Ally or Competitor?

GenAI Adoption in the Creative Industries: Examining the Impact of the Human-AI Creativity Tension

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ABSTRACT

As generative artificial intelligence (GenAI) has the potential to transform the creative industries, understanding its integration through human-AI co-creation is crucial for organizations. Emerging research has focused on the capabilities of GenAI but largely neglected how its psychological impact on creative professionals influences their willingness to engage with it. We introduce the concept of the *human-AI creativity tension* that reflects the potential conflict arising from GenAI challenging the unique human creative agency. We argue that higher creative self-efficacy leads to a more positive view of GenAI as an *ally* by easing the tension, whereas the level of perceived AI identity threat results in a more negative view of GenAI as a *competitor*, which amplifies the tension. To examine how this influences adoption, we used a correspondingly extended version of the unified theory of acceptance and use of technology (UTAUT) and conducted a quantitative analysis of responses from 214 creative professionals using structural equation modeling. Our results show that of the UTAUT factors, performance expectancy and social influence strongly and moderately influence their desire to use GenAI. Creative self-efficacy unexpectedly has a moderate negative impact on the perceived usefulness of GenAI, while higher AI identity threat leads to creative professionals placing more importance on social influence than performance expectancy for their adoption decisions. These findings suggest that for successful GenAI integration organizations should not only demonstrate its practical benefits but also strategically address the social dimensions. Creating an organizational climate that is sensitive to the psychological impact of the human-AI creativity tension and that promotes identity work may facilitate the adoption process through encouraging creative professionals to view GenAI as an *ally* rather than a *competitor*.

Keywords:

Generative Artificial Intelligence (GenAI), Creative Industries, Human-AI Co-creation, Human-AI Creativity Tension, Creative Self-Efficacy, AI Identity Threat, Unified Theory of Acceptance and Use of Technology (UTAUT), Structural Equation Modeling (SEM).

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GLOSSARY

Average Variance Extracted	A measure used in statistics to quantify the amount of variance captured by a latent variable from its indicators relative to the amount due to measurement error (Henseler et al., 2015).
Composite Reliability	A statistic that estimates the internal consistency of a set of variables or measurement indicators representing a latent construct in structural equation modeling (Raykov, 1997).
Confirmatory Factor Analysis	A statistical technique used to test the hypothesis that a relationship between observed variables and their underlying latent constructs exists (T. Brown, 2015).
Creative Industries	Sector of the economy that involves the creation and commercialization of creative content and products, such as advertising, music, film, and design (Towse, 2020).
Creative Self-Efficacy	An individual's belief in their capability to produce creative outcomes (Tierney & Farmer, 2002).
Cronbach's Alpha	A measure of internal consistency or reliability of a set of scale or test items (Cronbach, 1951).
Effort Expectancy	The degree to which a person believes that using a particular technology will be free of effort (Venkatesh et al., 2003).
Facilitating Conditions	The degree to which a person believes that an organizational and technical infrastructure exists to support the use of a technology (Venkatesh et al., 2003).
Generative Artificial Intelligence	AI technologies that can generate new content or data that resemble human-like output (Brock et al., 2019).
Heterotrait-Monotrait	A criterion for assessing discriminant validity in measurement models by comparing the correlations between measures of theoretically different constructs (Henseler et al., 2015).

Human-AI Co-Creation	Collaborative work between humans and AI systems, where both contribute to the creative process and output (Rezwana & Maher, 2023; Wu et al., 2021).
Human-AI Creativity Tension	The potential conflict that arises when GenAI's capability to produce creative output challenges human creative agency in professional contexts.
Identity Theory	Defines how group memberships form part of an individual's self-concept, influencing their behaviors and interactions (Tajfel & Turner, 1979).
Item/Indicator	Question in a survey that participants respond to, or observable variables used as manifestations of a latent variable in structural equation modeling (Byrne, 2016).
Intention to Use GenAI	The degree to which a person has formulated conscious plans to use GenAI.
Latent Variable	A variable that is not directly observed but is inferred from other variables (indicators/items) that are measured directly (Hair et al., 2009).
Performance Expectancy	The degree to which a person believes that using a technology will help them to achieve gains in job performance (Venkatesh et al., 2003).
Social Cognitive Theory	A theory that describes learning in a social context. People are active agents who both influence and are influenced by their environment (Bandura, 1986).
Social Influence	The effect that the people we admire or who are important to us have on our behavior or our opinions in the context of technology adoption (Venkatesh et al., 2003).
Structural Equation Modeling	A statistical technique for testing hypotheses about the relationships among observed and latent variables (Byrne, 2016).
Unified Theory of Acceptance and Use of Technology	A framework to understand the user's intention to use information technology, which integrates elements from previous technology adoption models (Venkatesh et al., 2003).

LIST OF ABBREVIATIONS

AIT	AI Identity Threat
AI	Artificial Intelligence
AVE	Average Variance Extracted
CR	Composite Reliability
CFA	Confirmatory Factor Analysis
CSE	Creative Self-Efficacy
CRM	Customer Relationship Management
EE	Effort Expectancy
FC	Facilitating Conditions
GenAI	Generative Artificial Intelligence
GPT	Generative Pre-trained Transformer
HTMT	Heterotrait-Monotrait
USE	Intention to Use GenAI
PE	Performance Expectancy
ML	Maximum Likelihood
SCT	Social Cognitive Theory
SI	Social Influence
SEM	Structural Equation Modeling
UTAUT	Unified Theory of Acceptance and Use of Technology

1 INTRODUCTION

The launch of ChatGPT by OpenAI in November 2022 introduced the broader society to the potential of generative artificial intelligence (GenAI). Powered by the GPT architecture, GPT-4 generates contextually appropriate text based on user input (OpenAI et al., 2023). But the scope of GenAI extends beyond the creation of text. Various models are capable of transforming user text input into outputs of different data types. Suno AI composes melodious music (Hiatt, 2024), Midjourney creates images in a wide range of art styles (Midjourney AI, 2023), and Sora generates videos with a remarkable understanding of the physical world (Brooks et al., 2024). This unprecedented capability to generate limitless and novel content challenges the traditional notions of artistic and creative processes (Mazzone & Elgammal, 2019). The creative industries, where creative processes are central to the businesses' value creation, are particularly impacted by these advancements (Anantrasirichai & Bull, 2022). Contributing nearly $3 trillion to the global GDP in 2020, this sector spans industries such as advertising, journalism, music, film, video games, and fashion (Smeets & Bain, 2022; Towse, 2020). These industries are now examining the potential of GenAI to enhance creative production, as it offers new forms of expression and streamlines processes by acting as a collaborator for creative professionals (Anantrasirichai & Bull, 2022).

1.1 Problematization

The integration of GenAI into creative processes is an emerging research area, driven by the technology's novelty. To date, the field has primarily focused on exploring interaction models and ethical considerations. The current consensus is that the integration of GenAI through a collaborative model between humans and AI, termed *human-AI co-creation*, is the most effective for GenAI in its present state (Rezwana & Maher, 2023; Wu et al., 2021). This approach advocates for a turn-based creation process where the creative professional employs GenAI as a co-creation partner for specific tasks, particularly in idea generation where GenAI excels (Guzdial & Riedl, 2019). While research has concentrated on the capabilities of GenAI, a crucial human component has received limited scholarly attention: the factors influencing if creative professionals are actually willing to integrate GenAI into their creative processes.

In this context, there is an underexplored yet critical dynamic that naturally arises from the capabilities of GenAI. Traditionally, professionals in the creative industries have been the sole masters of creativity. While tools such as image and video editing software have long been in

use, they serve merely as operative extensions of the professional's creativity who remains in full control of the outcome. However, GenAI acts as a creative agent by producing outputs that are often both novel and appropriate to the context (Amabile, 2020). This capacity is increasingly referred to as AI creativity in the literature (Wu et al., 2021), a term we adopt to describe the generative capabilities of GenAI. We argue that this inherently challenges the previously unwavering position of creative professionals as the only creative actors in the creative process. We term this challenge to human creative agency the *human-AI creativity tension*. In fact, initial research indicates that creative professional's reactions to AI creativity are polarized, with some perceiving it as an *ally* of their creativity, while others view it as a *competitor* that sparks fears of identity and job loss (J. Li et al., 2024; Vimpari et al., 2023). How those perceptions concretely impact the willingness of professionals in the creative industries to integrate GenAI as a creative collaborator remains unexplored. It is however crucial for businesses to understand its impact in order to design the GenAI integration process in a way that complements the perspectives of their employees, who remain essential to the creative process.

1.2 Purpose and Research Question

The purpose of this study is to bridge the research gap concerning the human-AI creativity tension and its impact on GenAI adoption by creative professionals in the creative industries. Consequently, we adopt an underexplored human-centric approach, emphasizing that the successful integration of GenAI as a co-creation partner is contingent on its acceptance by creative professionals. Our research is driven by the following main research question:

How does the human-AI creativity tension influence the adoption of GenAI among creative professionals in the creative industries?

To make its impact measurable, we anchor our research within the established frameworks in the literature on technology adoption in organizations. Furthermore, given the lack of research on the human-AI creativity tension, we turn to psychology literature to make its impact more tangible. The tension may result in certain individual characteristics of creative professionals becoming significant factors in their decision to adopt GenAI by shaping their reactions towards AI creativity. In this study, we focus on two key characteristics: creative self-efficacy (CSE), which may positively influence GenAI adoption, and perceived AI identity threat (AIT), which may have a negative impact.

On the one hand, creative professionals with higher levels of CSE (Tierney & Farmer, 2002) might be more likely to perceive AI creativity positively, which eases the tension. Bandura's (1997) social cognitive theory (SCT) argues in general terms that self-efficacy is the belief in one's ability to succeed in certain situations. Applied to the context of GenAI adoption, those with greater confidence in their creative abilities would be more likely to believe in their ability to effectively steer and utilize the output of GenAI. For example, a fashion designer with high CSE might use GenAI to quickly explore new patterns. Confident in their creative ability to modify AI-generated patterns effectively, they perceive AI creativity as valuable enhancement to their creativity, which increases their likelihood of permanently adopting it.

On the other hand, creative professionals who feel threatened in their creative professional identity due to GenAI may view AI creativity more negatively, which amplifies the tension. Building on identity theory, Mirbabaie et al. (2022) examined how factors such as a perceived loss of status position and autonomy at work can lead to AIT. This can trigger resistance responses (Jussupow et al., 2022) and thus negatively impact the intention of creative professionals to integrate GenAI. For instance, a music producer who fears that AI-generated music might make their production skills seem less valuable or unique might resist integrating GenAI into their creative process, worried that it could lead to a loss of recognition and status in the industry.

Therefore, to answer the main research question, we investigate the following sub-questions (SQ), which examine two individual characteristics that may shape the impact of the human-AI creativity tension:

SQ1: *How does creative self-efficacy influence the adoption of GenAI among creative professionals in the creative industries?*

SQ2: *How does AI identity threat influence the adoption of GenAI among creative professionals in the creative industries?*

1.3 Expected Contribution

By examining the impact of the human-AI creativity tension on the adoption of GenAI by professionals in the creative industries, we aim to make theoretical contributions to two fields of research. First, we seek to expand the current discourse on human-AI co-creation by adopting an underexplored human perspective. This is accomplished by exploring the roles of a professional's CSE and perceived AIT in the context of this tension. Second, we contribute

to the research area of technology adoption in organizations by being among the first to study the factors influencing GenAI adoption in the creative industries. Through integrating the human-AI creativity tension, we introduce a unique psychological perspective to the literature that arises from the distinctive capabilities of AI technology. This consideration of individual characteristics has been suggested by prominent researchers in the field (see, e.g., Belanche et al., 2019; Venkatesh, 2022).

For practitioners in the creative industries, we expect to contribute to the field of change management, particularly in the effective integration of GenAI. By focusing on how the novel form of AI creativity alongside creative professionals impacts their willingness to integrate GenAI into their workflows, we aim to provide managers with valuable guidance for their integration strategies that consider the diverse perspectives of their employees.

1.4 Research Outline

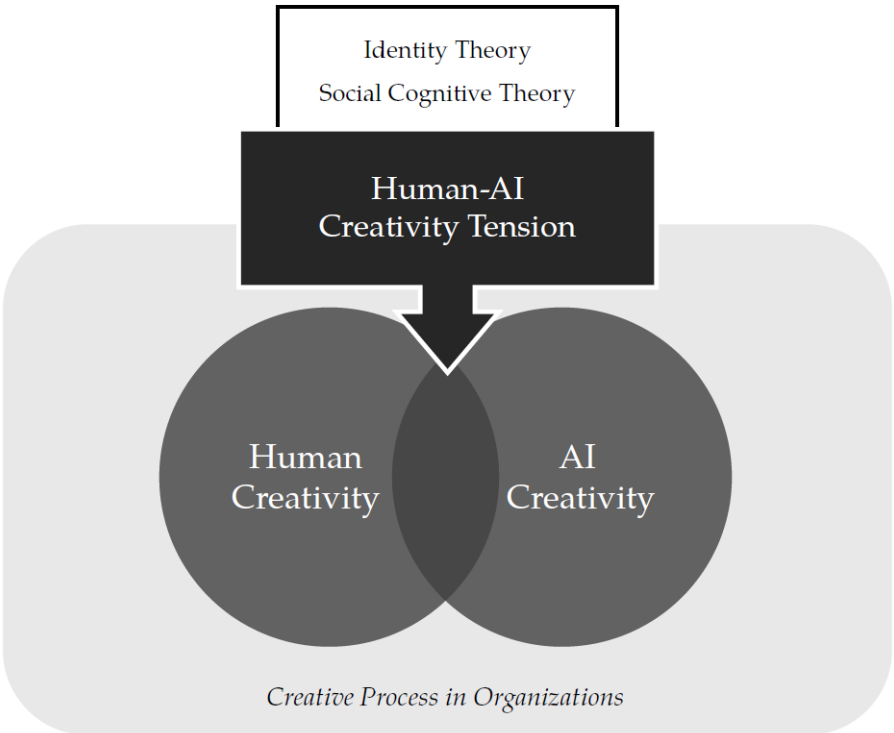
Our thesis is structured into seven chapters. In the *(1) Introduction* we outlined the transformative potential of GenAI and introduced the concept of the human-AI creativity tension, which established the foundation, purpose, and objectives of our study. Next, in the *(2) Literature Review* we synthesize themes from existing research on organizational creativity and AI to identify the research gap our study aims to fill. The *(3) Theoretical Framework* applies the unified theory of acceptance and use of technology (UTAUT) to hypothesize how CSE and perceived AIT influence GenAI adoption. In the *(4) Methodology* we outline our approach to empirically test this framework by presenting our research methods, sampling, and data analysis strategy. The *(5) Data Analysis* provides a detailed, step-by-step guide to our structural equation modeling (SEM) analysis and presents the results of our hypothesis testing. In the *(6) Discussion* we interpret our findings within the broader research context, discuss limitations, and suggest future research directions. Finally, the *(7) Conclusion* summarizes the key findings of our study on GenAI adoption in the creative industries in the context of the human-AI creativity tension and addresses theoretical contributions as well as managerial implications.

2 LITERATURE REVIEW

In this chapter, we develop a sequential understanding of the literature on the dynamics between human and AI creativity in organizations, as illustrated in Figure 1. First, we review the well-established research stream of creativity in organizations to give an overview of the creative process and characteristics of creative professionals in the creative industries. Second, we turn to the emerging literature of AI creativity resulting from the novel capabilities of GenAI and examine its potential as a co-creation partner that intersects with the human creativity of professionals. Third, we explore how this intersection not only holds great potential but also gives rise to the human-AI creativity tension, which we argue may affect the adoption of the technology. Given the limited literature on this dynamic, we draw upon SCT and identity theory to identify how CSE and AIT may shape creative professionals' views of AI creativity and influence its adoption by easing and amplifying the tension. We then synthesize those insights to identify the research gap that guides the focus of this study: the impact of the human-AI creativity tension on the adoption of GenAI within the creative industries.

Figure 1

Dynamics between Human and AI Creativity in the Creative Process.



Note. Own Creation.

2.1 Creativity in Organizations

Creative processes are central to the business models of enterprises in the creative industries (Towse, 2020). These businesses produce a wide range of material and immaterial products distinguished by their uniqueness and quality (Caves, 2000). Examples include developing marketing campaigns for newly launched products, creating TV productions, and producing new musical pieces. Creativity, at the core of these activities, helps to solve problems by combining and manipulating previously acquired knowledge, thus enabling the generation of novel and appropriate ideas (Boden, 2004). Conceptualizing creativity precisely has been a challenging and extensively studied subject. Rhodes (1961) synthesized various perspectives into a comprehensive framework known as the *4 Ps* of creativity: the *product*, the *press*, the *process*, and the *persons*. The aforementioned examples of creative outputs in the creative industries are considered the product of creativity (Lubart, 2001). They are conceived in the environments of creative organizations, the press, which are characterized by specific conditions and resources available to creative individuals (Rhodes, 1961). In the following, we examine the research streams on the other two perspectives of process and persons in the context of the organizations in the creative industries.

2.1.1 The Creative Process

The creative process encompasses the conscious and unconscious thoughts and actions that lead to the generation of novel and appropriate ideas (Lubart, 2001; Rhodes, 1961). It represents the application of a person's creative ability from a temporal perspective (Lubart, 2001). Historically, the first model to capture the stages of this creative thinking process was proposed by Wallas (1926) in his book *The Art of Thought*, consisting of the following stages: *preparation*, involving gaining a deep understanding of the problem and acquiring relevant knowledge, *incubation*, which entails unconscious thinking, *illumination*, a sudden spark of an original solution to the problem, and *verification*, where the individual tests the validity and utility of the idea. This model laid the foundation for further research to examine the creative process as a series of discrete stages. Cropley (1997) expanded this model by incorporating the stages of *intention*, *communication*, and *validation*, extending the creative process to a larger environmental context as it adds the external-oriented components of communication and validation.

Some researchers have applied the stage model of the creative process to organizational contexts. Amabile (1988) developed a model of individual and small-group creativity in organizations that includes the five stages of *task presentation*, *preparation*, *idea generation*, *idea*

validation, and *outcome assessment*. The impact of the work environment on the creative process in her model is particularly noticeable in the stage of outcome assessment, which categorizes the results as *success*, *failure*, or *progress* based on the criteria set by the organization (Amabile, 1988). While Amabile (1988) included only one evaluation stage after idea generation, Basadur (1991) highlighted the oscillating nature of ideation-evaluation at each stage of his *complete creative problem-solving process*. Building on similar themes, Woodman et al. (1993) conceptualized a model linking individual and group characteristics to organizational creativity, demonstrating how these traits influence the creative behavior and the resultant creative products within an organization.

Aiming to specify the creative process in organizations in the creative industries, Paris and Ben Mahmoud-Jouini (2019) studied 42 firms and found a similar pattern of stages: *inspiration*, where ideas are generated, *framing*, when ideas are expressed to others, *prototyping*, the first time that ideas are translated into reality, and *validation*, where the concepts are ultimately selected or rejected. They observed the importance of collaboration in these stages where team members cooperate under the direction of a primary contributor, "who commits personally in the creative project" (Paris & Ben Mahmoud-Jouini, 2019, p. 10). This builds on Becker's (1982) assertions that human collaboration is an integral part of the creative process. Furthermore, the ongoing digitalization of the creative industries has not only transformed outputs becoming more digital (Waldfogel, 2020), but also introduced digital technology that supports the creative professionals in the process (Cherry & Latulipe, 2014; Kirk & Pitches, 2013). The need to keep pace with technological developments highlights the importance for organizations to train their creative employees in the effective practice of the creative process, as suggested by Basadur (1991).

2.1.2 Creative Professionals

Engaging in the creative process to produce creative outputs are the professionals in creative roles, described as persons by Rhodes (1961). In the creative industries they are particularly important as they take a lead role in producing the unique content, which renders creative talent in high demand (Paris & Ben Mahmoud-Jouini, 2019). Research on this aspect of creativity mainly focuses on individual characteristics that contribute to a person's creativity. Early research by Mednick (1962) has explored the link of individual creativity levels to successful associative thinking, that is described to spark novel ideas by connecting (un)related concepts. Further studies have concentrated on the connection between personality and creativity, aiming to identify the *creative personality* (Helson, 1996).

Researchers have studied the correlation between personality test scores and creativity, with the Big Five personality test being the most prominent (Karwowski & Lebuda, 2016). The factor openness to experience has consistently shown a correlation with creativity measures (Dollinger et al., 2004; George & Zhou, 2001). In addition, researchers have identified various further overlapping and sometimes contradictory personality characteristics (Selby et al., 2005). A meta-analysis by Feist (1998) of 29 studies comparing artists and non-artists revealed that artists exhibit traits such as being open and imaginative in cognitive domains, and driven, ambitious, and impulsive in motivational domains. However, no definitive sets of traits have been identified, as creative professionals have significant individual differences.

