and other education, $r(171) = -.20$, $p = .008$, correlated significantly. With intention to use as dependent variable, age, $r(171) = -.16$, $p = .031$, and other education, $r(171) = -.29$, $p < .001$, correlated significantly. With job insecurity as dependent variable, part-time employment, $r(171) = .16$, $p = .033$, self-employed, $r(171) = -.19$, $p = .011$, and other education, $r(171) = -.18$, $p = .019$, correlated significantly. With actual use as dependent variable, age, $r(171) = -.19$, $p = .013$, other education, $r(171) = -.24$, $p = .001$, full-time employment, $r(171) = -.25$, $p = .001$, and student, $r(171) = .21$, $p = .006$, correlated significantly.

Moreover, there were significant correlations between the study's main variables of interest: neuroticism was significantly correlated with perceived usefulness, $r(171) = -.17$, $p = .029$, perceived ease of use, $r(171) = -.18$, $p = .017$, gender, $r(171) = .19$, $p = .012$, self-employment, $r(171) = -.19$, $p = .014$, and the attention check question, $r(171) = -.17$, $p = .030$; conscientiousness was significantly correlated with self-employment, $r(171) = -16$, $p = .361$; openness was significantly correlated with age, $r(171) = -.21$, $p = .005$, other education, $r(171) = -.16$, $p = .033$, and actual use, $r(171) = .24$, $p = .002$; actual use was significantly correlated with job insecurity, $r(171) = .20$, $p = .008$. See Appendix 3 for the plotted bivariate correlations.

As the dummy variable indicating whether the participant answered questions about GAI or AI did not significantly correlate with any other variable (all $p > .068$), the two datasets were combined to one dataset and all further analysis were made with the combined dataset.

4.3 Hypothesis Testing

To test the 14 hypotheses, six linear regression models were conducted. I added the control variables and the attention check variable found to be significantly correlated to the main variables of interest in the bivariate correlations to each model, resulting in up to three sub-models per model. Table 2 gives an overview of the conducted regression models and the tested hypothesis.

Table 2

Overview of the Study's Regression Models and What Hypotheses They Test

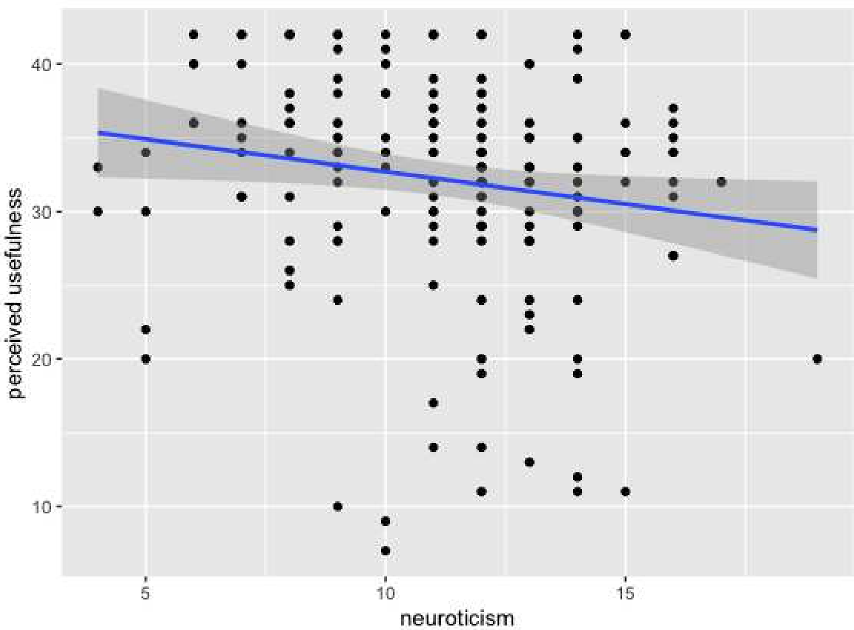
No.	Model	Hypothesis
1	Perceived usefulness ~ job insecurity + conscientiousness + neuroticism + openness	H1a, H2a, H4a, H6a
2	Perceived ease of use ~ conscientiousness + neuroticism + openness	H2b, H4b, H6b
3	intention ~ job insecurity + conscientiousness + neuroticism + openness	H1b, H2c, H4c, H6c
4	intention ~ conscientiousness * perceived usefulness	H3
5	intention ~ openness * perceived usefulness	H7
6	Job insecurity ~ neuroticism	H5

4.3.1 Regression 1 – Perceived Usefulness

The dependent variable of the first regression model was perceived usefulness and the independent variables were job insecurity, conscientiousness, neuroticism, and openness. This regression model had three sub-models: without control variables, with control variables, and with control variables and attention check variable. Job insecurity, conscientiousness, and openness were not statistically significant predictors, all $p > .10$, thus H1a, H2a, and H6a were not supported. H4a, which tested a negative association between neuroticism and the perceived usefulness of GAI/AI, was supported as the coefficient ($b = -0.45$, $SE = .20$) was statistically significant at a level of $p < .05$ in the model without the control variables, statistically significant at a level of $p < .10$ in the model with the control variables ($b = -0.31$, $SE = .19$), and statistically significant at a level of p < .10 in the model with the control variables and the attention check variable ($b = -0.34$, $SE = .19$). See Figure 4 for a graphical representation of the relationship between neuroticism and perceived usefulness. In the model with control variables and attention check variable, gender was statistically significant at a level of $p < .10$ ($b = -1.95$, $SE = 1.07$) and other education was statistically significant at a level of $p < .01$ ($b = -8.61$, $SE = 1.54$). The adjusted R^2 was .02, .22, and .22 for the model without control variables, the model with control variables, and the model with control variables and the attention check variable, respectively. See Appendix 4 for the output of the regression model.