In the creative industries, individuals' creativity is fundamental to their personal skills necessary for their work. Research has started to investigate the role of creativity in forming a role identity (Gotsi et al., 2010). Identity theory suggests that individuals' self-perceived identity is shaped by the roles they assume in society, influencing their behaviors, attitudes, and interactions with others (Stryker & Burke, 2000). Farmer et al. (2003) combined this theory with organizational creativity and found that the perception of employees as having been creative in the past predicts the formation of a creative role identity. In other words, creative individuals at work "regard personal creativity as a core part of who they are" (H. Zhang et al., 2020, p. 2). H. Zhang et al. (2020) further tested this idea and found that the strength of creative role identity significantly influences observed creativity. In the context of the creative industries, Paris and Ben Mahmoud-Jouini (2019) found that creative identities are particularly prevalent. In addition, Hackley and Kover (2007) examined the dynamics of personal and professional identity in organizations and highlighted how these interactions can sometimes lead to conflict. These findings indicate that certain creative professionals are inclined to incorporate their creativity into their professional identity, with the organization serving as a focal point for identity formation processes.

Altogether, creative professionals are a crucial asset in the creative process, which is fundamental to the value creation of firms in the creative industries. GenAI holds significant potential for improving the creative process and output, but its proper integration is essential. In the following section, we explore the role that AI creativity plays in the creative process and the potential benefits it offers.

2.2 AI Creativity

Due to the novelty of GenAI, the exploration of AI creativity represents a rather new research stream. As noted by Wu et al. (2021), prior creativity research has predominantly centered on

people, methods, and tools. With GenAI being developed to go beyond human's capabilities, Wu et al. (2021) argued that AI is more than just a tool. They propose a preliminary definition of AI creativity: "AI creativity is the ability for humans and AI to live and create together by playing to each other's strengths" (p. 176). While not all researchers agree that AI definitively possesses creativity, often engaging in deep analyses comparing it to the internal processes that make humans creative (see, e.g., Kirkpatrick, 2023; Lee, 2022; Wingström et al., 2022), many agree that GenAI represents a groundbreaking technology that positions it as a novel creator alongside humans (Amabile, 2020; Cetinic & She, 2022; Mazzone & Elgammal, 2019). For the purposes of this study, we build on the stance of some researchers that this can be described as AI creativity (Wu et al., 2021). Our focus is not on the philosophical debate about how GenAI produces its outputs, but on the fact that GenAI's output of novel and appropriate content is akin to that of human creativity.

2.2.1 Generative Artificial Intelligence

The reason for this emergent capability stems from the inherent nature of AI. AI is characterized by its capacity to simulate human cognitive functions through algorithms and data-driven models, which enables machines to learn from and adapt to new information, make decisions, and perform tasks that typically require human intelligence (Russell & Norvig, 2016). The concept of AI was formalized at Dartmouth College in 1956 during a seminal workshop organized by John McCarthy, which is widely considered to be the founding moment of AI as a field of study (McCarthy et al., 2006; Moor, 2006). Since then, research in this area has developed incrementally, evolving from basic machine learning algorithms to more advanced systems that are capable of performing specialized tasks that require human-like capabilities (Domingos, 2012; Rumelhart et al., 1986; Russell & Norvig, 2016). In recent years, the field has been significantly advanced by the work *Attention is All You Need* by Vaswani et al. (2017), which introduced the transformer model and thereby greatly improved the efficiency and effectiveness of machine learning, especially in natural language processing.

This advancement has facilitated the development of GenAI, a subcategory of AI that uses sophisticated models to generate novel and appropriate content (Brock et al., 2019; Goodfellow et al., 2014). This represents a shift in AI design from pure data interpretation to the attempted replication of human creativity (Amabile, 2020). Advanced systems in GenAI are often built on underlying language models that process human text input (Reed et al., 2016) and produce output in a variety of domains, ranging from text and images to music and

video (Anantrasirichai & Bull, 2022). Current state-of-the-art systems include GPT-4 and Gemini for large language models (Gemini Team et al., 2023; OpenAI et al., 2023), Midjourney for text-to-image models (Midjourney AI, 2023), and Sora for text-to-video applications (Brooks et al., 2024). These tools demonstrate a high degree of versatility and scalability, suggesting their use across various industries (Anantrasirichai & Bull, 2022).

2.2.2 Human-AI Co-creation in the Creative Process

Research on the integration of GenAI into the creative process is still evolving since GenAI is undergoing rapid development as a novel technology. This stream of research is referred to as *human-AI co-creation* (Rezwana & Maher, 2023; Wu et al., 2021). As the term implies, the current consensus is that a collaborative approach between human and AI creativity produces the most effective results. This is because GenAI in its current state cannot completely take over the creative process but has unique strengths that can be utilized (Mazzone & Elgammal, 2019). While humans develop creative ideas dynamically over time through different thought and reasoning processes, GenAI produces relatively static output directly tied to the human input prompt (Rezwana & Maher, 2023). Consequently, most interaction models advocate for turn-based co-creation where the user employs GenAI for specific tasks and builds on them with their human expertise (Guzdial & Riedl, 2019).

In the context of taking turns in the creative process, Kantosalo and Toivonen (2016) identified three roles for GenAI: as a generator of new ideas, as an evaluator providing feedback on human ideas, and as a concept-definer establishing boundaries for a creative task. These roles align with most stages of the creative process in organizations, as described by Amabile (1988), from preparation to outcome assessment. Among these, research has primarily focused on GenAI's role in generating new ideas (Hwang, 2022). Wu et al. (2021) noted that it enables humans to explore more ideas rapidly. As an example, in a study on human-AI co-creation in drawing, Karimi et al. (2020) found that GenAI facilitated ideation by presenting designers with new sketches when they were running out of ideas. Beyond drawing, GenAI supports idea generation in various domains in the creative industries, from journalism to animation (Anantrasirichai & Bull, 2022). For instance, in music generation, AI analyzes data to identify musical patterns and suggest new melodies (Louie et al., 2020). Although it has received less scholarly attention, GenAI can also be used for idea evaluation (Kantosalo & Toivonen, 2016), such as analyzing a creative piece of writing generated by the user (Rezwana & Maher, 2023). Still, most co-creative systems primarily assist in the idea generation stage. An analysis of 92 co-creative systems by Rezwana and Maher (2023) revealed that in 79.3% of these systems

GenAI acts as an idea generator, while it serves as both a generator and evaluator in 15.2% of systems. This underscores the existing need for human creativity to guide AI creativity in a turn-based manner. Vimpari et al. (2023) conducted qualitative interviews with designers about their perceptions of text-to-image GenAI. Most participants viewed their role in the creative process as evolving from a *first-hand craftsperson* to a *director of the AI* (Vimpari et al., 2023).

Ultimately, successful co-creation between humans and GenAI leads to positive effects for businesses that go beyond the creative product. For instance, in advertising and marketing, research has shown that GenAI as part of the creative process enables marketers to create more engaging, relevant, and impactful marketing campaigns (Haleem et al., 2022; Rabby et al., 2021). This improved efficiency and personalization has the potential to sustainably enhance customer relationships (Brynjolfsson et al., 2023; Kanbach et al., 2024; Rabby et al., 2021). This underscores how GenAI holds significant potential within the creative process through its capacity for co-creation with creative employees. However, reviewing the research on human-AI co-creation, much of the focus has been on the capabilities of GenAI, often overlooking the psychological impact of AI creativity on creative professionals and their individual characteristics that influence the adoption of GenAI.

2.3 Human-AI Creativity Tension

Building on the foundations laid in the preceding sections on creativity in organizations and AI creativity, it is evident that GenAI possesses significant potential when properly integrated into the creative process, particularly in the stages of idea generation (Paris & Ben Mahmoud-Jouini, 2019; Rezwana & Maher, 2023). We argue however that the willingness of professionals to integrate GenAI depends not only on the technical capabilities of GenAI, but also on the psychological impact of AI creativity on the creative professional. Unlike conventional software, GenAI contests the traditional role of creative professionals as the sole creative actors in the creative process (Mazzone & Elgammal, 2019). This novel and underexplored challenge to human creative agency is what we term the *human-AI creativity tension*.

In an effort to systematize the limited but emerging literature on reactions to AI creativity, we find that creative professionals often have a dualistic view: Many perceive it either as an *ally* or a *competitor* (Vimpari et al., 2023). As summarized in Table 1, a positive perception of GenAI is often rooted in its ability to inspire human creativity (Lundman & Nordström, 2023; Vimpari et al., 2023), free up time for work (Sun et al., 2024), and increase overall enjoyment in work (J. Li et al., 2024). Conversely, a negative perception, or viewing AI as a *competitor*, is

associated with fears of job loss (Jiang et al., 2023; Vimpari et al., 2023; Woodruff et al., 2024) and concerns about the devaluation of creative skills (J. Li et al., 2024). Additional factors influencing the perception of AI creativity can be found in Table 1.

Existing research recognizes the dualistic psychological impact of the human-AI creativity tension but lacks specificity on how this tension influences the adoption of GenAI. While broad perceptions have been identified, concrete individual characteristics of creative professionals that affect adoption remain undefined. The importance of individual differences in understanding AI adoption has been highlighted by prominent scholars, such as Belanche et al. (2019) and Venkatesh (2022). To address this gap, we explore two distinct individual characteristics that may shape creative professional's responses to AI creativity and subsequently affect GenAI adoption. Drawing on SCT and identity theory, we review literature on the potential role of CSE in contributing to a positive view of AI as an *ally*, which could facilitate adoption behavior through easing the tension. Conversely, we examine the impact of AIT, which may lead to a negative perception of AI as a *competitor*, potentially hindering adoption willingness through amplifying the tension.

Table 1

Reactions to AI Creativity: A Synthesis of Research Insights.

Stance	Perception	References
Ally	Freeing up time for fulfilling work	Vimpari et al., 2023; Sun et al., 2024
	Inspiring human creativity	Lundman and Nordström, 2023; Vimpari et al., 2023; Sun et al., 2024; Y. Li, 2024
	Higher enjoyment in work	Vimpari et al., 2023; J. Li et al., 2024
	Supporting exploration of identity	Vimpari et al., 2023
Competitor	Dehumanization	J. Li et al., 2024; Woodruff et al., 2024
	Fear of job loss	Jiang et al., 2023; Vimpari et al., 2023: Woodruff et al., 2024
	Loss of authenticity	Messer, 2024
	Devaluation of professional skills	Vimpari et al., 2023; J. Li et al., 2024; Woodruff et al., 2024
	Dependence on AI	Y. Li, 2024

2.3.1 Social Cognitive Theory: Creative Self-Efficacy

SCT, developed by Bandura (1986), provides a valuable framework for examining individual drivers of collaborative behavior. According to SCT, the decision to engage in a particular behavior is influenced by the evaluation of the expected outcome and the individual's belief in their ability to succeed, a concept known as *self-efficacy* (Bandura, 1986). Bandura (1997) defined it as "a judgment of one's ability to organize and execute given types of performances" (p. 21). Self-efficacy is therefore of key importance because individuals without confidence in their own ability to successfully complete a task will not engage in it, regardless of the possible positive outcome. This concept of self-efficacy has received considerable scholarly attention and has been applied to various contexts, including leadership (Paglis & Green, 2002), academia (Schunk & Pajares, 2002) and technology (C.-H. Wang et al., 2013). One specific application is CSE, that was first described by Tierney and Farmer (2002) as an individual's belief in their capacity to produce creative outcomes. We argue that the level of CSE of a creative professional could influence their adoption behavior of GenAI for two reasons.

First, while research indicates that adopting GenAI as a co-creation partner can significantly enhance creative outputs, it also concurs that in its current form, GenAI requires human creative abilities to effectively guide and evaluate AI creativity (Rezwana & Maher, 2023; Vimpari et al., 2023). Applying the framework of SCT to this context, creative professionals are more likely to engage in the behavior of integrating GenAI to improve their creative output when they believe to possess the creative abilities needed to steer and utilize its output. Consequently, they may have more positive views of AI creativity and perceive it as an *ally* that elevates their own creative performance, which could drive sustained adoption. Second, Karwowski et al. (2013) and Shin et al. (2012) found that CSE is positively related to openness to experience. Additionally, Gong et al. (2009) identified a link between higher levels of CSE and an increased motivation for learning. These findings suggest that creative professionals with higher CSE are more likely to seek out new experiences and learning opportunities, potentially making them more open to exploring and integrating GenAI as a tool for creative collaboration.

Viewing GenAI adoption by creative professionals through the lens of SCT therefore suggests that individuals with higher CSE are predisposed to embrace AI creativity. The positive reception and potential integration of GenAI can be attributed to two main reasons: first, they have confidence in their own creative abilities to utilize AI creativity effectively, and second, they are more open and motivated to learn about its proper integration. This implies that in

those cases AI is viewed as an *ally* and that the human-AI creativity tension is eased considerably through the integration of AI creativity.

2.3.2 Identity Theory: AI Identity Threat

According to identity theory as proposed by Tajfel and Turner (1979), social identity is a crucial part of an individual's self-concept that is derived from their perceived membership in social groups. Stryker and Burke (2000) contended that an individual can hold multiple identities, both as part of a group and individually. As such, role identity combines both dimensions as it is an individual view of the role they hold in a particular social context (Burke & Stets, 2009). As discussed in Section 2.1.2, research indicates that some creative employees build a part of their professional identity around being creative (Farmer et al., 2003; Gotsi et al., 2010; H. Zhang et al., 2020). With the emergence of GenAI, some creative professionals perceive AI creativity as a *competitor* that results in a loss of their professional skills and authenticity among other factors (Messer, 2024; Woodruff et al., 2024). Those negative reactions may be driven by a perceived threat to their creative role identity.

Craig et al. (2019) were among the first to examine how a challenged professional role identity can lead to IT resistance. Their research explored how the increased integration of IT into an individual's work life might prompt a resistance response when the individual perceives the new IT as being a threat to their role identity. They termed this dynamic the *IT identity threat* (Craig et al., 2019). Building on this concept, Mirbabaie et al. (2022) specified it to AI as a subset of IT, aiming to identify the specific drivers that predict the perceived AIT. Literature suggests a variety of possible predictors, ranging from a perceived loss of status position (Jussupow et al., 2018) to a loss of controllability (Schweitzer et al., 2019). Mirbabie et al. (2022) carried out a quantitative examination of the possible factors and identified loss of status position and changes to work as the main drivers of AIT. Jussupow et al. (2022) tested for AIT in the medical sector, identifying the threat to professional recognition and professional capabilities as the underlying drivers. Adding to this understanding, Gull et al. (2023) found that higher levels of perceived AIT led to higher affective job insecurity, highlighting the emotional impact of perceived threats to professional identity through AI.

Although no study to date has specifically tested the AIT for individuals in creative roles, the factors identified by Mirbabaie et al. (2022) and studies like Jussupow et al. (2022) suggest strong applicability to the creative industries. Professionals with a strong sense of creative identity might express resistance to the adoption of GenAI when they perceive their sense of self as being challenged by AI creativity. Thus, in the context of the human-AI creativity

tension, a higher perceived AIT may lead to negative reactions towards AI creativity. This perception positions GenAI as a *competitor* and amplifies the tension, potentially resulting in resistance responses that hinder its adoption.

2.4 Research Gap

The study of human creativity is well-established, but the emergence of GenAI, characterized by AI creativity, represents a new field of research. While the potential of GenAI in enhancing the creative process through human-AI co-creation has been well explored, the role of psychological factors in its adoption by creative professionals remains underexplored. As a second actor in the creative process, GenAI disrupts the unique human creative agency, creating what we term the human-AI creativity tension. This tension appears to involve a mostly dualistic stance among creative professionals towards GenAI, viewing it either as an *ally* that promotes human creativity or as a *competitor* that threatens job security and creative skills. The sparse body of literature provides first insights into the perceptions of AI creativity but falls short of identifying specific factors that influence the adoption of GenAI in the context of the human-AI creativity tension. Due to the tension, certain individual characteristics of creative professionals may now come into play in determining whether they choose to integrate GenAI into their creative processes.

To address the gap of how the human-AI creativity tension tangibly impacts the intention of creative professionals to integrate GenAI, we aim to investigate how the individual characteristics of CSE and perceived AIT influence their willingness to adopt GenAI as a co-creation partner. Specifically, we examine how CSE may positively impact adoption by aligning with the perception of GenAI as an *ally* and ease the tension, while perceived AIT may negatively affect adoption by amplifying the tension through framing GenAI as a *competitor*. This approach will not only advance the important human dimension to the theoretical discourse on human-AI co-creation but also offer practical insights for organizations in the creative industries looking to capture the potential of GenAI while addressing the psychological impact of AI creativity on its creative workforce.

3 THEORETICAL FRAMEWORK

To address the gap in research regarding the impact of the human-AI creativity tension on the adoption of GenAI in the creative industries, we develop a theoretical framework. This framework enables us to empirically test our hypotheses and interpret the data we collect in a structured manner (Kivunja, 2018). To holistically examine the influence of this tension on the adoption of GenAI, we construct the framework in two steps. First, based on existing research, we identify a general model for technology adoption in organizations, which serves as a foundation for empirical testing. Then, we integrate CSE and AIT as key individual characteristics related to the human-AI creativity tension into this model. Together, this allows for a comprehensive understanding of the impact of the human-AI creativity tension on GenAI adoption in the creative industries.

3.1 The Unified Theory of Acceptance and Use of Technology

Research on user acceptance of new information technology represents one of the most mature streams in information systems research, as highlighted by Venkatesh et al. (2003). The core concept of these models is to explain the use of information technology through a behavioral intention, which is rooted in individual perceptions of the technology (Venkatesh et al., 2003). Since the 1970s, a variety of models originally rooted in broader social contexts have been applied by researchers to explore technology adoption from diverse perspectives. The theory of reasoned action by Fishbein and Ajzen (1975) connects attitudes and subjective norms to behavior, paving the way for models like the theory of planned behavior by Ajzen (1991) and SCT by Bandura (1986), which views engagement in behavior from a socio-psychological perspective. The motivational model by Davis et al. (1992) focuses on intrinsic and extrinsic motivation, while the technology acceptance model by Davis (1985) emphasizes the importance of perceived usefulness and ease of use for technology adoption.

Due to the wide range of models rooted in broader social contexts but applied to technology adoption, Venkatesh et al. (2003) argued for the need to consolidate the most significant theories into a unified model of technology adoption. As a result, they developed the UTAUT, which is based on eight different models, such as the aforementioned motivational model and technology acceptance model. A total of 32 factors from existing models, which predicted the intention to use technology, were tested for their predictive power across different implementation timelines, including both before and after implementation. The analysis identified four factors with the most predictive power: *(a) performance expectancy (PE)*, the

degree to which an individual believes that using the technology will help them achieve improved job performance; *(b) effort expectancy (EE)*, the extent to which an individual perceives the technology as easy to use; *(c) social influence (SI)*, the magnitude to which an individual feels pressure from others to use the technology; and *(d) facilitating conditions (FC)*, the scale to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology. The relationships between these predictors and the intention to use the technology are moderated by age, gender, experience, and voluntariness of use.

Since its inception in 2003, the UTAUT model has been widely adopted for technology adoption research across various contexts, often with the introduction of additional predictors and moderators (Dwivedi et al., 2011; Williams et al., 2015). It has been applied in a diverse range of sectors, including healthcare (Hennington et al., 2009), mobile services (Koivumäki et al., 2007), and e-government (AlAwadhi & Morris, 2008). The model's application further spans a variety of technologies, ranging from enterprise resource planning systems (Seymour et al., 2007) to emerging domains such as cloud computing (Alharbi, 2014). In recent years, the UTAUT model has also been employed to examine the intention to use AI applications in various fields, including among librarians (Andrews et al., 2021), employee intentions to use AI-integrated customer relationship management (CRM) systems (Chatterjee et al., 2023), and AI adoption in HR recruitment (Tanantong & Wongras, 2024). Despite its broad applicability across sectors and technologies, through a meta-analysis Khechine et al. (2016) confirmed the general strength and robustness of the UTAUT model in explaining user adoption. Additionally, Rahimi (2020) recommended researchers to use the UTAUT model for examining technology adoption in the creative industries after contrasting several technology acceptance models. For these reasons, we will employ the UTAUT model as the foundational basis for the development of our theoretical framework.

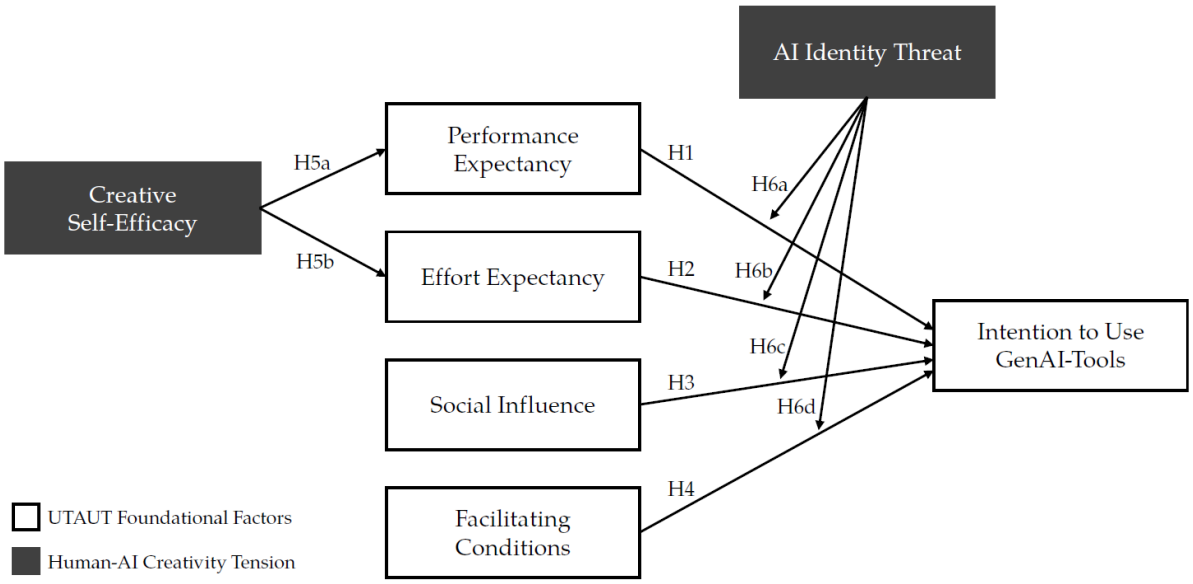
3.2 Synthesis and Hypothesis Development

Our theoretical framework is based on the UTAUT model discussed above and the literature review, which culminated in the identification of CSE and AIT as individual characteristics that might influence the adoption of GenAI by creative professionals. Figure 2 illustrates the theoretical framework, where variables of technology adoption from the UTAUT framework are represented by white boxes, and the two factors related to the human-AI creativity tension highlighted in dark gray. Based on the UTAUT, we hypothesize that the adoption of GenAI among creative professionals is influenced by their perceptions of its PE and EE as well as the

SI and FC surrounding GenAI. Connected to the human-AI creativity tension, professionals with higher levels of CSE perceive GenAI as more useful and easier to use through viewing AI as an *ally*. Conversely, the relationship between the predicting variables and the intention to use is moderated by the perceived AIT to their creative role identity by seeing AI as a *competitor*. We omit the demographic moderators from the original UTAUT because their exclusion is common in UTAUT studies (Dwivedi et al., 2011; Khechine et al., 2016) and we also do not expect that their addition would significantly impact the results in a way that would justify the increased complexity of the study. In the subsequent sections, we present the rationale behind each hypothesis in detail. Following this, a summary of the hypotheses is provided in Table 2.

Figure 2

Theoretical Framework for Human-AI Creativity Tension in GenAI Adoption.



Note. Adapted from the original UTAUT framework by Venkatesh et al. (2003).

3.2.1 UTAUT Foundational Factors

According to the UTAUT, Venkatesh et al. (2003) define PE as the degree to which an individual believes that using the system will improve job performance. In their original study, Venkatesh et al. (2003) identified PE as the strongest predictor of the intention to use new technology, a finding later confirmed by Khechine et al. (2016) in a meta-analysis. Recent research has extended this relationship to GenAI tools. Du et al. (2023) found a positive correlation between the perceived usefulness of GenAI and its adoption by artists, while Koponen (2023) reported similar results for the adoption of GenAI in knowledge work.

Additionally, Andrews et al. (2021) found that PE influences the intention to adopt AI among librarians in an organizational context. This suggests that the more useful creative professionals perceive GenAI to be for their creative process at work, the more likely they are to adopt it. Therefore, we propose the following hypothesis:

> **H1:** Performance expectancy positively influences the creative professional's intention to use GenAI.

In the UTAUT, Venkatesh et al. (2003) define EE as "the degree of ease associated with the use of the system" (p. 450). Recent studies support the notion that the easier GenAI is to use, the more likely it is to be adopted. Y. Wang and W. Zhang (2023) found that people in Generation Z are more likely to use GenAI when it requires less effort. Similarly, Gulati et al. (2024) identified a link between EE and marketing students' intention to adopt ChatGPT as a GenAI tool, and Du et al. (2023) discovered that the easier GenAI painting tools are to use, the higher their adoption by artists. In an organizational setting, Chatterjee et al. (2023) found that employees are more likely to adopt AI-integrated CRM systems when they perceive them as easy to use. This suggests that GenAI technology is more likely to be adopted in organizations when creative professionals perceive it as requiring little effort to use. Therefore, we propose the following hypothesis:

> **H2:** Effort expectancy positively influences the creative professional's intention to use GenAI.

SI is defined in the UTAUT as the extent to which an individual perceives that influential people in their life believe they should adopt a new technology (Venkatesh et al., 2003). This concept is linked to the perception of one's image and their position within the social system. Gulati et al. (2024) found that marketing students are more likely to use ChatGPT when their peers do the same. Similarly, the adoption of GenAI in knowledge work (Koponen, 2023) and GenAI painting tools by artists (Du et al., 2023) increases with higher SI. Given that creative professionals often interact with peers in their work, this suggests that they are more likely to use GenAI in their creative process if influential individuals in the organization endorse its use. Therefore, we propose the following hypothesis:

> **H3:** Social influence positively influences the creative professional's intention to use GenAI.

According to the UTAUT, FC are defined as the extent to which an individual perceives the availability of organizational support and resources to assist in using the technology (Venkatesh et al., 2003). Du et al. (2023) found a strong influence of FC on the adoption of GenAI painting tools by artists. Chatterjee et al. (2023) identified that the perception of an organizational infrastructure in place to support integration is positively linked with the intention to use AI-integrated CRM systems. Similarly, HR professionals' intention to use AI in recruitment systems was higher when they perceived the necessary resources and organizational support in place (Tanantong & Wongras, 2024). Considering the novelty of GenAI technology, this suggests that organizational support like training positively influences creative professionals' intention to adopt GenAI as a co-creation partner in their creative processes. Therefore, we propose the following hypothesis:

> **H4:** Facilitating conditions positively influences the creative professional's intention to use GenAI.

3.2.2 Human-AI Creativity Tension

As explored in Section 2.3., the human-AI creativity tension arises through the integration of GenAI as a co-creation partner, challenging the traditional agency of human creativity in the creative process. To understand its impact on GenAI adoption, we turned to SCT and identity theory to identify specific individual characteristics of creative professionals that might be significant factors in their perception and intention to adopt GenAI. SCT suggests that CSE leads to a positive engagement of creative professionals with AI creativity, which can result in an easing of the tension and encourage adoption. Conversely, identity theory provides a lens to understand how AIT might lead to an amplification of the tension, potentially discouraging adoption.

In the context of SCT, CSE, defined as the belief in one's capability to produce creative output (Tierney & Farmer, 2002), may positively influence the integration of GenAI in the creative process for two reasons. First, according to SCT, self-efficacy influences whether an individual engages in certain behaviors (Bandura, 1997). Co-creation with GenAI requires human creativity to effectively guide AI creativity (Mazzone & Elgammal, 2019). Therefore, creative professionals who are more confident in their creative abilities may feel more assured that they possess the creativity necessary to direct AI creativity in a way that complements their own creativity. As a result, they are likely to find the method of engaging with GenAI through prompting more straightforward and the output of GenAI more useful for their creative work. Thus, it's the confidence in their creative abilities – not objective creativity levels – that may

lead to an increased willingness to adopt GenAI because it affects the perception of its usefulness (PE) and ease of use (EE). Second, research has shown that individuals with higher CSE are more open to new experiences (Karwowski et al., 2013) and more motivated to learn (Gong et al., 2009). This suggests that professionals with higher CSE are more receptive to adopting new technologies like GenAI and more persistent in learning how to leverage its benefits. While, to our knowledge, no studies have specifically tested the role of CSE in technology adoption, various studies have empirically supported a similar hypothesis. They found a positive relationship between other forms of self-efficacy and adoption intention, such as computer self-efficacy in Compeau et al. (1999) and digital self-efficacy in Cavalheiro et al. (2020) within the context of the creative industries. Therefore, we propose the following hypotheses:

> **H5a:** Creative self-efficacy positively influences the creative professional's performance expectancy of GenAI.

> **H5b:** Creative self-efficacy positively influences the creative professional's effort expectancy of GenAI.

Based on identity theory, new technology can lead to resistance in adoption when it threatens an individual's identity (Craig et al., 2019). Translated to AI, Mirbabaie et al. (2022) identified a variety of factors that can invoke AIT, which we argue can also be applied to the introduction of GenAI. The emergence of AI creativity as a co-creation partner leads to a perceived loss of authenticity and fears of job loss by some creative professionals (Messer, 2024; Vimpari et al., 2023; Woodruff et al., 2024). This perception of AI as a *competitor* is impactful, as research indicates that some creative professionals build their identity around being creative at work (Farmer et al., 2003; Gotsi et al., 2010). Creative professionals whose core self-concept is challenged by AI creativity may experience a form of resistance that moderates their adoption behaviors. Even if they acknowledge the usefulness (PE) and ease of use (EE) of GenAI to the same extent as their peers who perceive a lower threat to their identity, their willingness to incorporate these tools into their creative processes may be decreased. This reluctance can be described as a psychological response to protect their sense of identity (Craig et al., 2019). Similarly, their efforts to preserve their creative identity could result in a lower intention to integrate GenAI into their work, despite experiencing similar levels of social pressure (SI) and organizational support (FC) as those who feel less threatened. Therefore, we propose the following hypotheses:

H6a: The influence of performance expectancy on the intention to use GenAI is moderated by AI identity threat.

H6b: The influence of effort expectancy on the intention to use GenAI is moderated by AI identity threat.

H6c: The influence of social influence on the intention to use GenAI is moderated by AI identity threat.

H6d: The influence of facilitating conditions on the intention to use GenAI is moderated by AI identity threat.

Table 2

Summary of Hypotheses.

Variable	Hypothesis	Relationship
		UTAUT Foundational Factors
PE	H1	Performance expectancy positively influences the creative professional's intention to use GenAI.
EE	H2	Effort expectancy positively influences the creative professional's intention to use GenAI.
SI	H3	Social influence positively influences the creative professional's intention to use GenAI.
FC	H4	Facilitating conditions positively influences the creative professional's intention to use GenAI.
		Human-AI Creativity Tension
CSE	H5a	Creative self-efficacy positively influences the creative professional's performance expectancy of GenAI.
CSE	H5b	Creative self-efficacy positively influences the creative professional's effort expectancy of GenAI.
AIT	H6a	The influence of performance expectancy on the intention to use GenAI is moderated by AI identity threat.
AIT	H6b	The influence of effort expectancy on the intention to use GenAI is moderated by AI identity threat.

AIT	H6c	The influence of social influence on the intention to use GenAI is moderated by AI identity threat.
AIT	H6d	The influence of facilitating conditions on the intention to use GenAI is moderated by AI identity threat.

4 METHODOLOGY

Building on the theoretical framework outlined in the previous chapter, we developed our methodology to merge key philosophical and methodological elements in order to thoroughly test our hypotheses and ensure relevance to the field. This chapter offers a detailed overview of our research approach, highlighting the philosophical foundations, data collection, and data analysis strategy as well as the reasoning behind our chosen methods.

4.1 Scientific Research Approach

In this study, we adopted a positive epistemological stance, which asserts the value of objective observation and measurement in the social sciences (Collis & Hussey, 2014). This stance aligns with our goal to quantify the relationships between latent variables to examine the impact of the human-AI creativity tension in GenAI adoption. By adopting positivism, we commit to a data-driven methodology, enabling us to test our hypotheses against the realities observed in the creative industries (Park et al., 2020). Adhering to deductive logic, our research strategy began with a theoretical framework adapted from the UTAUT model, from which we derived specific hypotheses about the factors influencing and moderating GenAI adoption. This deductive approach allowed us to systematically evaluate these hypotheses through the collection and analysis of data, thereby testing the applicability of our theoretical propositions to the realities of the creative workplace (Bell et al., 2019).

We used an objectivist research paradigm to guide our methodology by treating the phenomena under study - our latent variables - as external entities that exist independently of our subjective interpretations (Collis & Hussey, 2014). This aligns with our quantitative approach and supports the use of structured surveys as our data collection instrument to gather data for the UTAUT model. Within this objectivist and positivist framework, our study employed a correlational research design to explore the relationship between key latent variables (Bell et al., 2019). This design enabled us to identify and quantify the associations among factors influencing technology adoption, providing insights into how these latent variables interact within the creative industries. Our study is primarily explanatory, designed to identify and interpret potential relationships among variables influencing GenAI adoption by testing our formulated hypotheses. We must emphasize that the connections presented are hypothetical and based on observed correlations and therefore do not imply causality.

Finally, we chose to conduct a cross-sectional study to capture a comprehensive snapshot of the current state of GenAI adoption across the creative industries at a single point in time (X.

Wang & Cheng, 2020). This method aligned with our research objectives, providing an efficient way to collect data from a broad sample while avoiding the temporal and logistical complexities of longitudinal studies. Together, our methodological approach that integrates positivism, deductive logic, and an objectivist paradigm within a correlational and explanatory cross-sectional design, provided a robust framework for analyzing GenAI adoption in the creative industries and ensured reliable insights for both academic and practical applications.

4.2 Population and Sampling

4.2.1 Target Population

Our study targeted employees worldwide who possess a good level of English and who engage in creative roles within their organizations, indicating that their work requires a degree of creativity that could utilize GenAI. The creative industries, as defined in the introduction of this thesis, include a broad spectrum of professions in various disciplines such as marketing, design, and advertising (Smeets & Bain, 2022; Towse, 2020). We chose this broad categorization to capture the diverse array of creative activities since due to the universal accessibility of GenAI, creative professionals all around the globe are potential adopters. By not limiting our research to a specific country or region, we aimed to uncover broader trends and variances in adoption behaviors and provide a more comprehensive understanding of the impact of GenAI in the creative industries.

4.2.2 Sampling Technique

For this study, we chose a non-probability sampling method, specifically opting for convenience sampling due to the practical challenges to obtain a broad range of respondents across various creative disciplines, where access and willingness to participate is essential. Non-probability sampling, by its nature, does not afford every potential participant an equal chance of selection (Bell et al., 2019) but we considered it most suitable given our goal to engage a wide range of professionals from the creative industries. While this approach may limit the generalizability of the findings, it enabled rapid data collection from an easily accessible participant pool, which is crucial to keep pace with the fast-evolving field of GenAI.

To construct a robust and informative dataset, we employed three distinct approaches to data collection. We utilized *(a) Prolific*, which is a crowdsourcing platform with a large and diverse participant pool (Prolific, n.d.) and widely used in academia for consistent high-quality

answers (Palan & Schitter, 2018; Peer et al., 2017). Prolific allowed us to prescreen individuals from the creative industries through desired filters such as employment type and industry. We accessed *(b) online community forums* dedicated to various creative disciplines that gave us access to a pool of potential respondents deeply engaged with their respective fields. We used *(c) direct outreach* to creative professionals through LinkedIn, email, and direct contact, which allowed us to target individuals in key positions within the creative industries.

We set the sample size of our study to follow the established recommendations for SEM, which is the statistical method we used to analyze our data. Boomsma (1983) suggests a minimum of 200 participants, while Bentler and Chou (1987) recommend ratios of 1:5, and Wolf et al. (2013) ratios of 1:10 between the number of items and participants. As our survey consisted of 27 questions, this translated into a recommended number of participants between 135 and 270. We therefore set the target of obtaining a minimum of 200 valid responses to ensure a robust statistical analysis.

4.3 Survey Design

The survey design of this study was centered around the measurement of the seven latent variables presented in the theoretical framework in Chapter 3. These latent variables are PE, EE, SI, FC, intention to use GenAI (USE), CSE and AIT. We measured each variable with 3 to 4 targeted questions designed to collectively capture the underlying characteristic (Hair et al., 2009). This approach follows the original methodology of Venkatesh et al. (2003) and subsequent studies that incorporated external variables (see, e.g., Andrews et al., 2021; Y. Wang & W. Zhang, 2023).

The design and selection of questions for each latent variable were adapted from previous studies. Each uses a 5-point Likert scale that ranges from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). This format, which is well-established in social and behavioral science research due to its effectiveness in measuring attitude and evaluating opinions (Bell et al., 2019), enabled the following quantitative analysis. For PE, EE, SI, FC, and USE, we adapted the questions from the original UTAUT model by Venkatesh et al. (2003) to the specific context of GenAI. We developed the CSE items based on Tierney and Farmer (2002) and incorporated Reiter-Palmon et al.'s (2012) recommendations to include the work context. For AIT, we adapted the items by Mirbabaie et al. (2022) to better reflect the context of GenAI usage. These adaptations ensured that our survey questions were both contextually relevant and theoretically grounded. The exact content of the individual questions can be found in Appendix A.

To ensure accurate demographic capture, we included control questions on gender, age, current employment in the creative industries, and the requirement of working in a creative role. These controls helped mitigate potential biases and ensured the relevance of the responses to our study's focus. Furthermore, we incorporated an attention check by prompting participants to select *Disagree* on a question that was mixed in with the other questions in order to control for the quality of responses and reduce the risk of random responding (Muszyński, 2023; see Appendix A).

We conducted the survey in English using Qualtrics, acknowledging the diverse, international composition of the creative industries and the widespread use of English internationally. Given that the survey was distributed in English via Prolific, forums, and direct outreach, we assumed participants possessed a good level of English.

4.3.1 Pilot Survey

We conducted a pilot survey on the Qualtrics platform to assess its effectiveness ahead of the main study. The main purpose was (a) to test the usability to ensure easy navigation, (b) to determine the average completion time and (c) to preliminary assess the reliability of the adapted questions. We distributed the pilot survey via SurveySwap and SurveyCircle, receiving a total of 37 responses over a period of two days.

First, the usability of the survey appeared to be positive, as all participants completed the survey in a similar amount of time and reported no difficulties with navigation. This was consistent across different demographic groups in terms of age and gender, indicating that the survey was easily accessible for the entire target population. *Second*, the average completion time of the pilot survey was 4 minutes 56 seconds with about 90% of respondents finishing the survey in under 10 minutes. Consequently, in the main study we communicated a liberal estimated completion time of 5 to 10 minutes across the various distribution channels to provide transparent expectations to our participants (see Appendix A). Fair expectations are particularly important for distribution on Prolific, which calculates the monetary reward for participants according to the time taken to complete the survey. *Third*, due to adaptations of the questions to our context, particularly to items from Tierney and Farmer (2002) and Mirbabaie et al. (2022), we found it necessary to use the pilot survey to preliminarily assess the reliability of the adapted constructs. Calculating Cronbach's Alpha (α), a measure of internal consistency, showed an $\alpha > 0.7$ across all latent variables, aligning with Cronbach's (1951) recommendation for acceptable levels of internal reliability. We must stress that the small sample size strongly limits the reliability of this test, but we conducted it purely to detect

any immediate major issues. In light of this limitation, the results led to increased confidence in the reliability of the adapted questions for the main study.

4.3.2 Main Survey and Sample Characteristics

We administered the main survey through Qualtrics and distributed it using different platforms, as detailed in Section 4.2.2, to ensure a diverse respondent base from the creative industries and maximize response rates. We conducted the data collection from February 27th, 2024, to March 13th, 2024. During this period, we received a total of 364 responses[1], out of which 77 were blank responses, giving us 287 complete responses. After applying predetermined validity criteria based on the control questions and the attention check, we deemed 214 responses[2] valid. This represents a recovery rate of 58.79% or 74.56% when excluding blank responses.

Descriptive statistics of the final dataset showed a gender composition of 41.6% male, 54.2% female, and 4.2% preferring not to specify, which indicates a balanced gender distribution within our sample. Respondents ranged in age from 16 to 65 years, with a median age of 31, demonstrating a broad representation across various career stages. Table 3 displays the gender and age distribution of the sample. This shows that our methodological approach, which combines different distribution strategies and a thorough validation of responses, resulted in a robust data set that represents the different gender and age profiles of the creative industries. Further descriptive statistics on the distribution of the mean latent variable responses for each construct can be found in Appendix B.