Figure 4

Plot of Significant Relationship Between Neuroticism and Perceived Usefulness

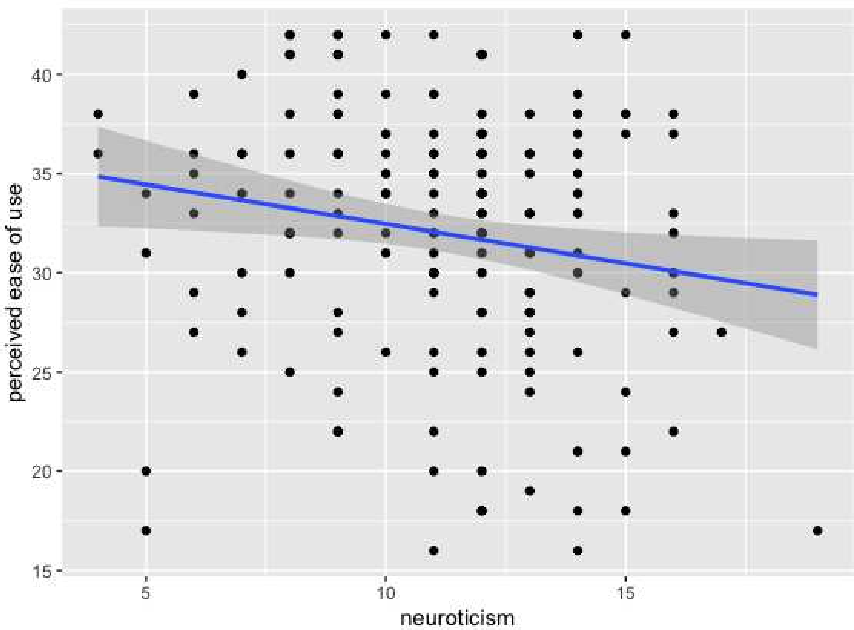


4.3.2 Regression 2 – Perceived Ease of Use

The dependent variable of the second regression model was perceived ease of use and the independent variables were conscientiousness, neuroticism, and openness. This regression model had three sub-models: without control variables, with control variables, and with control variables and attention check variable. The coefficients of conscientiousness and openness were not statistically significant, both $p > .10$, thus H2b and H6b were not supported. H4b, which tested a negative association between neuroticism and perceived ease of use of GAI/AI, was statistically significant at a level of $p < .05$ in all three models (model without control variables: $b = -0.39$, $SE = .17$; model with control variables: $b = -0.33$, $SE = .17$; model with control variables and attention check variable: $b = -0.36$, $SE = .17$). See Figure 5 for a graphical representation of the relationship between neuroticism and perceived ease of use. In the model with control variables and attention check variable, location of residence was statistically significant at $p < .10$ ($b = -3.79$, $SE = 1.98$). The adjusted R^2 was .02, .08, and .08 for the model without control variables, the model with control variables, and the model with control variables and the attention check variable, respectively. See Appendix 5 for the output of the regression model.

Figure 5

Plot of Significant Relationship Between Neuroticism and Perceived Ease of Use



4.3.3 Regression 3 – Intention to Use

The dependent variable of the third regression model was intention to use GAI/AI and the independent variables were job insecurity, conscientiousness, neuroticism, and openness. This regression model had three sub-models: without control variables, with control variables, and with control variables and attention check variable. The coefficients of the independent variables were not statistically significant, all $p > .10$, thus H1b, H2c, H4c, and H6c were not supported. Other education was statistically significant at a level of $p < .01$ in the model with the control variables and attention check variable ($b = -0.34$, $SE = .11$). The attention check variable was statistically significant at a level of $p < .10$ ($b = -.14$, $SE = .09$). The adjusted R^2 was .01, .08, and .09 for the model without control variables, the model with control variables, and the model with control variables and the attention check variable, respectively. See Appendix 6 for the output of the regression model.

4.3.4 Regression 4 – Moderating Effect on Intention to Use (Conscientiousness)

In the fourth regression model I tested if the personality trait conscientiousness moderates the relationship between perceived usefulness and the intention to use such that the relationship is stronger for individuals with higher conscientiousness. This regression model had two sub-models: without and with control variables. I could not determine such a moderating effect of conscientiousness ($p > .10$) and, thus, H3 was not supported. There was a statistically significant coefficient for conscientiousness (H2c) in the model without the control variables ($p < .10$, $b = -.08$, $SE = .05$), which was probably not reflective of a true effect, as conscientiousness only became significant in the model with the interaction of perceived usefulness and conscientiousness (see Appendix 10; note no effect beyond conscientiousness is significant). No control variable was statistically significant. The adjusted R^2 was .29 and .29 for the model without control variables and the model with control variables, respectively. See Appendix 7 for the output of the regression model.

4.3.5 Regression 5 – Moderating Effect on Intention to Use (Openness)

In the fifth regression model I tested if the personality trait openness moderates the relationship between perceived usefulness and the intention to use such that the relationship is stronger for individuals with higher openness. This regression model had two sub-models: without and with control variables. I could not determine such a moderating effect of openness ($p > .10$) and, thus, H7 was not supported. Moreover, I found a statistically significant correlation between perceived usefulness and the intention to use ($p < .10$, $b = 0.04$, $SE = .02$), which supports the structure of TAM (Davis, 1989). No control variable was statistically significant. The adjusted

R^2 was .28 and .28 for the model without control variables to the model with control variables, respectively. See Appendix 8 for the output of the regression model.

4.3.6 Regression 6 – Job Insecurity

The dependent variable of the sixth regression model was job insecurity and the independent variable was neuroticism. This regression model had three sub-models: without control variables, with control variables, and with control variables and attention check variable. The coefficient was not statistically significant ($p > .10$) and, thus, H5 was not supported. In the model with the control variables and attention check variable, part-time employment was statistically significant at a level of $p < .10$ ($b = 1.56$, $SE = .79$) and other education was statistically significant at a level of $p < .05$ ($b = -1.42$, $SE = .71$). The adjusted R^2 was .00, .06, and .05 for the model without control variables, the model with control variables, and the model with control variables and the attention check variable, respectively. See Appendix 9 for the output of the regression model.

4.3.7 Relation Between TAM Variables

In addition to the regressions testing the hypotheses, I conducted regressions to verify the data according to the structure of TAM. See Appendix 11 for the output of these three regression models. The first model tested the impact of intention to use on actual use. Intention to use was statistically significant at a level of $p < .01$ ($b = 1.34$, $SE = .19$). The second model tested the impact of perceived usefulness and perceived ease of use on intention to use. Perceived usefulness was statistically significant at a level of $p < .01$ ($b = 0.03$, $SE = .01$) and perceived ease of use was not statistically significant ($p > .10$). The third model tested the impact of perceived ease of use on perceived usefulness. Perceived ease of use was statistically significant at a level of $p < .01$ ($b = 0.64$, $SE = .01$).

5 Discussion

The results of this study supported two hypotheses addressing this thesis' research questions. It is possible to predict GAI acceptance using personality traits (RQ1), as evidenced by the significant negative association between neuroticism and perceived usefulness (H4a) and perceived ease of use (H4b) of GAI/AI. Moreover, I did not find a significant influence of job insecurity on GAI/AI acceptance (RQ2) and of personality traits on job insecurity (RQ3).