[1] Prolific: 150; Forums: 146; Direct Outreach: 68

[2] Prolific: 119; Forums: 64; Direct Outreach: 31

Table 3

Gender and Age Distribution of Sample.

Characteristic	Category	Frequency	Valid Percentage
Gender	Male	89	41.6%
	Female	115	54.2%
	Prefer not to say	9	4.2%
Age	Under 20	1	0.5%
	20-29	90	42.1%
	30-39	70	32.7%
	40-49	38	17.8%
	50-59	12	5.6%
	60 and over	3	1.4%

4.4 Data Analysis Strategy

After the data was collected through Qualtrics, it underwent preprocessing using SPSS, as outlined in Section 4.3.2. This included a comprehensive data cleaning process to ensure the quality and validity of the dataset for the following data analysis.

We conducted our primary data analysis using SEM, which is commonly used in behavioral sciences for examining complex theoretical frameworks, such as UTAUT models (Venkatesh et al., 2003). SEM is a flexible and comprehensive method used for analyzing multivariate relationships between latent and observed variables, while accounting for measurement errors (Byrne, 2016; Hair et al., 2009). This is achieved through successive steps in which a variety of statistical techniques are used (Byrne, 2016). SEM is therefore not a single statistical method, but a combination of statistical tools. To provide a transparent understanding of our data analysis, we present our process of SEM below in four organized steps, as illustrated in Figure 3. Throughout our analysis, we utilized IBM SPSS Statistics 29.0 and IBM SPSS Amos 26, which are standard tools for assessing UTAUT models (Williams et al., 2015).

The first step consisted of preliminary data checks to verify the dataset's suitability for in-depth analysis (Hair et al., 2009). An essential prerequisite for using Maximum Likelihood (ML) estimation in later stages is the multivariate normality of the data (T. Brown, 2015). Accordingly, we performed a multivariate normality test using Mardia's (1970) normalized estimate of multivariate kurtosis in SPSS Amos. As the data did not pass this test, we continued the SEM analysis with the remedial measure of bootstrapping to address non-

normality (T. Brown, 2015). Additionally, we assessed the internal reliability of our measured constructs using Cronbach's α, which is common practice among researchers (see, e.g., Andrews et al., 2021; Maican et al., 2023). However, there are limitations to this measure, which we will discuss in detail in Section 5.1.2 of the data analysis.

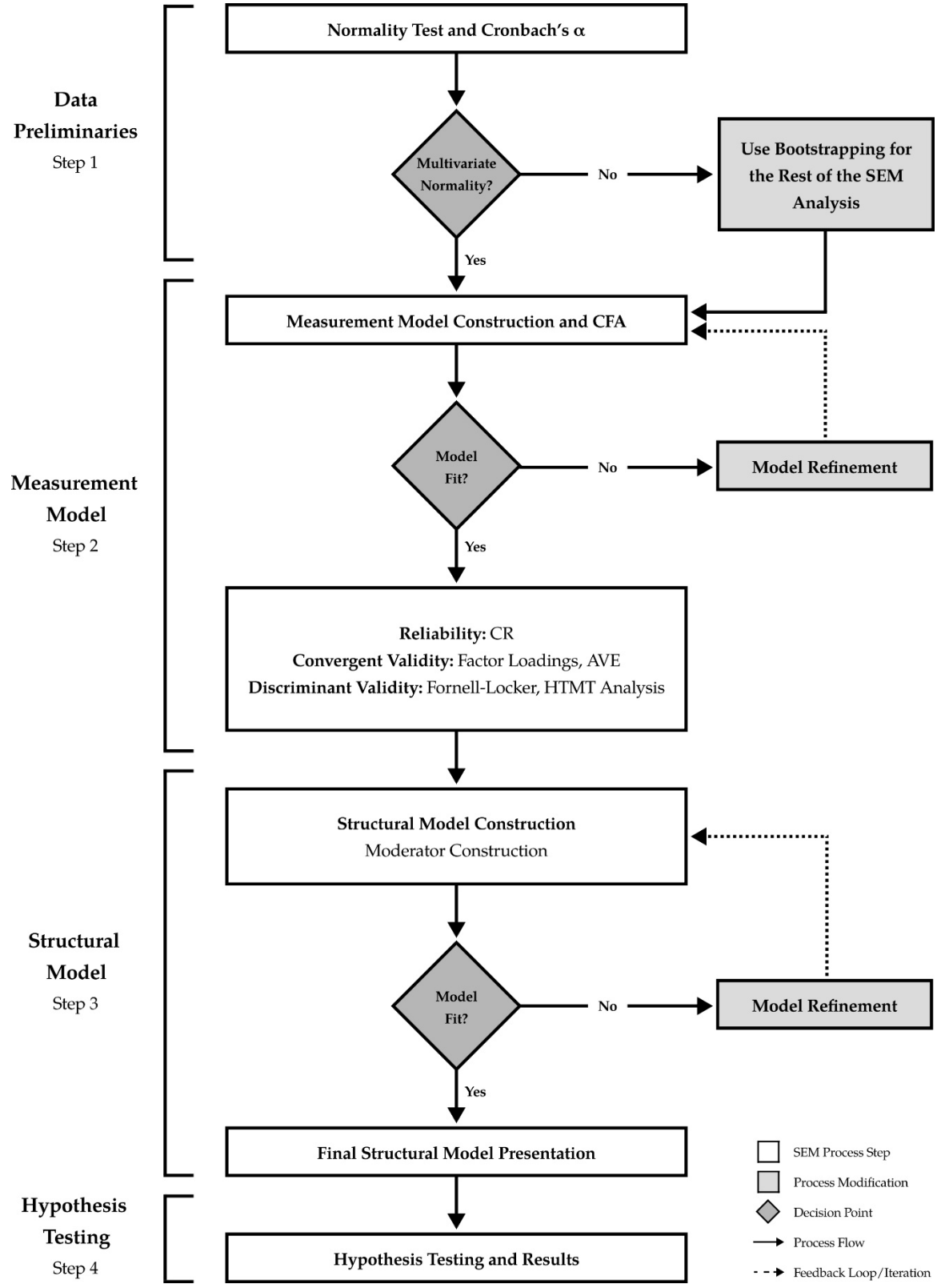
The second step aimed to verify that our data accurately reflected the constructs within our theoretical framework before analyzing their interrelationships (Hair et al., 2009). For this purpose, we constructed a measurement model in SPSS Amos, incorporating all latent and observed variables, to conduct a confirmatory factor analysis (CFA) (T. Brown, 2015). We assessed the model's fit to the data using various fit indices and were prepared to refine the model if the indices had indicated unsatisfactory results. With model to data fit achieved, ML estimation provided the factor loadings for each indicator on its corresponding latent variable. This enabled us to evaluate the reliability of our constructs through composite reliability (CR), assess construct validity via the factor loadings and average variance extracted (AVE), and verify discriminant validity using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. These calculations were performed in SPSS Amos using the plugin by Gaskin et al. (2019).

The third step comprised of the construction and validation of the structural model. Building upon the confirmed reliability and validity of our constructs from the measurement model, the structural model allowed us to analyze the hypothesized relationships between these constructs (Hair et al., 2009). Initially, we constructed the moderating effects of AIT on the relationships among PE, EE, SI, FC, and USE. We then specified the structural model to include all proposed relationships along with the moderation effects. As in the second step, we evaluated the fit of our model to the data using various indices. Since the model fit had not initially been satisfactory, we made iterative adjustments using SPSS Amos Modification Indices tool and Covariance Estimates tables to refine the structural model. After achieving a satisfactory fit, we were able to present the final structural model.

The fourth step involved testing all paths in the final structural model that mirrored our theoretical framework. Using ML as the estimation method in SPSS Amos, we obtained results indicating the strength, direction, and significance of each relationship. These findings allowed us to accept or reject our initial hypotheses. This concluded our data analysis using SEM, which allowed us to accurately assess the impact of the human-AI creative tension on the adoption of GenAI in the creative industries.

Figure 3

Overview of the Data Analysis Process.



Note. Own Creation.

4.5 Data Quality

4.5.1 Reliability and Validity

We confirmed the reliability and validity of the data in the second step of our SEM analysis through CFA. Reliability, referring to the consistency and stability of measurements across different instances (Bell et al., 2019), was specifically assessed using CR and Cronbach's α. Both metrics supported good internal consistency, confirming the reliability of our data measurements. However, we emphasize that although Cronbach's α is widely reported in SEM studies, we primarily relied on CR, which provides a more accurate measure of internal consistency (Cheung et al., 2023). We address the limitations of Cronbach's α for SEM in Section 5.1.2. of the data analysis in more detail.

Validity refers to the degree to which our methods and analyses accurately captured and reflected the constructs we aimed to investigate (Bell et al., 2019). We focused on content, convergent, and discriminant validity. Content validity assesses whether the survey items comprehensively represent the theoretical construct they are intended to measure (Fitzpatrick, 1983). By basing all our survey items on established scales and adapting them for the specific context of GenAI adoption, we ensured each item was not only relevant and representative of the underlying construct but also preserved the original construct's integrity as measured by previous researchers. Convergent validity confirms that indicators of a specific construct are indeed all measuring the same construct (Campbell & Fiske, 1959; Krabbe, 2017). We evaluated this through factor loadings and AVE values that were consistent with the suggested thresholds. Discriminant validity verifies that constructs are different from one another (Henseler et al., 2015). The Fornell-Larcker criterion and the HTMT ratio of correlations were utilized to confirm that our constructs are not overly similar, ensuring that every construct captures a distinct phenomenon (Fornell & Larcker, 1981; Henseler et al., 2015).

4.5.2 Replicability and Generalizability

The detailed documentation of our methodological steps from survey design to data analysis aims to enhance the replicability of our study. We therefore assume that other researchers who use our model and wish to replicate the questionnaire will obtain similar results to ours. Moreover, by employing the UTAUT model, our research serves as a partial replication that tests and potentially extends this well-established framework within the novel context of GenAI adoption. We provide clear guidelines for future researchers who wish to replicate our

study or explore the applicability of the UTAUT model in similar or different contexts by outlining the specific procedures and statistical tests we used.

While our sample selection strategy aimed to reach a diverse pool of participants within the creative industries by utilizing platforms like Prolific, forums, and LinkedIn, we acknowledge that the generalizability of our findings might be influenced by the specific characteristics of our sample, the varied ratios collected from these platforms, and their distinct operational contexts. Nevertheless, through careful data cleansing procedures and ensuring a targeted but diverse response base, we aimed to gain insights that are broadly applicable. Further limitations to generalizability are discussed in Section 6.4.

4.6 Ethical Considerations

In addressing the ethical considerations of this study, we informed all respondents about the nature, objectives, and use of their responses. The introduction to the survey clarified the academic context and university affiliation of the research and provided the names of the researchers involved. We further displayed our contact information in the survey's introductory text to give participants the opportunity to contact us directly if they have any questions or concerns. With this transparency, we wanted to encourage trust and ensure that all participants understood the purpose of their participation and the importance of their contribution.

Privacy and anonymity were core to our approach as all responses were recorded anonymously so that no answers could be traced back to the individual participants. We informed participants that their participation was based on their consent and emphasized that they could withdraw from the survey at any time. Respondents gave explicit consent before completing the questionnaire by confirming that they understood the details of the study and agreed to participate under the conditions outlined.

5 DATA ANALYSIS

This chapter presents the analysis and results of our data, structured into four steps as outlined in the data analysis strategy in Section 4.4. We began with preliminary checks, followed by verifying that the observed variables corresponded with our theoretical framework. We then constructed and refined the structural model, which formed the basis for the final hypothesis testing and presentation of results.

5.1 Data Preliminaries

5.1.1 Normality Assessment

We started our analysis with preliminary tests for multivariate normality, which is an important assumption for the ML estimation used in the assessment of both the measurement model through CFA and the structural model (T. Brown, 2015; Costa & Sarmento, 2019). Multivariate normality means that the multivariate combination of the items follows a normal distribution. To assess the presence of multivariate normality, we used SPSS Amos, which allows the calculation of Mardia's (1970) normalized estimate of multivariate kurtosis (Byrne, 2016). This value can be used to assess if the data is normally distributed. Bentler (2006) suggests that in practice a value of > 5.0 is indicative of data that is not normally distributed. The results from this assessment, found in Appendix C, show an estimated value of 14.601. This result implies that the data was non-normally distributed (> 5.0), which is also evident upon reviewing the distribution tables in Appendix B.

Given the sensitivity of multivariate normality tests to minor deviations and the difficulties in meeting the strict normality assumptions in real-world data (Abiodun et al., 2019), we employed bootstrapping as a remedial measure. This non-parametric statistical technique, which involves resampling with replacement, offers a significant advantage in situations like ours where the data does not meet normal distribution assumptions (T. Brown, 2015; Byrne, 2016). Accordingly, we selected a bootstrapping procedure with 2,000 resamples, which is sufficient for robust estimations of standard errors and confidence intervals in our measurement and structural model, aligning with common practices that recommend over 500 samples (T. Brown, 2015). This approach effectively addressed issues of non-normality, particularly the upper skewness observed in the CSE results, as detailed in Figure B6 in Appendix B.

5.1.2 Preliminary Reliability Assessment

Prior to conducting CFA, we assessed the reliability of our observed measurements using Cronbach's α. Cronbach's α is a measure of internal consistency, indicating how closely related a set of items are as a group (Cronbach, 1951). It is considered an estimate of the scale reliability, and a higher Cronbach's α coefficient suggests a higher level of internal consistency (Cronbach, 1951). This measure is particularly suited for assessing the reliability of Likert-type scales, which were utilized in this study. According to Tavakol and Dennick (2011), a Cronbach's α of > 0.7 is indicative of good reliability. The reliability testing using Cronbach's α served as a preliminary test, which is common practice in many studies involving SEM analyses (Davcik, 2014; Schumacker & Lomax, 2004). Table 4 presents a comprehensive overview of the obtained Cronbach's α values, demonstrating good reliability across all constructs with values exceeding 0.7.

We must note that despite its frequent reporting in SEM studies, Cronbach's α may not be the best measure for assessing reliability in this context, as indicated by numerous researchers (see, e.g., Cho & Kim, 2014; Hayes & Coutts, 2020). Two of the assumptions for Cronbach's α frequently do not apply to SEM: uncorrelated error terms, meaning that the measurement errors of the indicators should not influence each other (Tavakol & Dennick, 2011), and tau equivalence, which assumes that each indicator has an equal factor loading on a single latent variable (Cho & Kim, 2014). Since our model may have correlated error terms and the factor loadings shown in Section 5.2.2 proved to be in fact unequal, Cronbach's α is likely to produce inaccurate reliability estimates for our study. Although we acknowledge its common reporting, we will primarily rely on CR as a more accurate reliability metric for SEM analysis (Cheung et al., 2023), which is covered in Section 5.2.2.

Table 4

Results of Cronbach's Alpha.

Model Construct	Item	Cronbach's Alpha (α)
Performance Expectancy (PE)	PE1 PE2 PE3 PE4	0.936
Effort Expectancy (EE)	EE1 EE2 EE3 EE4	0.875
Social Influence (SI)	SI1 SI2 SI3 SI4	0.877
Facilitating Conditions (FC)	FC1 FC2 FC3 FC4	0.798
Intention to Use GenAI (USE)	USE1 USE2 USE3	0.939
Creative Self-Efficacy (CSE)	CSE1 CSE2 CSE3 CSE4	0.847
AI Identity Threat (AIT)	AIT1 AIT2 AIT3 AIT4	0.878

Note. Calculated using SPSS 29.

5.2 Measurement Model

5.2.1 Confirmatory Factor Analysis

CFA serves as a precise statistical method to validate the measurement model within SEM (T. Brown, 2015). We constructed the measurement model with the relationships between observed items and underlying latent variables of our theoretical framework (Byrne, 2016). It can be found in Appendix D. To confirm the data-to-model fit, we drew from a comprehensive range of model-fit indices, including absolute, incremental, and parsimonious indices, as recommended by Hooper et al. (2008). We used a variety of specific indices from

these categories to ensure a robust evaluation, drawing from guidelines by researchers like Bentler (1990), Bollen (1989) and others, while acknowledging that opinions on what constitutes a good fit may vary. A detailed description of these indices is available in Appendix E.

The measurement model fit results indicate a satisfactory fit across all employed indices based on the recommended criteria, except for the Chi-square value. We must however highlight that the Chi-square test is known for its sensitivity, which is why we anticipated its significance. Nevertheless, despite this limitation it is common practice to report this value (Hooper et al., 2008). But as all other measures demonstrate a satisfactory fit, the structural validity of the measurement model is affirmed, which supports proceeding with the SEM analysis. We present the fit indices in Table 5.

Table 5

Measurement Model Fit.

Fit Index	**Recommended Criterion**	**Measurement Model**
	Absolute Fit Indices	
Chi Square (χ^2)	Non-sig.	0.000
CMIN/DF	< 3.00	1.890
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.065
	Incremental Fit Indices	
Comparative Fit Index (CPI)	> 0.90	0.935
Incremental Fit Index (IFI)	> 0.90	0.936
	Parsimonious Fit Indices	
Parsimony Normed Fit Index (PNFI)	> 0.50 Relative to model (higher value better)	0.753
Parsimony Comparative Fit Index (PCFI)	> 0.50 Relative to model (higher value better)	0.807
Akaike Information Criterion (AIT)	Smaller value, better fit (model specific)	776.539

Note. Calculated using SPSS Amos 26.

5.2.2 Reliability and Validity Checks

CR was employed to evaluate the reliability of the data. CR evaluates the internal consistency of latent constructs (Raykov, 1997) and, although similar to Cronbach's α, is often deemed more reliable as it accounts for the varying factor loadings of indicator variables (Cheung et al., 2023). A CR value of 0.7 or above is considered acceptable and indicates good reliability (Cheung et al., 2023). Table 6 shows that all constructs exhibited high internal reliability with CR values of at least 0.8.

To assess convergent validity, we utilized factor loadings and AVE. Factor loadings indicate the strength of the association between observed items and their corresponding latent variables, serving as a measure of how well each item represents the latent construct (T. Brown, 2015; Tavakol & Wetzel, 2020). For robust convergent validity, Hair et al. (2009) suggest that factor loadings should ideally exceed 0.7, though values above 0.5 are acceptable. Similarly, Matsunaga (2010) considers factor loadings above 0.6 to be adequate. Accordingly, we set our threshold for factor loadings at above 0.6. AVE quantifies the average amount of variance that a construct explains in its indicators relative to the variance due to measurement error (Henseler et al., 2015). An AVE value of 0.5 or higher indicates that the construct, on average, accounts for more than half of the variance in its indicators, which signifies strong convergent validity (Cheung et al., 2023; Henseler et al., 2015). Table 6 demonstrates that all constructs exhibited good convergent validity in terms of AVE with values exceeding 0.5. Factor loadings were generally strong except for FC4, which had a loading of 0.505. This value is below our threshold of 0.6, which indicates a weak correlation with its latent variable. Consequently, we removed FC4 to improve the convergent validity of FC (Matsunaga, 2010).

Table 6

Reliability and Convergent Validity Assessment Summary.

Model Construct	Item	Factor Loading	CR	AVE
Performance Expectancy (PE)	PE1	0.923	0.936	0.786
	PE2	0.902		
	PE3	0.886		
	PE4	0.832		
Effort Expectancy (EE)	EE1	0.694	0.878	0.645
	EE2	0.790		
	EE3	0.843		
	EE4	0.875		
Social Influence (SI)	SI1	0.892	0.884	0.658
	SI2	0.819		
	SI3	0.842		
	SI4	0.676		
Facilitating Conditions (FC)	FC1	0.827	0.806	0.520
	FC2	0.848		
	FC3	0.648		
	FC4	**0.505**		
Intention to Use GenAI (USE)	USE1	0.902	0.941	0.842
	USE2	0.938		
	USE3	0.911		
Creative Self-Efficacy (CSE)	CSE1	0.705	0.851	0.591
	CSE2	0.884		
	CSE3	0.793		
	CSE4	0.675		
AI Identity Threat (AIT)	AIT1	0.861	0.876	0.640
	AIT2	0.744		
	AIT3	0.866		
	AIT4	0.717		

Note. Calculated using Gaskin et al. (2019) Amos plugin, in SPSS Amos 26.

Discriminant validity ensures that each construct of the model is different from each other, ensuring that one construct is not partly represented by other constructs in the model (Hair et al., 2009). The Fornell-Larcker criterion was employed, where the square root of the AVE of each construct should be greater than its highest correlation with any other construct (Fornell & Larcker, 1981). As shown in Table 7, the diagonal values numbers - which are the square root of AVEs - are greater than the off-diagonal values in their corresponding rows and columns, which indicates satisfactory discriminant validity among the constructs. This

suggests that each construct is unique and captures phenomena not represented by other constructs in the model.

Table 7

Fornell-Larcker Criterion.

Construct	PE	EE	SI	FC	CSE	AIT	USE
PE	**0.886**						
EE	0.175*	**0.803**					
SI	0.738***	0.207**	**0.811**				
FC	0.112	0.713***	0.088	**0.779**			
CSE	-0.257**	0.133†	-0.240**	0.182*	**0.769**		
AIT	-0.237**	-0.128	-0.336***	-0.113	0.015	**0.800**	
USE	0.879***	0.155*	0.792***	0.062	-0.230**	-0.405***	**0.917**

† p < 0.100, * p < 0.050, ** p < 0.010, *** p < 0.001

Note. Calculated using Gaskin et al. (2019) Amos plugin, in SPSS Amos 26.

We further assessed discriminant validity using the HTMT ratio of correlations, which compares the geometric mean of item correlations across constructs against the average of the item correlations within the same construct (Henseler et al., 2015). An HTMT value below 0.85 typically indicates adequate discriminant validity, suggesting that constructs are distinct from one another. Table 8 displays the results of the HTMT analysis and illustrates the correlations between the constructs. Correlations of a construct with itself are inherently 1, which is indicated by black boxes in the table. Reviewing Table 8, all values fell below the conservative threshold of 0.85, except for the PE with USE pairing, which recorded 0.882. Although this value exceeds the 0.85 guideline, it remains under the more liberal threshold of 0.90, which Henseler et al. (2015) indicates as an acceptable cut-off in certain contexts, such as when testing technology acceptance models like UTAUT. These results indicate that while our constructs share similarities, they are sufficiently distinct to meet discriminant validity criteria.

Table 8

HTMT Analysis.

Construct	PE	EE	SI	FC	CSE	AIT	USE
PE							
EE	0.199						
SI	0.758	0.251					
FC	0.135	0.757	0.150				
CSE	0.257	0.124	0.237	0.163			
AIT	0.237	0.151	0.318	0.171	0.003		
USE	**0.882**	0.187	0.812	0.097	0.233	0.397	

Note. Calculated using Gaskin et al. (2019) Amos plugin, in SPSS Amos 26.

5.3 Structural Model

5.3.1 Moderator Construction

To assess the impact of AIT as a moderator on the relationships between PE, EE, SI, and FC with USE in the structural model, we constructed the moderators using the method proposed by Sharif and Nia (2018). This process involved using the Data Imputation function in SPSS Amos to compute latent variable scores for PE, EE, SI, FC, and AIT which are derived from the specified measurement model (Appendix D). The Data Imputation function in SPSS Amos offers methods such as regression imputation for calculating these scores, which yields results equivalent to those obtained using factor score weights in SPSS (IBM SPSS Amos, 2018). Although the function can also impute missing values in observed variables, this feature did not affect our data set since it did not contain any missing values. We used it solely for the estimation of factor scores, which simplified the representation of interaction effects in the structural model.

After these scores were obtained, we standardized these values using SPSS and created the interaction terms (PExAIT, EExAIT, SIxAIT, FCxAIT) by multiplying the standardized latent scores of the predictors with their respective moderators. These interaction terms could then be incorporated into the SEM analysis to examine how AIT as a moderator influences the relationship between the predictors PE, EE, SI, FC, and the dependent variable USE. We acknowledge the requirement for multivariate normality of factor scores as an assumption for the ML estimation method, discussed in Section 5.1.1 (DiStefano et al., 2009). Although testing revealed multivariate non-normality, the continued use of bootstrapping during the whole SEM analysis serves as remedial measure for multivariate non-normality (T. Brown, 2015;

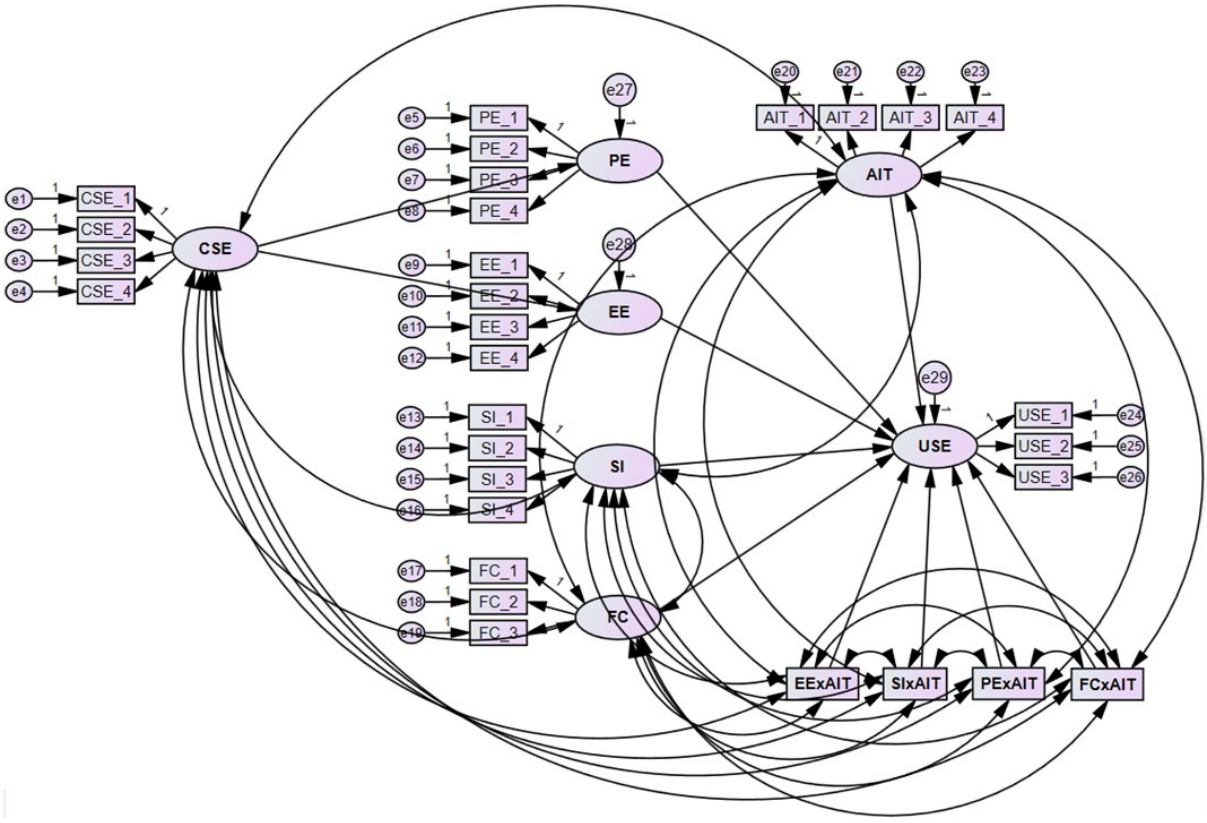
Byrne, 2016). It is also important to recognize the sensitivity and potential overestimation of non-normality in large samples (n > 150) (Abiodun et al., 2019).

5.3.2 Structural Model Fit and Iterations

Following the creation of the moderators, we constructed the first structural model. It reflects the relationships as specified in our theoretical framework, which consists of the seven constructs and four moderators. All exogenous latent variables are interconnected, suggesting that they covariate or correlate with each other to a certain extent. This interconnection is rooted in the understanding that perception of technology is not formed in isolation but through a network of interrelated experiences and perceptions (Candelon et al., 2023; Shook & Daugherty, 2024). Figure 4 illustrates the hypothesized paths and correlations within our initial structural model based on our theoretical framework.

Figure 4

Initial Proposed Structural Model.



Note. Constructed using SPSS Amos 26.

To assess the appropriateness of our hypothesized model based on the observed data, it is important to assess the fit of our structural model (T. Brown, 2015; Byrne, 2016). This approach follows the fit criteria through various indices as established in Section 5.2.1 for the

measurement model fit. In the following, we trace the evolution of our initial structural model to the final version that meets the required fit criteria.

The initial analysis revealed, as shown in Table 9, that the structural model did not meet the acceptable fit criteria for most indices, which indicated a need for refinement. To improve the fit of our hypothesized model to the data, we made iterative modifications that were guided by SPSS Amos's Modification Indices feature. Adjustments were only made when the index exceeded our set threshold of 10 and were theoretically justified (T. Brown, 2015; Byrne, 2016). This resulted in the addition of a covariance path between the error terms e21 and e23 (error terms of AIT2 and AIT4), as detailed in Appendix F. Since this modification had a direct impact on AIT, we recalculated the moderators using the same method as in Section 5.3.1 to account for the covariance between the error terms. The improved model fit after this first iteration is documented in Table 9 as *1st Iteration*.

Since the first iteration did not result in a satisfactory fit for most indices we performed a second iteration. This resulted in the removal of non-significant covariances in order to retain only those covariances between variables that were statistically validated. By examining the Covariance Estimates table in SPSS Amos, we sequentially eliminated the paths with the highest p-values above 0.05, as described in Appendix F. Each change was carefully checked for its impact on model fit. By removing the paths of AIT-EExAIT, CSE-FCxAIT and AIT-CSE, the fit was gradually improved until the model satisfied all selected indices. The exact fit metrics of the final model are outlined in Table 9 as *2nd Iteration*. Despite some paths remaining non-significant, we avoided further reductions to prevent overfitting and preserve the theoretical integrity of our framework (T. Brown, 2015; Byrne, 2016). Our aim was to make minimal yet impactful adjustments to reconcile empirical evidence with theoretical expectations.

Table 9

Structural Model Fit.

Fit Index	Recommended Criterion	(Initial) Structural Model	(1st Iteration) Structural Model	(2nd Iteration) Structural Model
		Absolute Fit Indices		
Chi Square (χ^2)	Non-sig.	0.000	0.000	0.000
CMIN/DF	< 3.00	2.341	2.262	2.245
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.079	0.077	0.076
		Incremental Fit Indices		
Comparative Fit Index (CPI)	> 0.90	0.892	0.899	0.900
Incremental Fit Index (IFI)	> 0.90	0.894	0.900	0.901
		Parsimonious Fit Indices		
Parsimony Normed Fit Index (PNFI)	> 0.50 Relative to model (higher value better)	0.705	0.708	0.714
Parsimony Comparative Fit Index (PCFI)	> 0.50 Relative to model (higher value better)	0.759	0.763	0.769
Akaike Information Criterion (AIT)	Smaller value, better fit (model specific)	1056.347	1026.623	1020.994

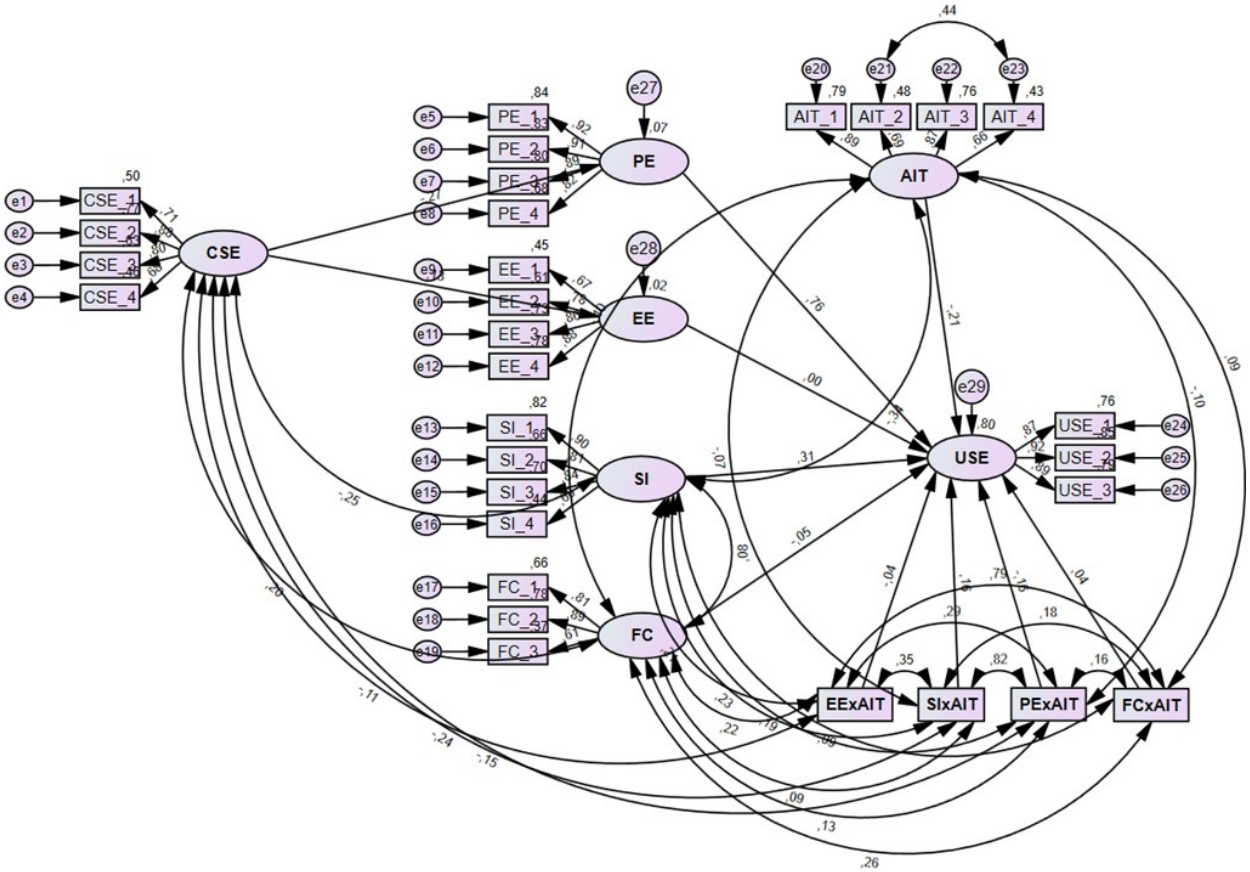
Note. Calculated using SPSS Amos 26.

5.3.3 Presentation of Final Structural Model

Figure 5 presents the final structural model, which achieved a good fit to the data after the iterations outlined in the previous section, indicating that it accurately represented the relationships among the variables as observed in our study. It included all constructs and moderators based on our theoretical framework as well as the exogenous latent variables with their observed covariation. This was the basis for the hypothesis testing where we evaluated the relationships posited in our model to confirm or refute our theoretical hypotheses.

Figure 5

Final Structural Model.



Note. Constructed using SPSS Amos 26.

5.4 Hypothesis Testing and Results

In this section, we present the final findings from the SEM analysis, which served to empirically evaluate our proposed hypotheses on the basis of the final structural model. The SEM outputs, specifically the standardized regression weights (β), the standard errors (SE), critical ratios (C.R.), and p-values, provided the basis for accepting or rejecting our hypotheses. Each of these metrics plays an important role: β represents the strength and direction of the relationship, SE measures the precision of the estimate, C.R. provides a standardized criterion for hypothesis testing, and the p-value indicates the probability that the observed estimate could occur by chance (Byrne, 2016).

We set our predetermined threshold for hypothesis rejection at a p-value of less than 0.05, as is common practice in scientific research (Dahiru, 2008). A p-value of less than 0.05 indicates that the probability that the observed results are due to random variation is less than 5%, which indicates with reasonable confidence that the results are not due to chance (Dahiru,

2008). Table 10 provides an overview of the values obtained for all paths and the associated acceptance or rejection of our hypotheses based on the p-value.

Table 10

Hypothesis Testing Results.

Hypothesis	Path	β	SE	C.R.	p-value	Result
		UTAUT Foundational Factors				
H1	**PE → USE**	**0.759****	**0.049**	**14.429**	**0.000**	**Accepted**
H2	EE → USE	-0.003	0.065	-0.066	0.947	Rejected
H3	**SI → USE**	**0.306****	**0.050**	**6.309**	**0.000**	**Accepted**
H4	FC → USE	-0.047	0.062	-1.048	0.295	Rejected
		Human-AI Creativity Tension				
H5a	CSE → PE	-0.269**	0.191	-3.555	0.000	Rejected
H5b	CSE → EE	0.128	0.109	1.637	0.099	Rejected
H6a	**PExAIT → USE**	**-0.155***	**0.066**	**-2.270**	**0.023**	**Accepted**
H6b	EExAIT → USE	-0.039	0.062	-0.565	0.572	Rejected
H6c	**SIxAIT → USE**	**0.164***	**0.069**	**2.324**	**0.020**	**Accepted**
H6d	FCxAIT → USE	0.043	0.061	0.642	0.521	Rejected

* $p < 0.05$, ** $p < 0.001$

Note. Calculated using SPSS Amos 26

5.4.1 UTAUT Foundational Factors

For the first factor, PE, the SEM analysis revealed a strong positive influence of PE on USE ($\beta = 0.759$, $p < 0.001$). This suggests that creative professionals who perceive GenAI as likely to enhance their job performance are substantially more inclined to use it. This aligns with our hypothesis that higher PE would lead to a higher intention to use GenAI. Therefore, H1 is accepted.

Conversely, despite our anticipations, the perceived difficulty of engaging with GenAI did not show a significant positive impact on the intention to use GenAI, with a near null effect for EE on USE of $\beta = -0.003$ and $p = 0.947$. H2 is rejected.

Additionally, the SEM findings show that SI positively influences USE, with a medium positive effect of $\beta = 0.306$ ($p < 0.001$). This highlights the importance of social context in the decision-making process when it comes to adopting GenAI, indicating that the influence of social factors and peer opinion on GenAI positively correlates with the intention to use GenAI. Thus, H3 is accepted.

FC had a negligible effect on USE and did not achieve statistical significance, $\beta = -0.047$ and $p = 0.295$, which suggests that FC do not have a positive impact on the intention of creative professionals to use GenAI. H4 is rejected.

5.4.2 Creative Self-Efficacy

Unexpectedly, CSE showed a significant negative medium effect on PE, with $\beta = -0.269$ and $p < 0.001$, suggesting that creative professionals who have higher confidence in their creative abilities perceive GenAI as less useful for their work. Therefore, H5a is rejected because we hypothesized a positive effect.

Additionally, CSE showed a small positive but non-significant effect on EE, with $\beta = 0.128$ and $p = 0.099$. This suggests that the level of creative confidence does not influence the perception of how easy it is to interact effectively with GenAI. Therefore, H5b is rejected.

5.4.3 AI Identity Threat as a Moderator

The moderation effect of AIT on the relationship between PE and USE (PExAIT) showed a significant small negative interaction with $\beta = -0.155$ and $p < 0.05$. This shows that as AIT increases, the positive effect of PE on the intention to use GenAI decreases. This indicates that creative professionals who perceive GenAI as a threat to their identity are less likely to be influenced by PE in their decision to use GenAI. Figure 6A visually demonstrates this effect, depicting a noticeably flatter slope for individuals with high AIT compared to those with low AIT. Thus, H6a is accepted.

The lack of a significant influence of AIT as a moderator in the relationship between EE and USE (EExAIT), with a near null effect of $\beta = -0.039$ and $p = 0.572$, suggests that the importance of ease of using GenAI for adoption decisions is not substantially affected by identity-related concerns among creative professionals. H6b is rejected.

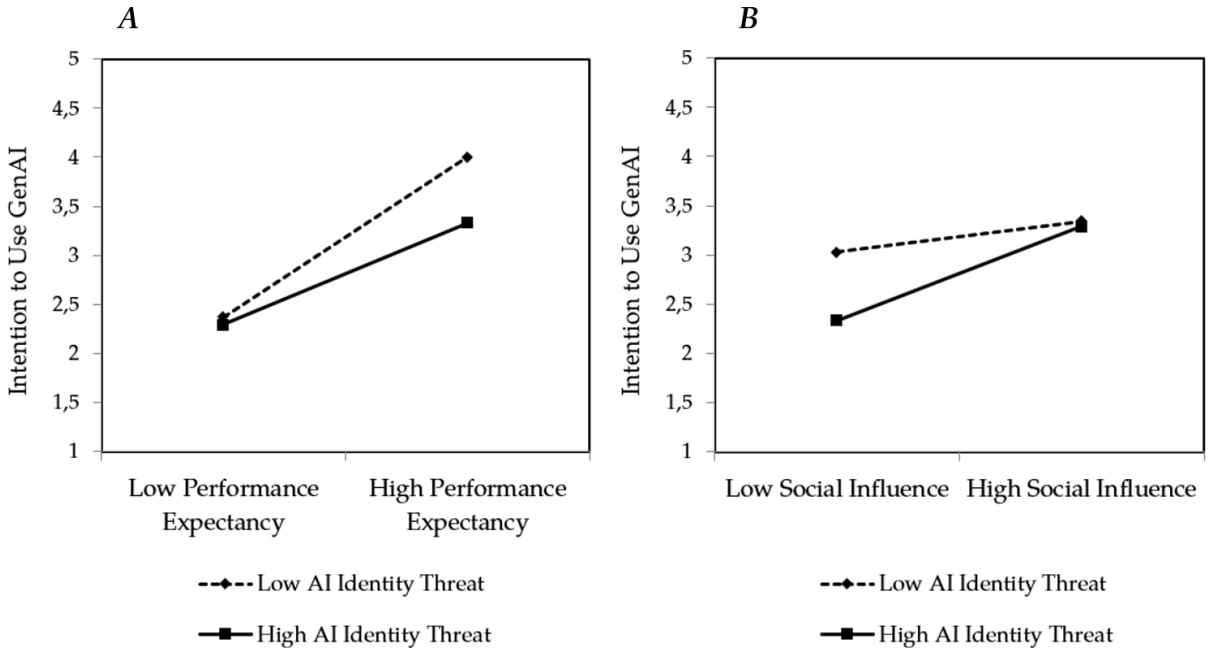
A significant small positive interaction was observed for AIT as a moderator in the relationship between SI and USE (SIxAIT) ($\beta = 0.164$, $p < 0.05$). This indicates that AIT enhances the

positive relationship between SI and USE. As illustrated in Figure 6B, for those with high levels of AIT, SI appears to play a stronger role in USE, shown by the steeper slope of the line compared to those with lower levels of AIT. Therefore, peer perception becomes more important among creative professionals who feel their identity is under threat by GenAI. Hence, H6c is accepted.