I found statistically significant correlations between neuroticism and perceived usefulness as well as perceived ease of use. This means that people who are high in neuroticism have a lower perceived usefulness and perceived ease of use of GAI/AI, compared to people who are low in neuroticism. This finding is in line with the fact that highly neurotic people struggle adapting to new situations and technologies due to insecurities (Barrick & Mount, 2000; Devaraj et al., 2008; Özbek et al., 2014). Devaraj and collaborators (2008), as well as Özbek and collaborators (2014), found statistically significant correlations between neuroticism and perceived usefulness. The reason that I found an additional significant correlation between neuroticism and perceived ease of use of GAI/AI, whereas Devaraj and collaborators (2008) as well as Özbek and collaborators (2014) did not, could be the difference in the assessed technologies (Chau, 1996). Devaraj and collaborators (2008) assessed collaborative technology acceptance and Özbek and collaborators (2014) assessed smartphone use, which were both established technologies at the time the studies were conducted. Although ChatGPT in particular has been frequently used in the past months, GAI/AI technology adoption is still in a rather early stage. According to the innovation diffusion theory by Rogers (1995), innovators and early adopters are willing to adopt new technologies despite challenges, whereas subsequent customer groups hesitate using technologies in such early stages. I assume that innovators and early adopters use technology at least several times a week (n = 77), meaning that most participants have not yet adopted GAI/AI. The stage of adoption, novelty of innovation, and aversion of highly neurotic people to adapt new technologies could be the reason for a significant correlation of neuroticism with perceived ease of use in this study, whereas other studies (Devaraj et al., 2008; Özbek et al., 2014) could not find a significance.

I found a statistically significant negative correlation between conscientiousness and intention to use GAI/AI, although I expected conscientiousness to have a positive effect on GAI/AI acceptance. This result is probably not reflective of a true effect, as 1) there was no significant impact of conscientiousness on intention to use GAI/AI in the bivariate correlations, nor 2) in the regressions without moderation, nor 3) is there a significant correlation between perceived usefulness and conscientiousness which could explain the significance of conscientiousness only in the presence of perceived usefulness. I expected conscientiousness to be positively correlated with TAM variables because, according to Barrick and Mount (2000), conscientious people perform better on the job and give more effort, no matter which job type or level, compared to people low in conscientiousness. Man Tang and collaborators (2022) found that conscientious employees were highly valued in the 20th century, as machines required motivated and precisely operating employees to function. The authors continue by noting that technological innovations of the 21st century reduce the importance of the personality trait conscientiousness, as machines and intelligent technologies are increasingly capable of performing tasks independently. Man Tang and collaborators (2022) conclude that conscientiousness is not as highly valued in the job market anymore, compared to the past decade. In my opinion, this change in the importance of conscientiousness could decrease conscientious employees' motivation and let them perceive GAI/AI as threat. Besides that, as conscientious employees work accurately and perform well without using GAI/AI, they might not notice an improvement in their performance when using GAI/AI and thus perceive it as less useful, compared to less conscientious people, leading to a decreased intention to use it. Relating this to the non-significant results of this study, I assume that some highly conscientious participants might perceive GAI/AI as beneficial, while other participants might perceive it as useless or threat, cancelling out the expected positive effect and leading to non-significant values due to inconsistent answers.

I expected to find a positive correlation between openness and the TAM variables, as people who have a high degree of openness are more comfortable with change (McCrae & Costa, 1992), which is crucial as the adoption of GAI/AI is expected to change workplaces, organizations, and industries (Chui et al., 2022). I could not find a statistically significant relationship between openness and the TAM variables and there are various possible reasons for the non-significance of the values. Devaraj and collaborators (2008) could also not find a statistically significant connection between openness and perceived usefulness. As a reason, Devaraj and collaborators (2008) mentioned the possible existence of a more complex relationship between the variables, instead of a simple linear relationship. Testing for a direct connection between openness and the intention to use in a structural equation model, Devaraj and collaborators (2008) found a statistically significant coefficient. In my study, I could not support this finding, as H6c was not supported. Svendsen and collaborators (2013) could also not find a significant relation between openness and intention to use but found a statistically significant positive relation between openness and perceived ease of use. Moreover, I could not find a significant moderating effect of openness on the relation between perceived usefulness and intention to use. Behrenbruch and collaborators (2013) also could not find a significant moderating effect. Another reason for the non-significant values of openness in my study could be that GAI/AI is a relatively new and substantial technological innovation, as it is the first time that technology accesses creativity, an area that was reserved only by humans in the past (Chui et al., 2022). As previously mentioned, I assume that mostly innovators and early adopters use GAI/AI and are aware of its potential effect on organizations and humans' lives (Rogers, 1995). The mere personality trait of openness might not be sufficient to perceive such an innovation as useful, easy to use, and have the intention to use it, as openness does include but is not limited to openness towards technological innovations. I assume that early and late majority customers, which is the majority of this study's sample, are not yet using GAI/AI on a regular basis and/or are not fully aware of its potential use cases and impact (Rogers, 1995), even though they might have a high degree of openness. In fact, the personality trait openness describes a person's general openness to experience, which can but must not apply to openness to explore technological innovations (McCrae & Costa, 1992). Factors like self-efficacy and knowledge of GAI/AI and its potential use cases could influence the correlation between openness and the TAM variables.

In this study, participants on average disagreed with the job insecurity statements. This is not consistent with estimations about a high number of jobs being threatened by automation (Briggs et al., 2023; Chui et al., 2022). There could be different reasons for this result. First, GAI/AI is not likely to automate less technical jobs or jobs including physical human action. People in those jobs might feel less threatened by GAI/AI than people in jobs that will likely be automated (Coupe, 2019). Nevertheless, I assume that a rather small number of participants works in such jobs, as I shared the survey with people in rather technical jobs that mostly only require limited physical action from humans. Second, people might not yet be aware of the changes GAI/AI might bring to their lives. As previously mentioned, most participants are not yet using GAI/AI on a regular basis and/or are not fully aware of its potential use cases (Rogers, 1995). Thus, participants might not fear losing their job because they are not yet aware of the possible changes GAI/AI might bring in the future. As job insecurity assessed in this study was rather low, job insecurity did not significantly influence perceived usefulness and the intention to use GAI/AI. Furthermore, neuroticism and job insecurity were not significantly correlated. Regression model 6 showed that job insecurity is determined by other factors than personality traits. R^2 is very low, even in the model with the control variables (.08), indicating that other variables, which are not included in the model, influence job insecurity. This could be, for example, education, welfare system, personal financial condition, or regulations for the application of GAI/AI.

According to Chau (1996), the influence of perceived usefulness and perceived ease of use on intention to use and, thus, actual use, varies depending on the underlying technology. Thus, it is possible that perceived usefulness and perceived ease of use have less influence on GAI/AI acceptance, compared to other technologies. This could influence the number of supported hypotheses in this study. In addition to perceived usefulness and perceived ease of use, other factors, such as knowledge, awareness, and the type and technicality of job, could be predictors of GAI/AI acceptance. This is reflected by the rather low values of R^2 in the regression analysis (max. R^2 determined in Regression Model 4 at .31), showing that the dependent variables were not fully described by the predictors.

Moreover, I gained various demographic insights. Women perceive GAI/AI as less useful, compared to men. This is in line with the findings of Venkatesh and Morris (2000), who found that men are driven by functionality and productivity, while women take into consideration other factors, possibly leading to a lower perceived usefulness of women in this study.