Lastly, the absence of a significant effect of AIT as a moderator in the relationship between FC and USE (FCxAIT), with a negligible effect of $\beta = 0.043$ and $p = 0.521$, leads us to reject H6d.

Figure 6

Moderator Interaction Graphs.



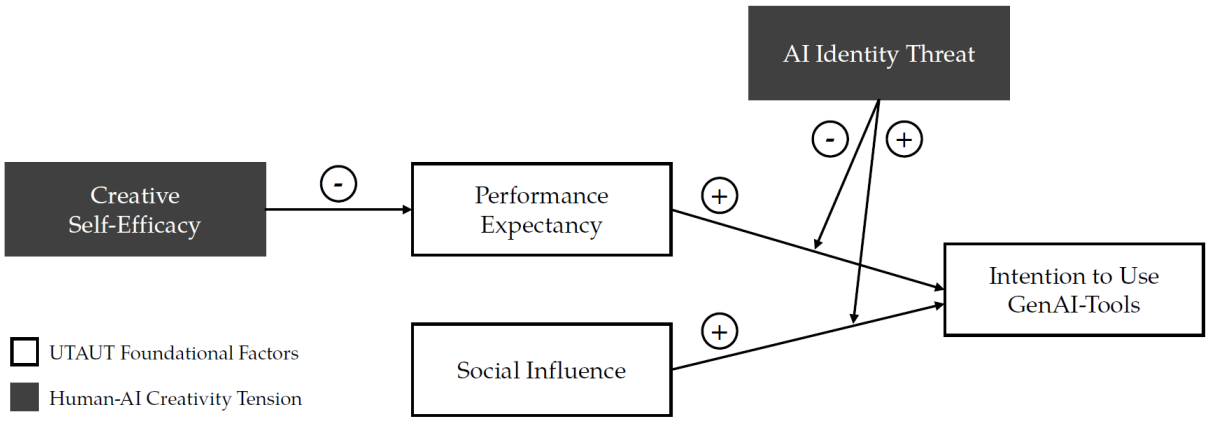
Note. Figure 6 illustrates the moderating effects of AIT. Figure 6A shows AIT's moderation of PE on USE. Figure 6B depicts AIT's moderation of SI on USE.

6 DISCUSSION

The purpose of this study was to examine factors influencing GenAI adoption by creative professionals in the creative industries. A particular emphasis was placed on factors related to GenAI's unprecedented creative capabilities, leading to a unique dynamic we termed the human-AI creativity tension. We hypothesized that because of this tension the individual characteristics of CSE and AIT are significant factors in creative professionals' decision to integrate GenAI as a co-creation partner. Grounded in the UTAUT model, we conducted an online survey with 214 creative professionals and analyzed our data using SEM. As illustrated in Figure 7, our findings revealed that among the UTAUT factors, PE and SI positively influenced their intention to use GenAI, while EE and FC did not have a considerable effect. Our analysis further showed that the individual characteristics of CSE and AIT, connected to the human-AI creativity tension, moderately impacted adoption behavior. Contrary to expectations, CSE negatively influenced the perceived usefulness of GenAI, and AIT moderated the effects of PE and SI, with a small negative and positive interaction effect, respectively. In the following sections, we will first discuss and interpret our findings of the traditional UTAUT factors, then examine the influence of the human-AI creativity tension, and ultimately combine these perspectives for a holistic interpretation in the context of relevant literature. We will conclude by addressing key limitations of our study and suggesting possible directions for future research.

Figure 7

Empirically Validated Conceptual Model of GenAI Adoption.



Note. Own Creation.

6.1 Evaluating UTAUT Factors in GenAI Adoption

According to our findings, GenAI's unique capabilities not only introduce new dynamics like the human-AI creativity tension, but also challenge the relevance of traditional predictors for technology adoption in organizations. Contrary to the UTAUT framework proposed by Venkatesh et al. (2003), our study found that neither EE nor FC were significant predictors of GenAI adoption. Only PE and SI emerged as significant, with PE exerting a strong influence and SI showing a moderate yet significant effect on creative professionals' intentions to adopt GenAI. Such results, where certain predictors do not align with the UTAUT framework, are not uncommon, as evidenced by a meta-analysis by Khechine et al. (2016). In their analysis, the factors of EE and FC, which did not have significant effects in our study, also had the lowest rates of significance in other studies, with EE being significant in only 64% of studies and FC in 62%. Although published research on the UTAUT in the context of AI is limited due to the technology's novelty, similar patterns of results that diverge from the established framework can be observed (see, e.g., Andrews et al., 2021; Chatterjee et al., 2023). This highlights the importance of examining the UTAUT predictors individually to better understand our specific results.

PE had the strongest impact on creative professionals' intention to use GenAI which aligns with the findings of Venkatesh et al. (2003) in the original UTAUT study. Subsequent meta-analyses by Khechine et al. (2016) and Dwivedi et al. (2011) further confirmed that PE generally has the strongest impact on intention to use. This makes intuitive sense to us for our context as well, as creative professionals already use various intertwined digital technologies in their work. For them to integrate GenAI, which is still evolving and in its current form not seamlessly integrated with other tools, it must be perceived as highly useful to compensate for any loss of comfort. This is further emphasized by the fact that engaging in human-AI co-creation and directing AI creativity represents a novel approach to the creative workflow. Creative professionals are likely to invest time in learning this new process and integrate GenAI only if they perceive its output as genuinely useful for their creative process. Thus, organizations in the creative industries aiming to broadly implement GenAI should focus on showcasing the benefits of human-AI co-creation for individuals in their creative work and project performance.

SI was the second strongest factor after PE on the intention of creative professionals to use GenAI and showed a significant moderate impact. While this factor has not been included in several UTAUT-based studies on AI adoption, such as AI in CRM systems (Chatterjee et al.,

2023) and the use of AI in organizational decision-making (Cao et al., 2021), our findings indicate that it might be relevant to consider for AI adoption. This aligns with other studies that did include SI and found a significant impact, such as in the adoption of ChatGPT (Menon & Shilpa, 2023) and AI-enabled tools in social development organizations (Jain et al., 2022). Our results suggest that in the current polarized debate on the use of GenAI in creative industries, creative professionals place considerable importance on the opinions of their colleagues and influential figures towards AI. This may be related to identity theory, where belonging to a certain group at work influences behavior (Tajfel & Turner, 1979). If the company's stance towards GenAI is negative, creative professionals might hesitate to use it because they fear isolation or conflict with their peers. Conversely, if it is positive and their colleagues use and encourage GenAI, they might be more inclined to adopt it to align with the group's norms and maintain their social identity within the organization.

On the other hand, both EE and FC had no discernible impact on creative professionals' intention to use GenAI, as they were neither statistically significant nor demonstrated a notable effect size. Even though these factors influence adoption behavior in a majority of UTAUT studies, EE and FC have shown in meta-analyses to have the lowest rates of significance (Khechine et al., 2016) and the lowest average effect sizes (Dwivedi et al., 2011) among the UTAUT factors. Still, the limited studies on AI adoption thus far have mostly identified them to be important in adoption behavior (see, e.g., Chatterjee et al., 2023; Tanantong & Wongras, 2024). As our research methodology does not differ considerably from the other studies, one possible explanation for our different results could lie in the industry we observed.

Since professionals in the creative industries may be more creative on average than in other industries, the perceived difficulties and organizational support for the integration of GenAI may not be as important to them, because they inherently tend to have greater adaptability and problem-solving skills (Feist, 1998). Moreover, technical proficiency is important in the creative industries due to the nature of their work (Van Laar et al., 2019), where creative professionals are accustomed to regularly learning and integrating new digital tools into their creative processes. As a result, even when GenAI is perceived as challenging to use, they might still be willing to integrate it to keep up with digital developments in their organizations. Additionally, the online method of our data collection might have attracted participants who are inherently more familiar with digital technologies, potentially biasing our sample towards higher technical proficiency.

6.2 The Impact of the Human-AI Creativity Tension

The main research objective of our study was the investigation of additional individual characteristics influencing GenAI adoption, which are not considered in the original UTAUT framework but potentially important due to the psychological impact of GenAI's unique capabilities in form of the human-AI creativity tension. We hypothesized that the confidence of creative professionals in their creative abilities would positively influence their perception of GenAI's usefulness and ease of use. Conversely, we assumed that some creative professionals might perceive GenAI as a threat to their creative identity, which could reduce their willingness to adopt the technology, manifesting as a form of resistance.

6.2.1 Unpacking the Surprising Effect of Creative Self-Efficacy

We hypothesized that higher CSE would ease the human-AI creativity tension through a positive effect on PE and EE, as it would increase the confidence of creative professionals for directing AI creativity to benefit their own creativity and for effectively utilizing GenAI's outputs in human-AI co-creation. Our results showed that CSE indeed had a small positive effect on the EE of GenAI. However, this effect was not statistically significant, falling short of our significance threshold. Against this background, the result does not align with other studies of the UTAUT where self-efficacy was a significant strong predictor for EE (Altalhi, 2021; Lutfi, 2022). This discrepancy may be due to our focus on a specific form of self-efficacy related solely to creative confidence. Our findings indicate that the innovative methods of interacting with GenAI, such as through prompting, are not perceived as more accessible by creative professionals with higher CSE. This suggests that GenAI is viewed as a technology that does not necessarily require human creative abilities to facilitate easier collaboration.

Unexpectedly, our findings revealed a surprising significant moderate negative relationship between CSE and PE. Contrary to our hypothesis, higher CSE is not indicated to ease the tension, since creative professionals with higher confidence in their creative abilities perceive GenAI as less useful for their work instead of viewing it as an *ally* that positively impacts their creative work. This contrasts with the application of SCT to our context, which suggests that higher CSE should lead to a proactive engagement with technology and higher motivation levels (Bandura, 1997; Gong et al., 2009). Instead, the observed decrease in perceived usefulness lowers the intention to use GenAI. This finding also deviates from recent UTAUT studies, where different forms of self-efficacy showed positive effects on PE, attitudes towards technology, and actual usage behavior (Altalhi, 2021; Cavalheiro et al., 2020; Kundu et al., 2021; Kwak et al., 2022).

It is interesting that the typically observed effect of self-efficacy as a proactive factor for adoption is inverted in the context of creativity, becoming an inhibiting factor instead. In interpreting the unexpected result that higher levels of CSE correlate with lower perceived usefulness of GenAI, we suggest two possible explanations: One interpretation is that those with lower CSE might see GenAI as a helpful co-creator, while those with higher creative confidence may genuinely view GenAI as inadequate for their creative needs and process - a nuance not much addressed in the literature on human-AI co-creation. This would imply that contrary to the view of many researchers (Mazzone & Elgammal, 2019; Wu et al., 2021), human creativity may not be as important to effectively guide AI creativity since also professionals with lower CSE perceive GenAI as useful. Alternatively, it could reflect resistance behavior towards AI creativity associated with the human-AI creativity tension. In this period of disruption caused by GenAI, creative professionals with higher CSE might adopt a more defiant stance about its usefulness, as opposed to those with lower confidence in their creative abilities, who might be more receptive. Ultimately, our results cannot determine to which extent which interpretation is correct.

We can only conclude that CSE considerably impacts creative professionals' perceptions of the usefulness of GenAI and should be considered in organizational integration processes. For organizations who aim to widely implement GenAI, this presents a challenge: While there are naturally variations in CSE among creative professionals in the organization, explicitly identifying these levels through self-assessment surveys is often not feasible on a broad scale due to time constraints and privacy concerns. Instead, given the individual differences in CSE, organizations should find the right balance in their GenAI integration strategies. It may be beneficial for organizations to encourage the utilization of GenAI in certain situations on a voluntary basis rather than mandate its use at all times. As Amabile (1988) pointed out, organizational constraint is one of the biggest environmental factors that can have a detrimental impact on an individual's motivation and creativity. Therefore, simply demonstrating successful use of GenAI by creative professionals with lower CSE - who are more likely to adopt it initially - might create a spillover effect that encourages those with higher CSE to reassess and potentially overcome their initial skepticism about its usefulness after observing positive outcomes.

6.2.2 The Interplay of Resistance with Social Influence in AI Identity Threat

The second individual characteristic of creative professionals that we hypothesized to become a significant factor in their intention to use GenAI was the level of perceived AIT as a

moderating factor. We posited that due to AI creativity some creative professionals might feel threatened in their creative role identity, leading to an amplification of the tension that hinders adoption because GenAI is viewed as a *competitor*. Our descriptive results indeed showed that perceived AIT varies from lower to higher levels in our sample (see Figure B7 in Appendix B for detailed statistics). This reinforces the findings of Paris and Ben Mahmoud-Jouini's (2019) on the existence of strong creative identities in the creative industries and supports our underlying assumption that some of those creatives feel more threatened in their identity by GenAI than others. We have thus successfully demonstrated that the concept of AIT introduced by Mirbabaie et al. (2022) can be observed in the specific context of GenAI adoption in the creative industries. As there is limited research on it to date, our findings provide interesting insights into the mechanisms behind the resistance behavior resulting from AIT.

AIT did not moderate the impact of EE and FC on adoption behavior, likely due to their non-significant influence on intention to use. However, it had opposing moderating effects on other factors: It reduced the impact of PE on intention to use but increased the impact of SI with low to moderate effect. These results paint a differentiated picture of the mechanisms of resistance behavior. Creative professionals who perceive a greater threat to their creative identity from AI creativity attach less importance to the expected performance benefits, which reduces their intention to use GenAI. Simultaneously, they place more emphasis on the social opinion regarding GenAI compared to PE, which significantly influences their adoption decision.

Although the moderating effect of AIT on technology adoption factors is small to moderate, it provides empirical support for the prevalence of creative identity conflict in organizations in the creative industries, as explored by Hackley and Kover (2007). Simultaneously, it indicates a potential leverage point for organizations: Rather than creating a general resistance to all technology acceptance factors for the decision to adopt GenAI, increased AIT amplifies the role of the organizational climate in shaping technology acceptance. This aligns with literature on identity threat responses, which suggests that individuals' actions are heavily influenced by their social environment when their identity is perceived to be under threat (see, e.g., Petriglieri, 2011). As a protective mechanism, creative professionals in those situations might seek validation or guidance from their colleagues and organization, suggesting that strategic adjustments in this climate may increase the receptivity to adoption. In conclusion the findings imply that, in line with our hypothesis, some creative professionals view AI creativity as a *competitor*. However, it does not amplify the tension through generally reducing

adoption willingness. Instead, our results suggest that organizations can leverage their internal culture and collective opinion regarding GenAI to potentially mitigate resistance behavior.

6.3 Connecting Multifaceted Creative Professionals with GenAI

When viewed in aggregate, our findings provide a deeper understanding of how the unique capabilities of GenAI shape its acceptance in the creative industries. In contrast to other sectors where AI adoption may be primarily driven by efficiency or cost-saving considerations, the creative industries are uniquely characterized by the intrinsic value placed on human creativity. This distinction highlights the central role of creativity in the human-AI creativity tension, which emerges as a defining feature of GenAI adoption in the creative industries, as our results indicate that this tension is not merely theoretical but has tangible effects on adoption. Building upon the well-established UTAUT framework, GenAI adoption by creative professionals is influenced not only by traditional factors such as PE and SI but also by individual characteristics related to the tension. Specifically, creative professionals' confidence in their creative abilities and their perception of AI as a potential threat to their creative identity impact their intention to adopt GenAI in different ways. This provides first empirical insights into how individual characteristics of potential users uniquely shape AI adoption, which has been proposed as an avenue for research by Venkatesh (2022), one of the original authors of the UTAUT model.

At the same time, our findings contribute to a more nuanced understanding of the factors that are important for human-AI co-creation to be successful. While current literature emphasizes GenAI's capabilities in this regard, our study highlights the importance of individual differences among creative professionals. Research on the human-AI co-creation model often describes the interaction from a static perspective of the *one* creative professional that simply directs AI creativity in the creative process. However, our results stress that instead there are a *multitude* of different creative professionals that perceive GenAI in diverse ways and may be inclined or disinclined to adopt it due to varying levels of CSE and perceived AIT. This emphasizes the importance of considering CSE and AIT not as isolated factors but as interconnected elements within the broader context of the human-AI creativity tension. Therefore, effective human-AI co-creation requires not only a focus on GenAI's technological capabilities but also an understanding of how individual traits of creative professionals influence their adoption of GenAI.

Together, our findings suggest that companies in the creative industries that aim for broad implementation of GenAI can substantially impact the readiness of their workforce to adopt it. However, we found that it's not the organizational infrastructure or resources, as represented by FC, that influence creative professionals. Instead, organizations may facilitate GenAI adoption indirectly through its organizational climate, as SI plays a moderate role in adoption behavior, which is intensified when creative professionals perceive a threat to their identity from AI creativity. The importance of the work environment is reflected in previous research on organizational creativity, such as Amabile (1988) and Woodman et al. (1993). Amabile (1988) emphasized its impact on individuals' motivation for creative work within organizations, which supports the assertion that organizations should cultivate a culture conducive to GenAI adoption.

To develop effective strategies in this regard, drawing on existing literature on threat resistance responses can be a useful basis for organizations (see, e.g., Petriglieri, 2011), as it emphasizes the importance of social factors, which reflects our findings. Applying these principles, it is crucial for organizations to implement communication strategies and nurture an organizational culture that together support professional identity by affirming the value of human creativity. This approach should include creating space for identity work, as outlined by A. D. Brown (2015), allowing creative professionals to actively engage with and adapt to GenAI at their own pace. This is consistent with Amabile's (1988) theory of organizational creativity, which emphasizes that freedom in how a creative task is accomplished is the most important organizational factor for individual motivation and creativity. Additionally, identity work should be enabled through organic interactions with colleagues to promote recognition of the benefits of GenAI. Bilton and Leary (2002) recommend this facilitative management style in the creative industries and describe it as that of a *creativity broker* that adds value to the creative process through connecting different people, experiences, and technology. By positioning GenAI as a complementary tool - *ally* - that augments rather than replaces creative capabilities in a manner that respects the autonomy of creative professionals, organizations can enable a smoother process of identity adaptation that leads to a sustainable and accepted integration of GenAI across the workforce.

6.4 Limitations

The findings of this study have to be seen in light of some limitations to fully understand the context and applicability of our results. To provide a structured overview, the limitations are clustered into the areas of methodology, research design, and theoretical framework.

In terms of methodology, the use of convenience sampling may limit the generalizability of our findings, as our sample may not be representative of all employees in the creative industries globally (Bell et al., 2019). Additionally, there may be a self-selection bias in our survey sample, as respondents voluntarily chose to participate. This could have had the effect that creative professionals with particular traits or more negative views on GenAI were more likely to respond, given the polarized views on AI creativity and a general human tendency to express dissatisfaction more readily than satisfaction. This further includes a potential social desirability and acquiescence bias, where respondents might have altered their answers based on perceived expectations or desirability (Furnham, 1986). In addition to the detailed statistical considerations outlined in the chapter on the methodology, our results are subject to the risks of Type I errors, where we incorrectly reject the null hypothesis, and Type II errors, where we fail to reject a false null hypothesis.

Concerning the research design, our study was designed to encompass a broad range of creative industries and generalize various GenAI tools under the term *GenAI*, which limits the specificity of our findings to particular creative contexts and specific GenAI tools. Nevertheless, our study might face potential data dependence issues if respondents were from the same organizations or had the same types of creative roles, which would lead to reduced variability and skew our results due to shared organizational cultures and policies that influence perceptions of GenAI. However, we believe that this is unlikely given our data collection methodology, which mainly involved Prolific that typically attracts a diverse set of respondents (Palan & Schitter, 2018). Furthermore, as GenAI is a rapidly evolving topic, we were only able to capture a snapshot in time, which potentially limits its long-term applicability as technological advances may outpace the naturally slower evolution of human attitudes towards new technology (Rogers et al., 2008). This suggests it might be interesting to continuously track both AI developments and the more gradual shifts in human responses to gain insights into their impact on the creative industries and society at large.

Regarding the theoretical framework, we utilized the UTAUT model, which provides a holistic perspective on GenAI adoption by incorporating a selection of predictors statistically shown to be significant in determining technology adoption behavior. However, these factors naturally explain a substantial but not complete portion of the variance in adoption behavior. This indicates that there are other factors at play that we did not capture. This is particularly relevant for the individual characteristics examined in the context of the human-AI creativity tension. While we chose CSE and AIT due to their thematic and theoretical relevance to the tension, there may be other important characteristics that we did not consider.

6.5 Future Research

Against this background, we recommend future research to further explore the human-AI creativity tension and other individual characteristics of creative professionals that are potentially related to it, possibly also including qualitative methods that can provide deeper insights into the underlying perceptions and attitudes. It would be particularly interesting to explore why higher CSE levels lead to decreased PE and which factors influence the intensity of AIT that a creative professional experiences. Building on the work by Mirbabaie et al. (2022) characteristics such as a loss of status position could be significant. Additionally, considering our findings regarding a possible resistance response from CSE on the adoption of GenAI, investigating the influence of CSE on perceived AIT would be valuable. Conversely, future studies could explore which individual characteristics may facilitate a more positive view of GenAI as an *ally* that eases the tension, since we were unable to identify any specific factors in our study. Drivers such as technological readiness, openness to change, or other personality dimensions might be relevant.

From an organizational perspective, we recommend applying insights from threat resistance literature to examine the effectiveness of specific identity adaptation strategies. We advocate that this should involve longitudinal studies within organizations to track how perceptions and the use of GenAI evolve as creative professionals become more familiar with its capabilities or as the technology itself advances. Such research could specifically assess how strategic changes in organizational communication and culture influence attitudes over time. To generate more nuanced insights, future studies may benefit from focusing on specific creative contexts or particular GenAI tools to provide targeted recommendations for improved organizational GenAI integration.

7 CONCLUSION

GenAI is currently one of the most prevalent topics in the creative industries as it holds great potential for enhancing creativity and increasing efficiency in the creative process through human-AI co-creation. Yet, research has not adequately explored what drives adoption of the technology among creative professionals in these organizations, who are critical to this unprecedented collaborative process with GenAI. We argued that an inherent dynamic between creative professionals and GenAI, resulting from its challenge to the uniqueness of human creative agency, may significantly influence their receptivity to GenAI implementation: the human-AI creativity tension. While some perceive AI creativity in the creative process negatively as a *competitor*, others regard it positively as an *ally* that enhances their creative performance (Vimpari et al., 2023). We examined how CSE and AIT, as individual characteristics of creative professionals, contribute to these differing perceptions and impact their willingness to use GenAI.

By grounding our study in the UTAUT framework, we found that creative professionals not only place great value on the perceived usefulness of GenAI and surrounding social opinion in their integration decisions. Their adoption behavior indeed also depends on their level of CSE and perceived AIT with a moderate and small effect. Interestingly, contrary to our hypothesis, our findings suggest that CSE does not ease the tension since the more confident a creative professional is in their creative abilities, the less useful they perceive GenAI for their creative work. Furthermore, professionals who feel threatened by AI in their creative role identity tend to value GenAI's usefulness less and instead place greater emphasis on social opinion when making integration decisions, hinting at a typical threat resistance response. This indicates that organizations in the creative industries looking to broadly implement GenAI could positively influence adoption by creating a social environment conducive to identity work: an organizational climate and communication strategy that encourage creative professionals to voluntarily and gradually adapt to GenAI. By encouraging interactions with GenAI among colleagues, organizations can demonstrate to all individuals how AI creativity can potentially be an asset to their creative work.

It is a genuine challenge for organizations in the creative industries to identify the best use cases for GenAI's capabilities. Nevertheless, our research highlights that these decisions should not only be driven by the abilities of GenAI, but also by the assessment of AI creativity's unique psychological impact on the workforce. Ultimately, the creative professional is still the driving force behind the creative process and is in charge of directing

AI creativity in a way that is most beneficial to them and their craft. We hope that our research will motivate a greater focus on the impact of individual human differences on human-AI co-creation and the importance of considering the unique implications of AI creativity for GenAI adoption. While we have provided initial empirical evidence of the relevance of the human-AI creativity tension for adoption behavior, we encourage future research to further explore the underlying factors that shape creative professionals' largely dualistic perceptions of GenAI: *ally* or *competitor*.

7.1 Theoretical Contributions

The findings of this study add to the emerging body of research on human-AI co-creation and GenAI adoption. They address a significant research gap by examining how individual characteristics of creative professionals become important factors for GenAI integration due to the unprecedented psychological impact of AI creativity. In doing so, this study makes several important theoretical contributions.

First, the current discourse on human-AI co-creation is extended by the introduction of the concept of the human-AI creativity tension that encapsulates the challenge to human creative agency posed by GenAI. While existing research has previously focused predominantly on the capabilities of GenAI, our findings emphasize the importance of considering individual differences in models for successful human-AI co-creation, specifically CSE and AIT, which are connected to this tension. *Second*, this study is the first to empirically demonstrate that AIT is also prevalent in creative professionals in the creative industries when adjusting to GenAI, validating the applicability of the concept of AIT as proposed by Mirbabaie et al. (2022) within this context. *Third*, although the UTAUT framework has been used extensively to examine technology adoption across various contexts (Williams et al., 2015), this study is, to the best of our knowledge, the first to apply it specifically to GenAI adoption within the creative industries. The results only partially confirm the theory as they show that PE and SI significantly affect adoption intentions, whereas FC and EE do not. *Finally*, by expanding the original UTAUT framework to include CSE and AIT as individual characteristics due to the human-AI creativity tension, this study offers empirical evidence on the unique and important role of individual characteristics in GenAI adoption. This adaptation of the UTAUT aligns with recent suggestions by Venkatesh (2022), who highlighted the importance of considering individual differences in understanding AI adoption behavior.

7.2 Managerial Implications

This study further offers interesting managerial implications for organizations in the creative industries that seek to integrate GenAI into their creative processes. Its integration presents challenges not only due to the current ambiguity in regulations in the broader context but also because of its psychological impact on creative professionals. Therefore, practitioners who want to capture the benefits of enhanced idea generation and increased efficiency need to consider the diverse perspectives of their employees on GenAI implementation. In this regard, this study suggests that demonstrating the tangible benefits of AI creativity in the creative process is essential. This in turn requires a deep understanding from management about where and how GenAI can be most effectively applied, particularly in terms of project types and stages within the creative process. This allows managers to provide their employees with a more positive experience of GenAI when they are first introduced to it, which can mitigate initial skepticism about its usefulness and enhance receptivity also among more creatively confident professionals.

Beyond this, this study indicates that it is not just about perceived usefulness, but that there is also a tension between human and AI creativity that impacts the willingness of creatives to engage with the technology. Specifically, our results suggest that some employees may feel threatened by GenAI, perceiving it as a challenge to their creative identity, which can lead to resistance towards its integration. In such cases, these professionals tend to rely more on the opinions of their peers and the broader social environment in making their decisions about adopting the technology. Therefore, managers must be aware of this dynamic and leverage their social influence to promote adoption effectively. This can be achieved on a larger scale by creating an organizational climate that highlights GenAI's role in enhancing rather than replacing human creativity. On a more immediate level, it can be beneficial to encourage open social interactions among employees to share feedback and concerns. Thus, managers are advised not to rush the widespread integration of GenAI, as they may encounter significant resistance from parts of their workforce. Instead, we recommend first identifying the most appropriate use cases for GenAI and then demonstrating its benefits on a voluntary basis. In addition, through maintaining an ongoing dialog about the psychological impact of GenAI during the rollout phase, managers can facilitate identity work and contribute to creative professionals seeing AI as an *ally* rather than a *competitor*. This can ultimately stimulate a sustainable motivation to adopt GenAI across the organization.

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APPENDIX

Appendix A: Survey and Survey Questions

Navigating AI-Creativity: Understanding Your Experience with GenAI Tools

Welcome and Purpose of the Study

Thank you for considering participating in our research study conducted by Nicolas Arias and Christoph Horner as part of our master thesis at the Stockholm School of Economics. Our exploration, titled "Navigating AI-Creativity" aims to delve into the experiences and perceptions of creative professionals like yourself regarding the use of generative Artificial Intelligence (GenAI) tools in your work. As the creative industry continues to evolve, your insights are invaluable in understanding how these technologies impact creativity, productivity, and innovation.

What We Need From You

We invite you to share your thoughts and experiences through this survey, which will take approximately 5-10 minutes to complete. Your responses will help us identify the factors that influence the adoption of GenAI tools in creative sectors, from performance and ease of use to ethical considerations and personal creativity perceptions.

Examples of Generative AI (GenAI) Tools

In our study, the tools we refer to as GenAI tools encompass any tool that leverages artificial intelligence to generate or augment creative content. Examples of such tools include: ChatGPT-3, GPT-4, Copilot, Bard, Gemini, BERT, DALL-E, MidJourney, Adobe Sensei, StyleGAN, Jukebox, WaveNet, Synthesia, Codex, RunwayML, and many others.

Anonymity and Data Protection

Please rest assured that your participation in this survey is entirely voluntary, and all responses will be kept strictly confidential. We are committed to ensuring the anonymity of your answers, and no personally identifiable information will be collected. This study complies with General Data Protection Regulation (GDPR) standards, and the data gathered will only be used for academic purposes, contributing to our understanding of GenAI tool adoption in the creative industry.

Voluntary Participation

Your participation is fully voluntary, and you have the freedom to withdraw from the survey at any time without any consequences. Your honest and thoughtful responses are what make this research meaningful, and we appreciate your time and contribution to this study.

Questions

If you have any questions about the study, you may contact 42338@student.hhs.se.

Table A1

Survey Questions.

Construct	Corresponding Item	Item Sources
Consent Agreement	By selecting "I consent" you acknowledge that you have read the text and agree to participate voluntarily in this survey.	N/A
Sample Characteristics	(Gender) Male / Female / Prefer not to say	N/A
Control Questions	(Control 1) Do you currently work in the creative sector? (Control 2) Does your current role require you to use any level of creativity?	N/A
Performance Expectancy (PE)	(PE1) I find GenAI tools useful in my job. (PE2) Using GenAI tools enables me to accomplish tasks more quickly. (PE3) Using GenAI tools increases my productivity. (PE4) Using GenAI tools increase my chances of achieving things that are important to me.	Venkatesh et al. (2003)
Effort Expectancy (EE)	(EE1) My interaction with GenAI tools is clear and understandable. (EE2) It is easy for me to become skillful at using GenAI tools. (EE3) I find GenAI tools easy to use. (EE4) Learning how to use GenAI tools is easy for me.	Venkatesh et al. (2003)
Social Influence (SI)	(SI1) People who are important to me think that I should use GenAI tools. (SI2) People who influence my behavior think that I should use GenAI tools. (SI3) People whose opinions I value prefer that I use GenAI tools. (SI4) In general, the organization I work at has supported the use of GenAI tools.	Venkatesh et al. (2003)

Facilitating Conditions (FC)	(FC1) I have the resources necessary to use GenAI tools. (FC2) I have the knowledge necessary to use GenAI tools. (FC3) GenAI tools are compatible with other technologies/applications I use. (FC4) I can get help from others when I have difficulties using GenAI tools.	Venkatesh et al. (2003)
Creative Self-Efficacy (CSE)	(CSE1) I consider myself to be a creative person. (CSE2) I have confidence in my ability to solve problems creatively at work. (CSE3) I feel that I am good at generating novel ideas at work. (CSE4) I have the ability to further develop someone else's ideas.	Tierney and Farmer (2002) Reiter-Palmon et al. (2012)
AI Identity Threat (AIT)	(AIT1) I am concerned that using GenAI tools extensively may lead to a loss of respect from my colleagues. (AIT2) I am worried that using GenAI tools extensively might make feel less confident about having the skills and knowledge needed to get work done. (AIT3) I am concerned that if I support the use of GenAI, I will feel that others will consider me to be a poor member of my peer group. (AIT4) I am worried that using GenAI tools extensively might make me feel that I am losing the unique qualities that distinguish me in my professional role.	Mirbabaie et al. (2022)
Intention to Use GenAI (USE)	(USE1) I intend to continue using GenAI tools in the future. (USE2) I will try to use GenAI tools at work. (USE3) I plan to use GenAI at work frequently. (USE4 - Attention Check) Please select "Disagree"	Venkatesh et al. (2003) Muszyński (2023)

Note. Survey made and distributed using Qualtrics.

Appendix B: Distribution Figures of Latent Variables

Distribution of the latent variables, using the means of all observed items from the same construct. Figures made using SPSS.

Figure B1

Performance Expectancy Means Distribution.

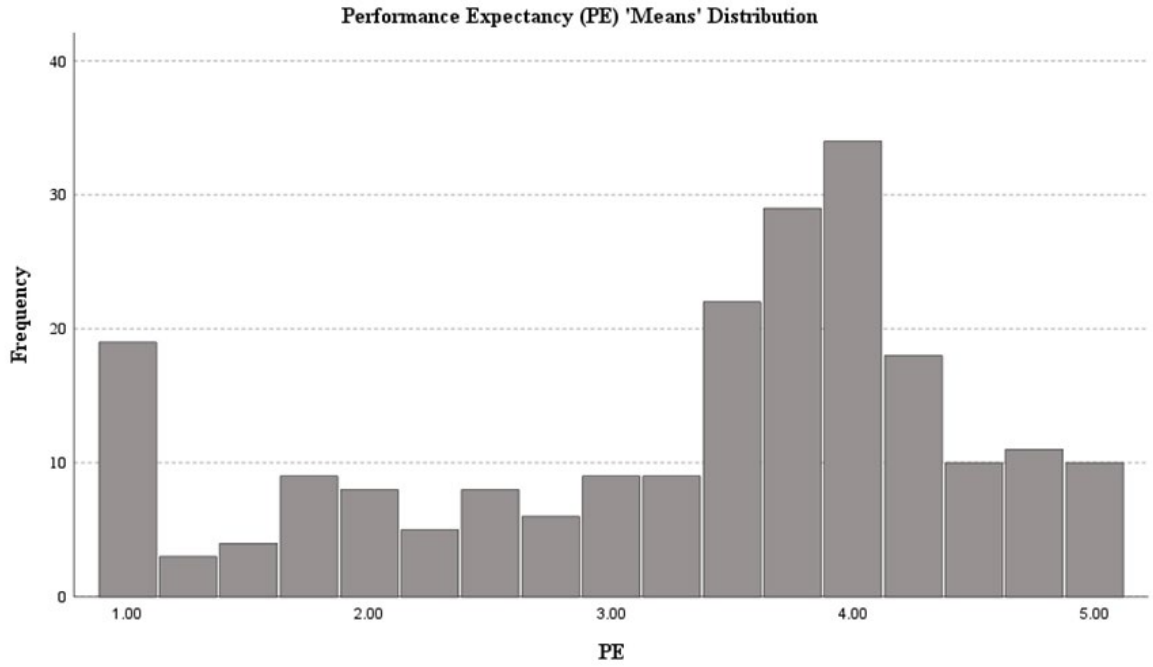


Figure B2

Effort Expectancy Means Distribution.

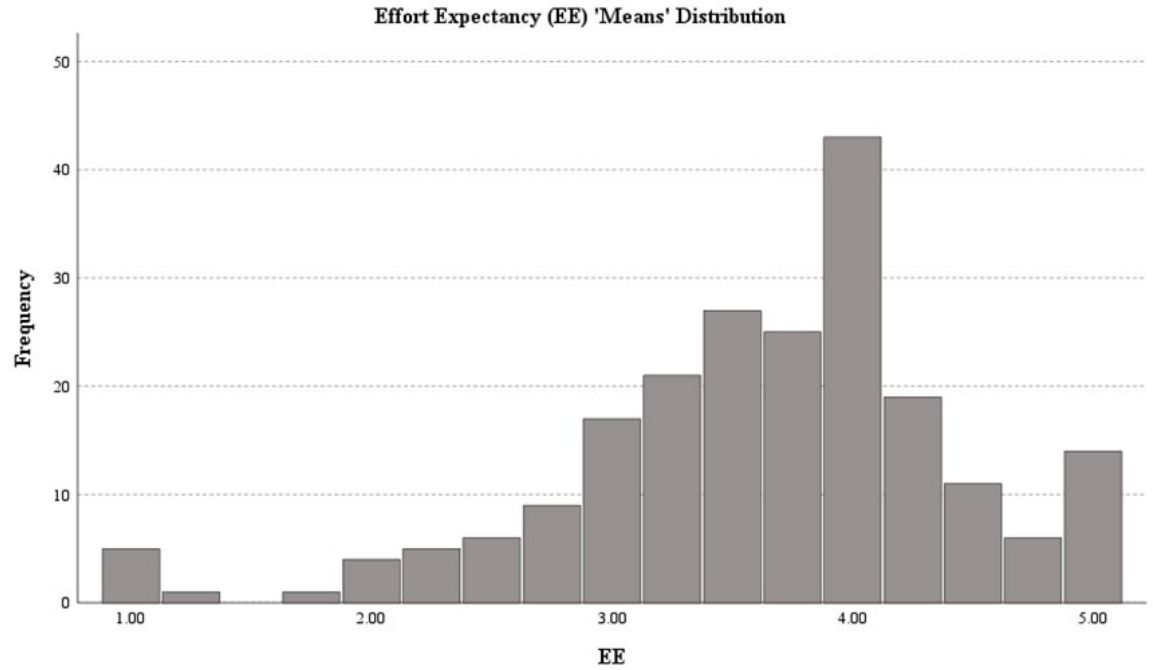


Figure B3

Social Influence Means Distribution.

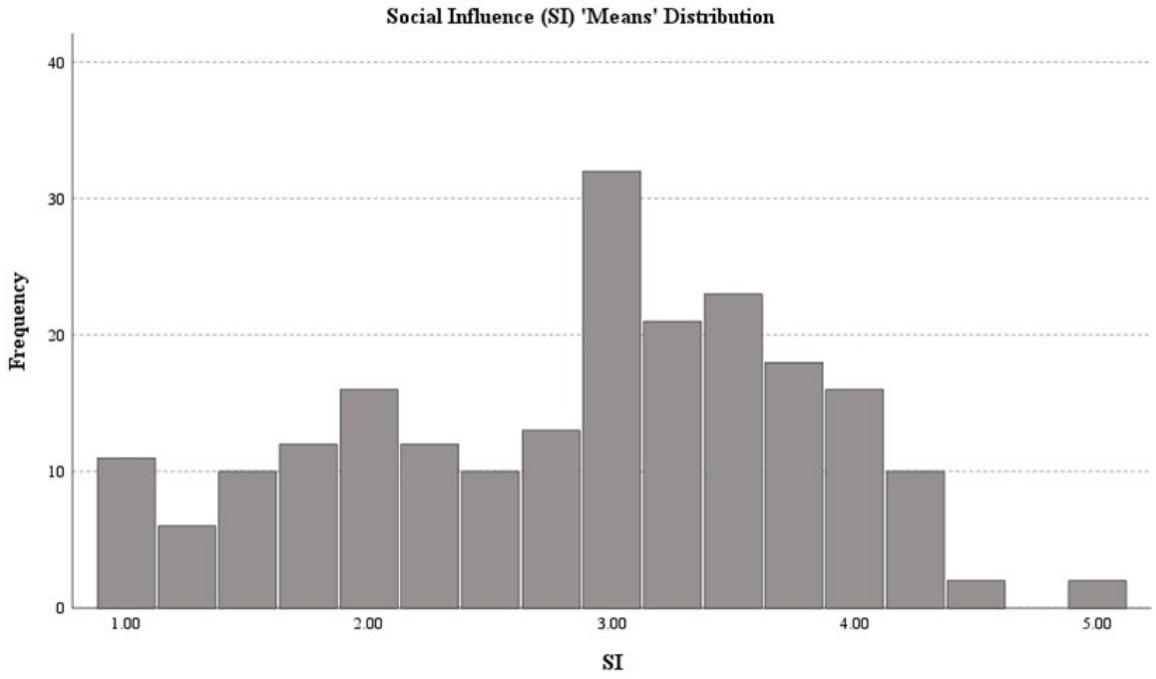


Figure B4

Facilitating Conditions Means Distribution.