Participants with other education (combining Ph.D., high school, apprenticeship, other, and prefer not to say, n = 29) perceived GAI/AI as less useful and had a lower intention to use GAI/AI, compared to participants with a bachelor's or master's degree. Considering that the number of participants with a Ph.D. in other education was rather low (n = 5), I assume that most participants with other education work in less technical jobs. As GAI/AI is mostly applicable in technical jobs requiring only limited physical human action (Chui et al., 2022), participants with other education might perceive GAI/AI as less useful and have a lower intention to use GAI/AI due to their type of job. Furthermore, participants with other education perceive less job insecurity, compared to people with a bachelor's or master's degree. This might also be due to the technicality of job, assuming that most participants with other education work in less technical jobs, which are less threatened by automation.

Participants living in Europe perceived GAI/AI as less easy to use, compared to participants living on other continents. One needs to keep in mind that there was an unequal distribution of locations of residence in this study (Europe: n = 162, North America: n = 4, South America: n = 4, Asia: n = 2, Australia: n = 1). This finding is in line with Müller's (2019), who assessed autonomous and battery-electric vehicles technology acceptance and found a stronger link between the TAM variables in North America compared to Europe and China.

Participants working in part-time employment perceived a higher job insecurity compared to participants in other forms of employment. A reason for this finding could be that part-time employees have, in general, a higher threat to be replaced by technology. This is in line with Näswall and De Witte's (2003) finding that part-time workers in Italy have a higher job insecurity compared to full-time workers. Nevertheless, the authors found opposing results for the Netherlands, suggesting considering the economic situation and whether the type of job is voluntary or involuntary in future research.

Lastly, the data was validated according to Davis' TAM (1989), as the variables were positively correlated in line with the TAM relationships. Even the non-significant impact of perceived ease of use on intention to use (Regression Model 2, Appendix 11) is reflected by TAM, as perceived ease of use is an antecedent of perceived usefulness, which could have shifted the effect of perceived ease of use on intention to use on perceived usefulness.

5.1 Implications

This study has theoretical and managerial implications. It contributes to existing literature on the impact of personality traits on technology acceptance, as no previous study focused on GAI/AI acceptance. Other than previous research expected (Matthews et al., 2021), I could not find a difference between GAI and AI. A reason could be that participants were not aware of differences in technologies due to lack of knowledge. Moreover, I could not find an impact of job insecurity on GAI/AI acceptance or of personality traits on job insecurity. This could also be reasoned in participants' lack of knowledge and awareness of the changes GAI/AI might bring. Besides theoretical implications, this study has managerial implications.

Considering the possible changes GAI/AI might bring, organizations need to optimize its implementation to maximize GAI/AI's benefit by streamlining employees' acceptance of this technology. I suggest adapting recruiting and training of employees in line with the findings of this thesis. I recommend to thoroughly consider which person to hire for management positions that are crucial for a successful implementation of GAI/AI on an organizational level, as this could influence GAI/AI acceptance of subordinate team members and interfere with the application on an organizational level (Telli & Shelenkova, 2018). Additionally, I suggest offering trainings for the needs of neurotic employees to improve their GAI/AI acceptance. Considering the statistically significant positive correlation between perceived usefulness and intention to use GAI/AI (Davis, 1989), it is important to emphasize the utility of the technology by focusing on its practical benefits to individual employees. This could be achieved by offering dedicated trainings for each department, focusing on practical examples on how to use GAI/AI (e.g., marketing department could learn how to create social media content using GAI/AI).

5.2 Limitations

While this study has important implications, there are limitations that need to be considered. First, as all methods are based on self-reports and the different variables were measured in the same survey. This may have influenced the findings and relationship between the variables. This common method bias (Podsakoff et al., 2003) could have been prevented by, for example, assessing the participants' acceptance of GAI/AI in a practical experiment. However, this was not practically feasible due to the limited scope of the study.

Second, as noted by Allport (1937), a person's personality cannot be fully assessed through one questionnaire, considering the short measurement scale to keep the length of the survey rather short. To fully assess a person's personality, it is important to take into consideration the whole circumstances of the situation as well as the general level of stress on the nervous system, as they can influence human behavior and thus the responses on the survey.

Therefore, the survey assesses the participants' personality in broader terms, which could lead to slightly different outcomes, compared to the participants' real personality. Nevertheless, these rather small deviations are acceptable for the purposes of this study.

Third, in keeping the measurement scales for personality traits short, a certain degree of detail gets lost. As previously mentioned, the personality trait openness might not be detailed enough to capture openness towards technological innovations, whereas, for example, the facets self-efficacy and knowledge might influence the openness towards technological innovations.

Fourth, the attention check question was not clearly understood by all participants, leading to a high number of responses that should have been technically deleted. As the time to conduct the study was limited and the attention check question did not have a large statistical impact on the results, the responses were not deleted.

Fifth, the diversity of participants was somewhat limited: 70.52% of participants were 30 years old or younger and 86.12% of participants had an academic degree (bachelor, master, or Ph.D.), making the sample somewhat unbalanced.

5.3 Future Research

To build on the knowledge gained from this study and broaden the general knowledge about the acceptance of GAI/AI, I suggest the following topics for future research: First, future research should take into consideration regulations that restrict the use or development of GAI (Browne, 2023; Mukherjee et al., 2023) and that official communication, such as the official letter asking for a development pause of GAI (Future of Life Institute, 2023), might raise bias or prevent people from using GAI. Regulations restricting use could negatively influence perceived ease of use, whereas official communication about potential threats of GAI/AI could decrease perceived usefulness.

Second, information about the technicality of participants' job and position could be used to get deeper insights into differences in GAI/AI acceptance and its impact on job insecurity.

Third, job insecurity and awareness of GAI/AI could be assessed at different points in time to see how the variables change, once the technology is more established.

Fourth, to complement the prediction of acceptance of GAI/AI and job insecurity, I suggest including additional variables to the conceptual model. Interesting variables could be self-efficacy and knowledge of the technology and possible applications. I suggest testing the knowledge of participants by asking questions instead of letting participants rate their own knowledge to get unbiased answers that can be evaluated in a standardized manner. Additionally, once people's knowledge and awareness increase, it might be possible to detect differences between GAI and AI acceptance, as proposed by Matthews and collaborators (2021).

Lastly, although a sensitivity power analysis using G*Power (Faul et al., 2009) showed that the study had enough power (power = 80%, $\alpha = .05$, two-tailed) to detect correlations of .22 or higher, future studies attempting to find a relationship between job insecurity and the acceptance of GAI/AI, or between personality traits and job insecurity, should try to either increase the power probability to a greater level (e.g., 95%) or to estimate the size of effect as even smaller than .22 (e.g., $r = .10$).

6 Conclusion

In conclusion, this study found a negative impact of neuroticism on perceived usefulness and perceived ease of use of GAI/AI. This finding is in line with the fact that highly neurotic people struggle adapting to new situations and technologies due to insecurities. While the application of GAI/AI is expected to fundamentally change workplaces, organizations, and industries, highly neurotic people will likely have difficulties to accept GAI/AI. Therefore, I suggest to thoroughly consider who to recruit for management positions that are crucial for a successful GAI/AI implementation on an organizational level. Additionally, I recommend offering dedicated trainings that emphasize the utility of GAI/AI. Finally, future studies should accompany the rapid technological development to see how individual differences help predict who is more likely to accept and make use of GAI/AI.

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Appendix 1 – Survey in Both Versions

Survey Flow

Block: Start **Standard: Mini IPIP-FFM**
BlockRandomizer: 1 - Evenly Present Elements
Standard: TAM & job insecurity - generative AI **Standard: TAM & job insecurity - AI**
Standard: Demographics

Start of Block: Start

Q3 Thank you for your interest in taking part in my Master's thesis' study. I really appreciate your help!

With this study, I want to research whether certain individual characteristics predict a better acceptance of systems using artificial intelligence (AI) and generative artificial intelligence (generative AI). AI can analyze data, recognize patterns, make predictions, automate tasks, and learn from experience to improve its performance. Systems using generative AI, such as ChatGTP, can create new content in the form of text, images, programming code, videos, or audio. To conduct my research, I kindly ask you to answer a few questionnaires that should take about 4 minutes to complete.

Your answers will be recorded anonymously and will be used exclusively for the analysis within the scope of my Master's thesis. Your participation is voluntary. You have the right to decline to participate and to withdraw once participation has begun. To do so, simply close this web page. There are no foreseeable consequences of participating, declining, or withdrawing from this study.
If you have any questions, please contact me, Debora Tassone, at [email address, retracted].

Start of Block: Mini IPIP-FFM

Q5 Thank you for accepting to take part in my study! To start, please tell me how well each of the statements below describe you. I kindly ask you to indicate, as honestly as possible, whether the statements accurately describe you or not.

	Very inaccurate	Moderately inaccurate	Neither inaccurate nor accurate	Moderately accurate	Very accurate
Get chores done right away.	○	○	○	○	○

Often forget to put things back in their proper place.	○	○	○	○	○
Like order.	○	○	○	○	○
Make a mess of things.	○	○	○	○	○
Have frequent mood swings.	○	○	○	○	○
Am relaxed most of the time.	○	○	○	○	○
Get upset easily.	○	○	○	○	○
Seldom feel blue.	○	○	○	○	○
Have a vivid imagination.	○	○	○	○	○
Am not interested in abstract ideas.	○	○	○	○	○
Have difficulty understanding abstract ideas.	○	○	○	○	○
Do not have a good imagination.	○	○	○	○	○

End of Block: Mini IPIP-FFM

Start of Block: TAM & job insecurity - generative AI

Q8 Generative AI is a powerful subset of AI that uses deep learning algorithms to create new and original content. Unlike traditional AI models that are designed to recognize and categorize existing data, generative AI has the ability to create entirely new datasets, which makes it an exciting technology with immense potential in the workplace.

Here are four examples of how generative AI can be used in the workplace:
1. Content creation: Generative AI can be used to create engaging content, such as blog posts, product descriptions, and social media updates, which can save time and resources for businesses.
2. Product design: Generative AI can assist in the creation of innovative and unique product designs, improving the efficiency of the design process.
3. Language translation: Generative AI can be used for language translation in real-time, improving communication and collaboration across different regions and languages.
4. Personalized recommendations: Generative AI can be used to create personalized recommendations for customers based on their browsing or purchasing history, improving customer satisfaction and loyalty.

Generative AI has the potential to revolutionize the workplace and improve the efficiency of many processes. As businesses continue to seek innovative solutions to improve their operations, generative AI is poised to become an increasingly important technology.

In fact, this page, excluding for this sentence, was generated by ChatGTP. Impressive, right?

Page Break

Q9 Please indicate your agreement with the statements below using the scales provided.

	Extremely unlikely	Quite unlikely	Slightly unlikely	Neither unlikely nor likely	Slightly likely	Quite likely	Extremely likely
Using generative AI in my job would enable me to accomplish tasks more quickly.	○	○	○	○	○	○	○
Using generative AI would improve my job performance.	○	○	○	○	○	○	○
Using generative AI in my job would increase my productivity.	○	○	○	○	○	○	○
Using generative AI	○	○	○	○	○	○	○

would enhance my effectiveness on the job.							
Using generative AI would make it easier to do my job.	○	○	○	○	○	○	○
I would find generative AI useful in my job.	○	○	○	○	○	○	○
Learning to operate generative AI would be easy for me.	○	○	○	○	○	○	○
I would find it easy to get generative AI to do what I want it to do.	○	○	○	○	○	○	○
My interaction with generative AI would be clear and understandable.	○	○	○	○	○	○	○
I would find generative AI to be flexible to interact with.	○	○	○	○	○	○	○
It would be easy for me to become skillful at using generative AI.	○	○	○	○	○	○	○
I would find generative AI easy to use.	○	○	○	○	○	○	○

Page Break

Q12 I already use generative AI.

- Daily
- Several times a week
- Once a week
- Less than once a week
- Never

Q13 I intend to use generative AI in the future.

- Yes
- Maybe
- No

Page Break

Q16 Generative AI can be useful in various situations and has the potential to revolutionize workplaces. Please indicate your agreement with the following statements, keeping in mind the potential impact of generative AI.

	Strongly disagree	Somewhat disagree	Partly agree partly disagree	Somewhat agree	Strongly agree
Chances are, I will soon lose my job.	○	○	○	○	○
I am sure I can keep my job.	○	○	○	○	○
I feel insecure about the future of my job.	○	○	○	○	○
I think I might lose my job in	○	○	○	○	○

the near future.

End of Block: TAM & job insecurity - generative AI

Start of Block: TAM & job insecurity - AI

Q60 AI is a technology that aims to mimic human intelligence with machines. It involves the development of computer systems, performing tasks such as learning, problem-solving, decision making, and language processing.

Here are four examples of how AI can be used in the workplace:

1. Chatbots: AI-powered chatbots can be used to provide customer service support or answer common employee questions. They can be programmed to understand natural language, recognize customer intent, and provide appropriate responses, all without human intervention.
2. Predictive analytics: AI can be used to analyze vast amounts of data to identify patterns and predict future outcomes. This can be useful in many areas of business, such as marketing, finance, and HR. For example, predictive analytics can be used to identify which job candidates are most likely to be successful in a particular role.
3. Robotic process automation: This involves using software robots to automate repetitive, rules-based tasks.
4. Image and speech recognition: AI can be used to analyze images or audio to identify patterns or recognize specific objects or people. This can be useful in many areas of business, such as security and surveillance, where images or audio can be used to identify potential threats.

AI has the potential to create significant value for businesses and improve the efficiency of many processes. As businesses continue to seek innovative solutions to improve their operations, AI is an increasingly important technology.

Page Break

Q61 Please indicate your agreement with the statements below using the scales provided

	Extremely unlikely	Quite unlikely	Slightly unlikely	Neither unlikely nor likely	Slightly likely	Quite likely	Extremely likely
Using AI in my job would enable me to accomplish tasks more quickly.	○	○	○	○	○	○	○
Using AI would improve my job performance.	○	○	○	○	○	○	○
Using AI in my job would increase my productivity.	○	○	○	○	○	○	○
Using AI would enhance my effectiveness on the job.	○	○	○	○	○	○	○
Using AI would make it easier to do my job.	○	○	○	○	○	○	○
I would find AI useful in my job.	○	○	○	○	○	○	○
Learning to operate AI would be easy for me.	○	○	○	○	○	○	○
I would find it easy to get AI to do what I want it to do.	○	○	○	○	○	○	○
My interaction with AI would be clear and understandable.	○	○	○	○	○	○	○

I would find AI to be flexible to interact with.	○	○	○	○	○	○	○
It would be easy for me to become skillful at using AI.	○	○	○	○	○	○	○
I would find AI easy to use.	○	○	○	○	○	○	○

Page Break

Q62 I already use AI.

- ○ Daily
- ○ Several times a week
- ○ Once a week
- ○ Less than once a week
- ○ Never

Q63 I intend to use AI in the future.

- ○ Yes
- ○ Maybe
- ○ No

Page Break

Q58 AI can be useful in various situations and has the potential to revolutionize workplaces. Please indicate your agreement with the following statements, keeping in mind the potential impact of AI.

	Strongly disagree	Somewhat disagree	Partly agree partly disagree	Somewhat agree	Strongly agree
Chances are, I will soon lose my job.	○	○	○	○	○
I am sure I can keep my job.	○	○	○	○	○
I feel insecure about the future of my job.	○	○	○	○	○
I think I might lose my job in the near future.	○	○	○	○	○

End of Block: TAM & job insecurity - AI

Start of Block: Demographics

Q17 Thank you for your answers so far. To finish, I would like you to please answer a couple of demographic questions.

Q18 What is your age?

____

Q19 What gender do you identify as?

○ Female

○ Male

○ Non-binary / third gender

○ Prefer not to say

○ Other ____

Q20 Where do you live?

- ◯ Europe
- ◯ North America
- ◯ South America
- ◯ Africa
- ◯ Asia
- ◯ Australia
- ◯ Prefer not to say

Q55 What is your favorite fruit? This is an attention check, please write computer in the text box.

____

Q21 What is the highest degree or level of education that you have completed/ are pursuing right now?

- ◯ High School
- ◯ Apprenticeship
- ◯ Bachelor's Degree
- ◯ Master's Degree
- ◯ Ph.D.
- ◯ Other ____
- ◯ Prefer not to say

Q22 What is your current employment status?

- ○ Student
- ○ Employed full-time
- ○ Employed part-time
- ○ Self-employed
- ○ Retired
- ○ Other ____
- ○ Prefer not to say

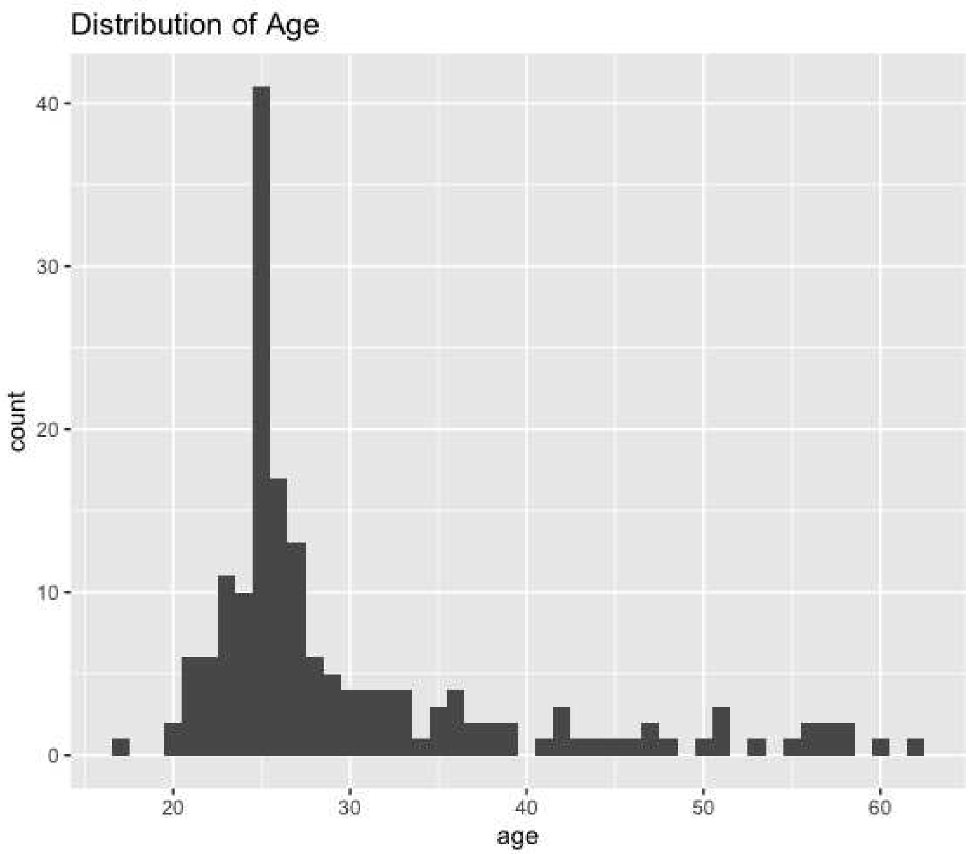
End of Block: Demographics

Thank you again for answering my survey.
Feel free to contact me in case of questions, comments or if you want to exchange ideas on the topic. Also, please send me an email if you are interested in the results of my study. By doing so, your survey responses will remain anonymous [email address, retracted].

Appendix 2 – Descriptive Statistics of Sample (Demographics)

Age

M = 30.15, *SD* = 9.56, Min = 17, Max = 62.



Gender

Value	Frequency	Percentage	Cumulative percentage
Female	96	55.49	55.49
Male	74	42.77	98.27
Non-binary/third gender	1	0.58	98.84
Other	2	1.16	100.00

Location of residence (continents)

Value	Frequency	Percentage	Cumulative percentage
Asia	2	1.16	1.16
Australia	1	0.58	1.73
Europe	162	93.64	95.38
North America	4	2.31	97.69
South America	4	2.31	100.00

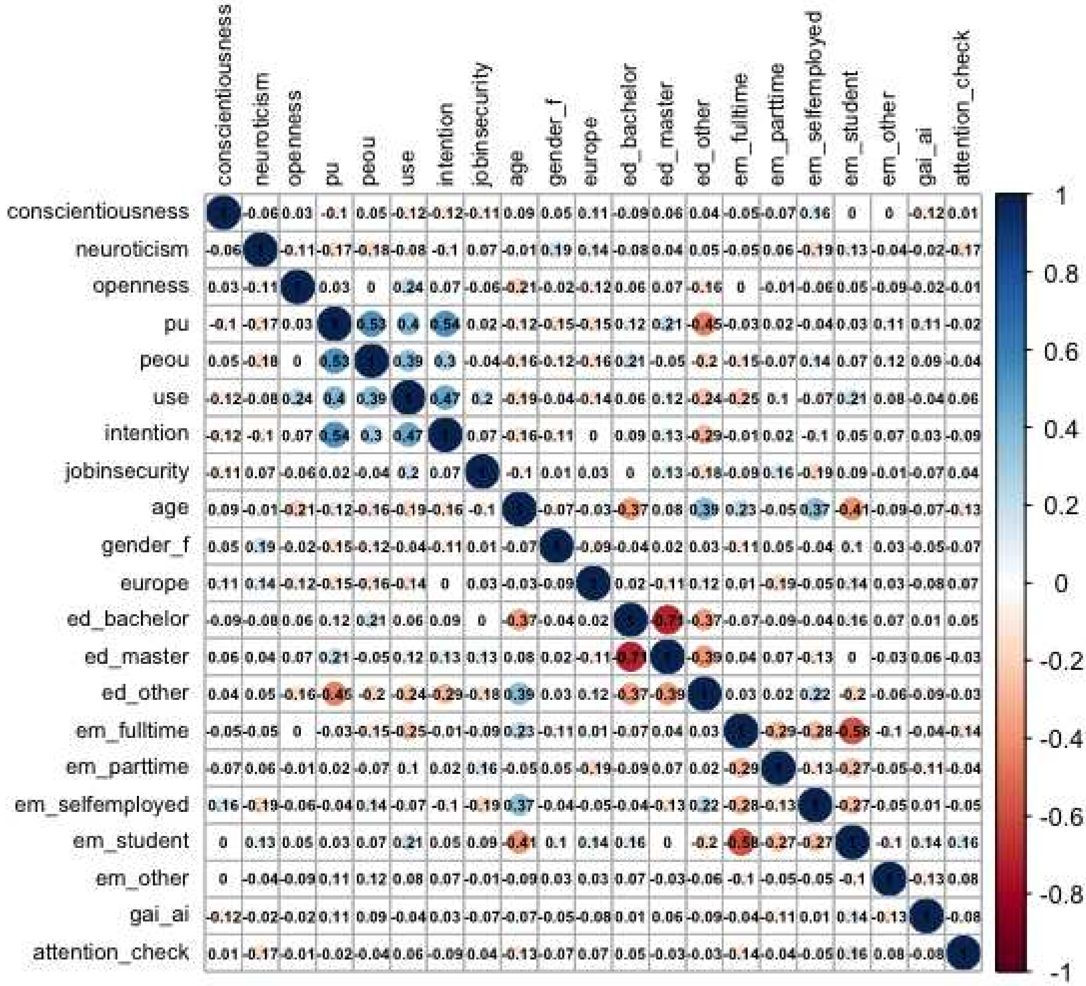
Education

Value	Frequency	Percentage	Cumulative percentage
Apprenticeship	9	5.20	5.20
Bachelor’s degree	70	40.46	45.66
High School	8	4.62	50.29
Master’s degree	74	42.77	93.06
Other	6	3.47	96.53
Ph.D.	5	2.89	99.42
Prefer not to say	1	0.58	100.00

Employment

Value	Frequency	Percentage	Cumulative percentage
Employed full-time	65	37.57	37.57
Employed full-time, self employed	1	0.58	38.15
Employed part-time	14	8.09	46.24
Employed part-time, self employed	1	0.58	46.82
Other	3	1.73	48.55
Prefer not to say	1	0.58	49.13
Self-employed	18	10.40	59.54
Student	61	35.26	94.80
Student, employed full-time	1	0.58	95.38
Student, employed part-time	7	4.05	99.42
Student, self-employed	1	0.58	100.00

Appendix 3 – Bivariate Correlations of the Study’s Main Variables of Interest and Demographics



Note: pu = perceived usefulness; peou = perceived ease of use; use = actual use of technology; intention = intention to use technology; jobinsecurity = perceived job insecurity; gender_f = dummy for gender (1 = female); europe = dummy for location of residence (1 = Europe); ed_bachelor = Bachelor’s degree; ed_master = Master’s degree; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; em_fulltime = employed full-time; em_parttime = employed part-time; em_selfemployed = self-employed; em_student = student; em_other = combined variable including other employment and responses prefer not to say; gai_ai = dummy variable for different versions of survey (GAI vs

AI; 1 = GAI); attention_check = dummy variable for correct answers to attention check question and wrong answers that imply that the question was read (1 = correct answer).

All effects of size |.15| or above are significant at $p < .05$, expect the relationship between perceived ease of use and full-time employment, $p = .0561$.

Appendix 4 – Output Regression Model 1 – H1a, H2a, H4a, H6a

Multiple Regression Analysis 1 - H1a, H2a, H4a, H6a

	Dependent variable:		
		pu	
	(1)	(2)	(3)
jobinsecurity	0.040	-0.147	-0.142
	(0.169)	(0.154)	(0.154)
conscientiousness	-0.255	-0.192	-0.192
	(0.176)	(0.159)	(0.159)
neuroticism	-0.454**	-0.309*	-0.335*
	(0.202)	(0.186)	(0.189)
openness	0.052	-0.171	-0.174
	(0.197)	(0.179)	(0.179)
gender_f		-1.921*	-1.947*
		(1.066)	(1.068)
europe		-2.796	-2.631
		(2.200)	(2.211)
ed_master		1.009	0.982
		(1.143)	(1.144)
ed_other		-8.563***	-8.614***
		(1.538)	(1.541)
attention_check			-1.008
			(1.227)
Constant	39.994***	46.832***	47.784***
	(4.979)	(4.798)	(4.941)
Observations	173	173	173
R2	0.041	0.257	0.261
Adjusted R2	0.018	0.221	0.220
Note:	*p<0.1; **p<0.05; ***p<0.01		

Note: pu = perceived usefulness; jobinsecurity = perceived job insecurity; gender_f = dummy for gender (1 = female); europe = dummy for location of residence (1 = Europe); ed_master = Master's degree; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; attention_check = dummy variable for correct answers to attention check question and wrong answers that imply that the question was read (1 = correct answer).

Appendix 5 – Output Regression Model 2 – H2b, H4b, H6b

Multiple Regression Analysis 2 - H2b, H4b, H6b

	Dependent variable:		
		peou	
	(1)	(2)	(3)
conscientiousness	0.081	0.170	0.171
	(0.145)	(0.143)	(0.143)
neuroticism	-0.398**	-0.326**	-0.359**
	(0.168)	(0.165)	(0.167)
openness	-0.048	-0.182	-0.191
	(0.164)	(0.164)	(0.164)
age		-0.067	-0.075
		(0.056)	(0.057)
europe		-3.976**	-3.795*
		(1.973)	(1.980)
ed_bachelor		1.742	1.730
		(1.067)	(1.067)
ed_other		-1.762	-1.747
		(1.418)	(1.417)
attention_check			-1.173
			(1.115)
Constant	35.961***	41.163***	42.618***
	(3.943)	(4.782)	(4.977)
Observations	173	173	173
R2	0.035	0.120	0.126
Adjusted R2	0.018	0.083	0.083
Note:	*p<0.1; **p<0.05; ***p<0.01		

Note: peou = perceived ease of use; europe = dummy for location of residence (1 = Europe); ed_bachelor = Bachelor's degree; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; attention_check = dummy variable for correct answers to attention check question and wrong answers that imply that the question was read (1 = correct answer).

Appendix 6 – Output Regression Model 3 – H1b, H2c, H4c, H6c

Multiple Regression Analysis 3 - H1b, H2c, H4c, H6c

	Dependent variable:		
	intention		
	(1)	(2)	(3)
jobinsecurity	0.009	0.002	0.002
	(0.011)	(0.011)	(0.011)
conscientiousness	-0.018	-0.016	-0.016
	(0.011)	(0.011)	(0.011)
neuroticism	-0.018	-0.016	-0.020
	(0.013)	(0.013)	(0.013)
openness	0.011	0.001	0.0002
	(0.013)	(0.013)	(0.013)
age		-0.003	-0.004
		(0.004)	(0.004)
ed_other		-0.341***	-0.335***
		(0.106)	(0.106)
attention_check			-0.142*
			(0.086)
Constant	2.976***	3.261***	3.449***
	(0.321)	(0.348)	(0.364)
Observations	173	173	173
R2	0.034	0.109	0.123
Adjusted R2	0.011	0.076	0.086
Note:	*p<0.1;	**p<0.05;	***p<0.01

Note: intention = intention to use technology; jobinsecurity = perceived job insecurity; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; attention_check = dummy variable for correct answers to attention check question and wrong answers that imply that the question was read (1 = correct answer).

Appendix 7 – Output Regression Model 4 – H3

Multiple Regression Analysis 4 - H3

	Dependent variable:	
	intention	
	(1)	(2)
conscientiousness	-0.080*	-0.073
	(0.045)	(0.045)
pu	0.001	0.003
	(0.021)	(0.021)
age		-0.004
		(0.004)
ed_other		-0.038
		(0.102)
conscientiousness:pu	0.002	0.002
	(0.001)	(0.001)
Constant	2.892***	2.953***
	(0.721)	(0.722)
Observations	173	173
R2	0.302	0.310
Adjusted R2	0.290	0.289
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: intention = intention to use technology; pu = perceived usefulness; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; conscientiousness:pu = interaction term between conscientiousness and perceived usefulness.

Appendix 8 – Output Regression Model 5 – H7

Multiple Regression Analysis 5 - H7

	Dependent variable:	
	intention	
	(1)	(2)
openness	0.009	-0.004
	(0.041)	(0.042)
pu	0.035*	0.029
	(0.019)	(0.019)
age		-0.005
		(0.004)
ed_other		-0.034
		(0.103)
openness:pu	-0.00001	0.0003
	(0.001)	(0.001)
Constant	1.498**	1.873***
	(0.619)	(0.672)
Observations	173	173
R2	0.290	0.299
Adjusted R2	0.277	0.278
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: intention = intention to use technology; pu = perceived usefulness; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; openness:pu = interaction term between openness and perceived usefulness.

Appendix 9 – Output Regression Model 6 – H5

Multiple Regression Analysis 6 - H5

	Dependent variable:		
	jobinsecurity		
	(1)	(2)	(3)
neuroticism	0.079	0.049	0.057
	(0.091)	(0.091)	(0.092)
em_parttime		1.540*	1.555*
		(0.793)	(0.795)
em_selfemployed		-1.426*	-1.389
		(0.847)	(0.852)
ed_other		-1.422**	-1.420**
		(0.708)	(0.709)
attention_check			0.318
			(0.609)
Constant	6.420***	6.972***	6.632***
	(1.051)	(1.060)	(1.247)
Observations	173	173	173
R2	0.004	0.079	0.081
Adjusted R2	-0.001	0.057	0.053
Note:	*p<0.1; **p<0.05; ***p<0.01		

Note: jobinsecurity = perceived job insecurity; m_parttime = employed part-time; em_selfemployed = self-employed; ed_other = combined variable including apprenticeship, high school, Ph.D., other, and prefer not so say; attention_check = dummy variable for correct answers to attention check question and wrong answers that imply that the question was read (1 = correct answer).

Appendix 10 – Output Regression Model – Relation Between Intention to Use and Conscientiousness

Multiple Regression Analysis: Intention to Use and Conscientiousness

	Dependent variable:		
	intention		
	(1)	(2)	(3)
conscientiousness	-0.018	-0.010	-0.080*
	(0.011)	(0.010)	(0.045)
pu		0.034***	0.001
		(0.004)	(0.021)
conscientiousness:pu			0.002
			(0.001)
Constant	3.002***	1.787***	2.892***
	(0.172)	(0.209)	(0.721)
Observations	173	173	173
R2	0.015	0.292	0.302
Adjusted R2	0.009	0.283	0.290
Note:	*p<0.1; **p<0.05; ***p<0.01		

Note: pu = perceived usefulness; intention = intention to use technology.

Appendix 11 – Output Regression Model – Relation Between TAM Variables

Multiple Regression Analysis: Relation between TAM variables

	Dependent variable:		
	use	intention	pu
	(1)	(2)	(3)
intention	1.338***		
	(0.193)		
pu		0.034***	
		(0.005)	
peou		0.002	0.641***
		(0.006)	(0.078)
Constant	-0.791	1.589***	11.691***
	(0.535)	(0.173)	(2.539)
Observations	173	173	173
R2	0.220	0.288	0.284
Adjusted R2	0.215	0.279	0.280
Note:	*p<0.1; **p<0.05; ***p<0.01		

Note: pu = perceived usefulness; peou = perceived ease of use; use = actual use of technology; intention = intention to use technology.