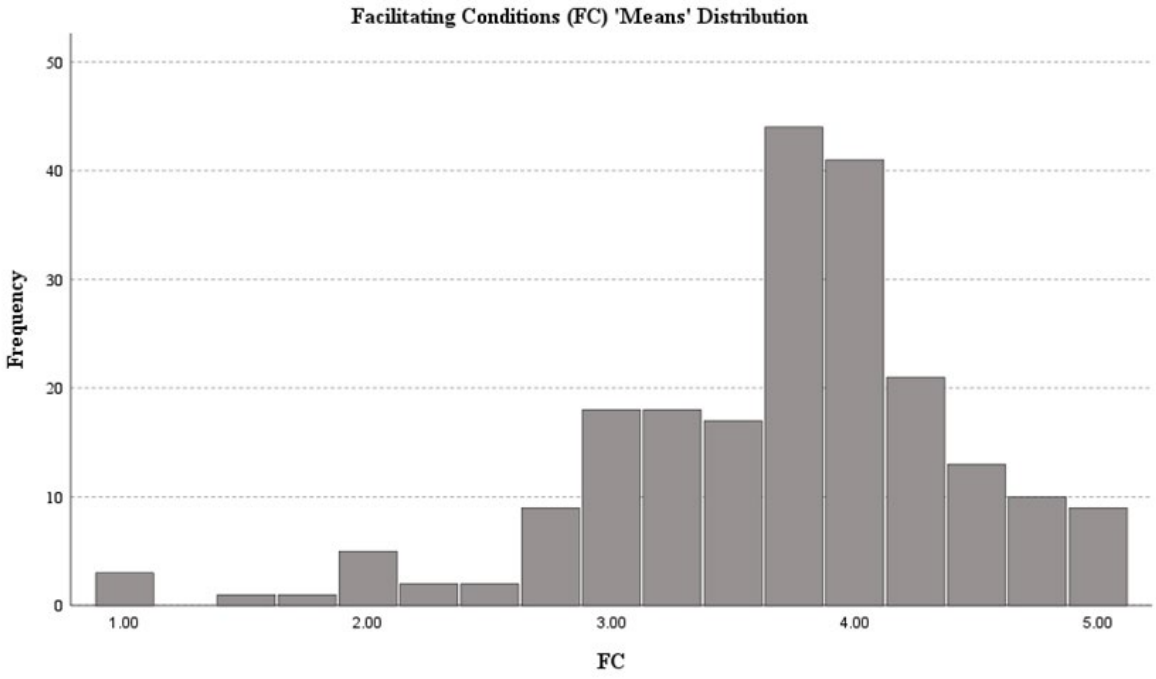


Figure B5

Intention to Use GenAI Tools Means Distribution.

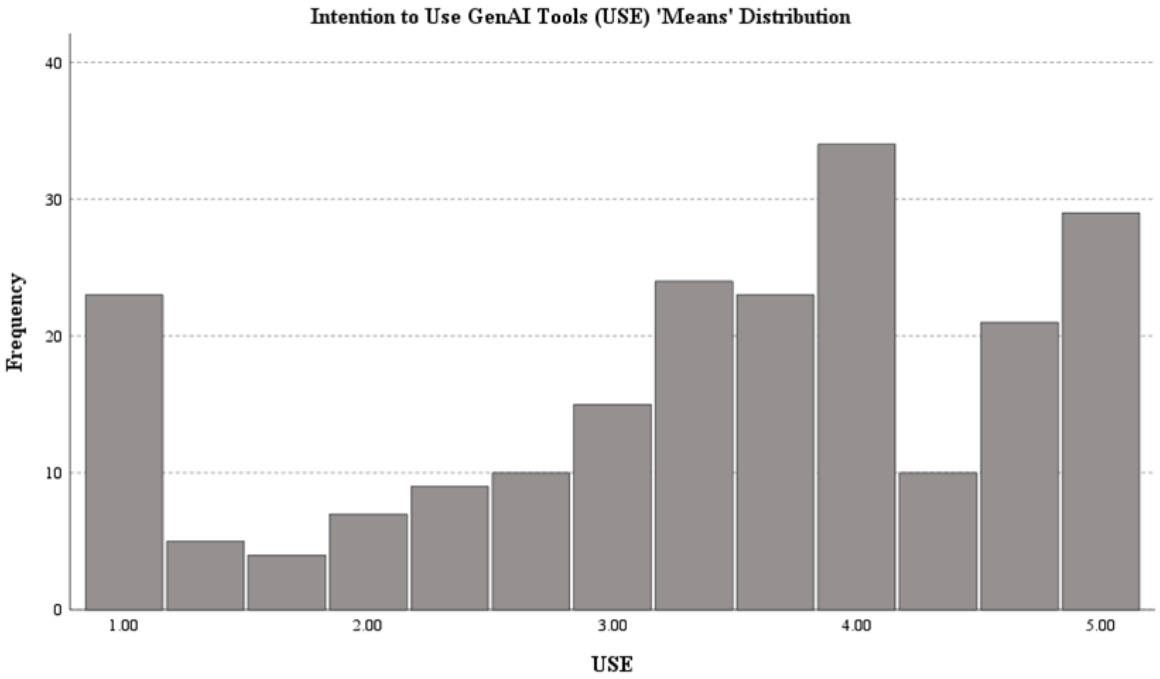


Figure B6

Creative Self-Efficacy Means Distribution.

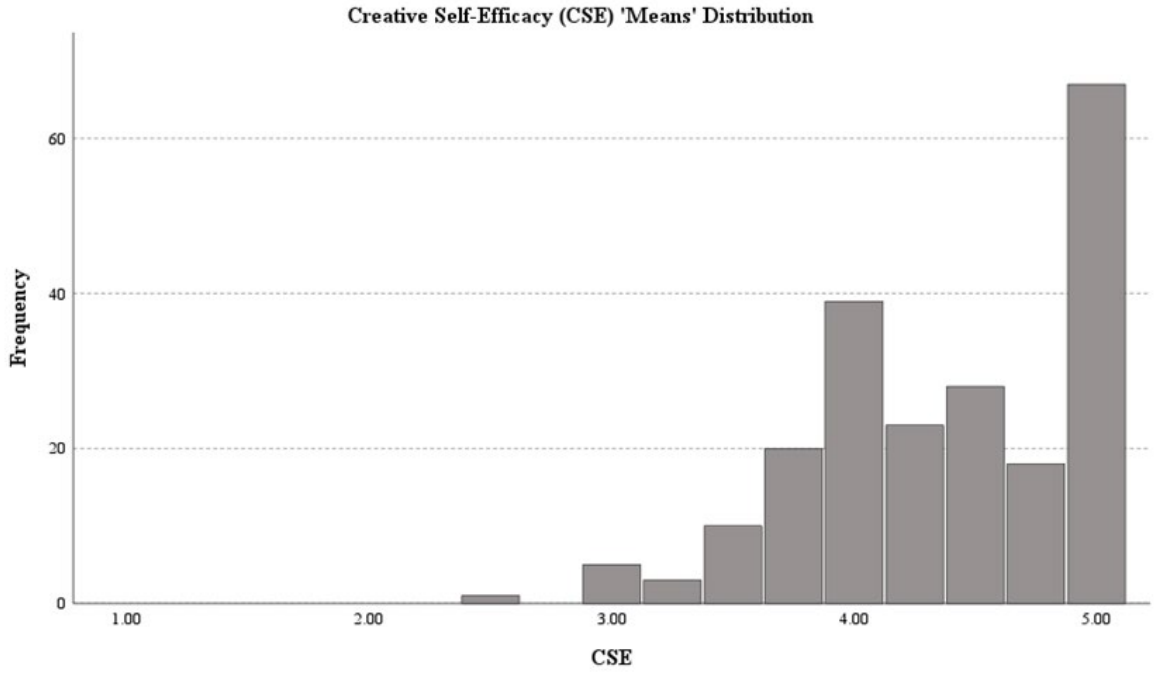
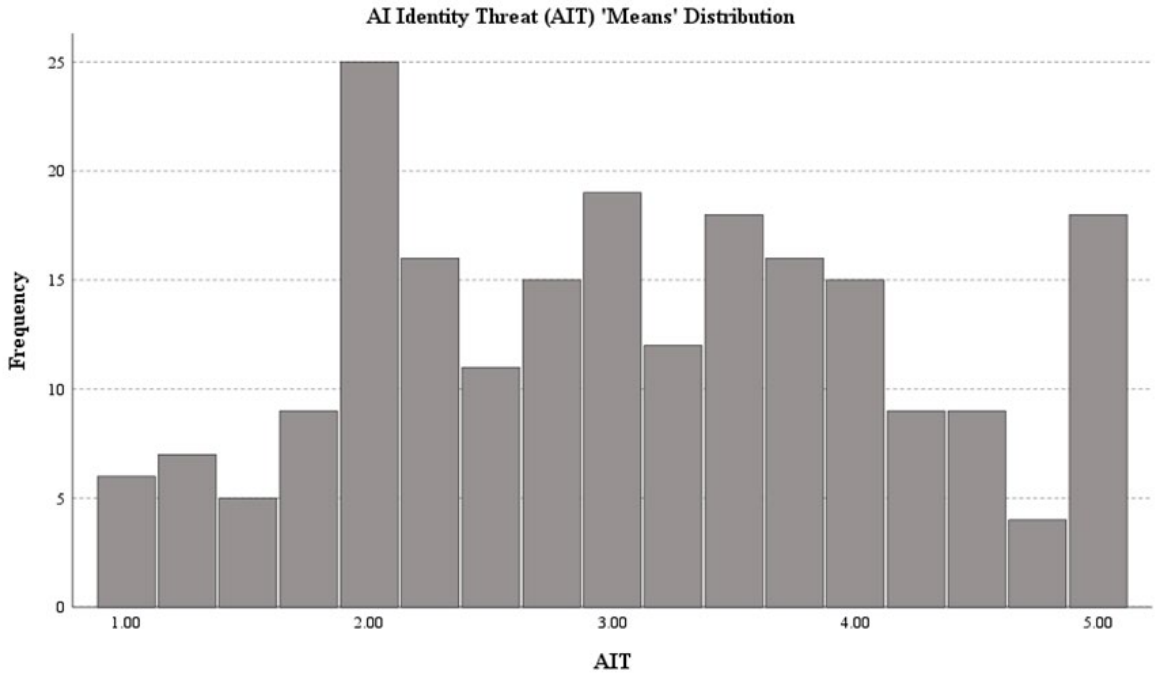


Figure B7

AI Identity Threat Means Distribution.



Appendix C: Test of Multivariate Normality

Table C1

Results of Multivariate Normality.

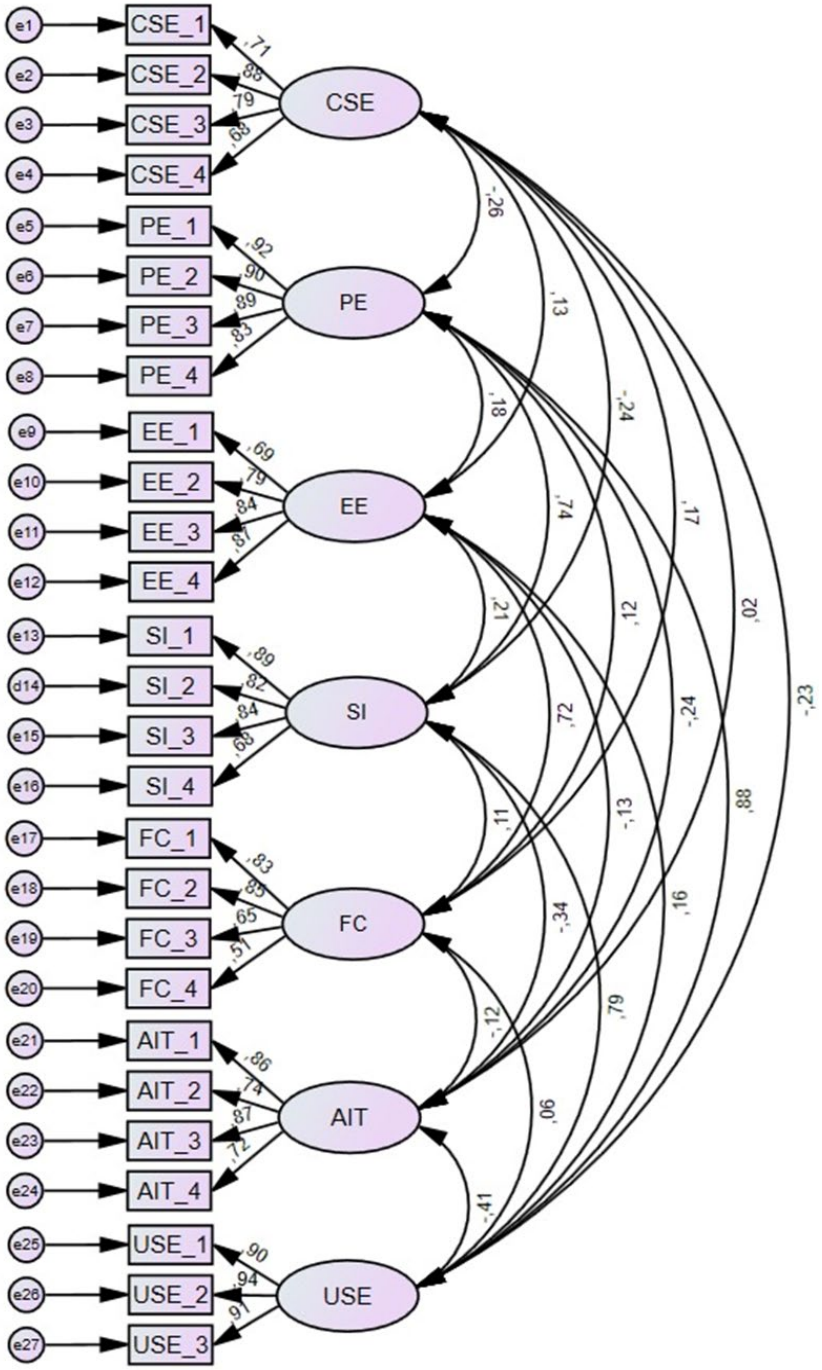
Variable	Min	Max	Skew	C.R.	Kurtosis	C.R.
PE_1	1,000	5,000	-,665	-3,973	-,605	-1,807
PE_2	1,000	5,000	-,775	-4,629	-,445	-1,328
PE_3	1,000	5,000	-,490	-2,927	-,723	-2,160
PE_4	1,000	5,000	-,247	-1,473	-1,079	-3,223
EE_1	1,000	5,000	-,821	-4,905	,632	1,887
EE_2	1,000	5,000	-,493	-2,942	-,108	-,321
EE_3	1,000	5,000	-,727	-4,343	,297	,887
EE_4	1,000	5,000	-,800	-4,778	,690	2,061
SI_1	1,000	5,000	-,158	-,941	-,853	-2,548
SI_2	1,000	5,000	-,097	-,582	-,572	-1,707
SI_3	1,000	5,000	-,072	-,430	-,992	-2,963
SI_4	1,000	5,000	-,434	-2,593	-,646	-1,928
FC_1	1,000	5,000	-1,043	-6,227	1,559	4,656
FC_2	1,000	5,000	-,872	-5,209	,860	2,569
FC_3	1,000	5,000	-,727	-4,343	,301	,900
FC_4	1,000	5,000	-,508	-3,032	-,403	-1,204
USE_1	1,000	5,000	-,817	-4,881	-,328	-,980
USE_2	1,000	5,000	-,723	-4,316	-,619	-1,849
USE_3	1,000	5,000	-,170	-1,017	-1,166	-3,482
AIT_1	1,000	5,000	-,020	-,119	-1,137	-3,396
AIT_2	1,000	5,000	-,027	-,159	-1,169	-3,490
AIT_3	1,000	5,000	,293	1,750	-1,087	-3,246
AIT_4	1,000	5,000	-,171	-1,023	-1,172	-3,499
CSE_1	2,000	5,000	-,933	-5,575	,285	,851
CSE_2	2,000	5,000	-,894	-5,337	,480	1,434
CSE_3	2,000	5,000	-,655	-3,909	-,102	-,305
CSE_4	2,000	5,000	-,801	-4,783	,227	,678
Multivariate					78,995	**14,601**

Note. Using Mardia's (1970) normalized estimate of multivariate kurtosis. Calculated using SPSS Amos 26.

Appendix D: Measurement Model for CFA

Figure D1

Measurement Model.



Note. Made using SPSS Amos 26.

Appendix E: Background Information on Fit Indices

Absolute Fit Indices: Indicate how well a priori model fits the sample data (Hooper et al., 2008).

- **Chi-square (χ^2):** Tests the model's lack of fit with the data; non significance suggests a good fit (Hooper et al., 2008).
- **CMIN/DF (Normed Chi-square):** Assesses model fit relative to the degrees of freedom; values less than 3 suggest a good fit (Hooper et al., 2008)wol
- **Root Mean Square Error of Approximation (RMSEA):** Estimates how well the model, if perfectly specified, would fit the population data; values less than 0.08 indicate a good fit (Hooper et al., 2008; MacCallum et al., 1996).

Incremental Fit Indices: Compare the specified model with a baseline model (Hooper et al., 2008).

- **Comparative Fit Index (CFI):** Compares the fit of the target model to the fit of an independent model; values above 0.90 are indicative of good fit (Bentler, 1990; Hooper et al., 2008; Sánchez et al., 2020).
- **Incremental Fit Index (IFI):** Similar to CFI, but more sensitive to sample size; values above 0.90 suggest good fit (Bentler, 1990; Bollen, 1989).

Parsimonious Fit Indices: Evaluate the fit of the model while taking into account the number of estimated parameters (Hooper et al., 2008).

- **Parsimony Normed Fit Index (PNFI):** Value greater than 0.5 is generally considered good, higher values indicate a parsimonious model (Hooper et al., 2008; Mulaik et al., 1989; Sánchez et al., 2020).
- **Parsimony Comparative Fit Index (PCFI):** Value greater than 0.5 is generally considered good, higher values indicate a parsimonious model (Hooper et al., 2008; Mulaik et al., 1989; Sánchez et al., 2020).
- **Akaike Information Criterion (AIC):** A measure of the relative quality of statistical models for a given set of data. Lower AIC values indicate a model that better explains the variation with fewer parameters (Hooper et al., 2008).

Appendix F: Modifications to the Structural Model

Step 1: Add suggested paths based on results from Table F1. Path from error of AIT2 and AIT4 was added

Table F1

Modification Indices Result

			M.I.	Par Change
e28	<-->	FC	63,090	,376
e27	<-->	SI	74,581	,561
e8	<-->	SI	11,862	,160
e25	<-->	e8	10,282	-,095
e9	<-->	e27	10,665	,180
e2	<-->	e7	10,698	,058
e22	<-->	e26	12,258	,118
e21	**<-->**	**e23**	**32,082**	**,329**
e20	<-->	e23	15,348	-,189

Note. Table extracted from Modification Indices in SPSS Amos 26.

Step 2.1: Removal of nonsignificant paths based on results from Table F2. Path from AIT and EExAIT was removed.

Table F2

Covariance Estimates First Result

			Estimate	SE	C.R.	P
SIxAIT	<-->	EExAIT	,417	,085	4,914	***
PExAIT	<-->	EExAIT	,342	,084	4,053	***
EExAIT	<-->	FCxAIT	,988	,109	9,069	***
PExAIT	<-->	SIxAIT	,879	,095	9,233	***
SIxAIT	<-->	FCxAIT	,207	,079	2,618	,009
PExAIT	<-->	FCxAIT	,188	,080	2,351	,019
FC	<-->	FCxAIT	,229	,067	3,416	***
CSE	<-->	SI	-,140	,043	-3,270	,001
CSE	<-->	FC	,086	,037	2,308	,021
AIT	<-->	SI	-,358	,084	-4,285	***
AIT	<-->	FCxAIT	,105	,089	1,173	,241
CSE	<-->	PExAIT	-,093	,045	-2,072	,038
CSE	<-->	SIxAIT	-,147	,046	-3,233	,001
CSE	<-->	EExAIT	-,082	,049	-1,682	,093
SI	<-->	PExAIT	,186	,070	2,645	,008
SI	<-->	SIxAIT	,215	,070	3,077	,002
SI	<-->	EExAIT	,218	,076	2,850	,004
FC	<-->	EExAIT	,194	,068	2,855	,004
FC	<-->	PExAIT	,110	,062	1,772	,076
FC	<-->	SIxAIT	,072	,061	1,185	,236
SI	<-->	FC	,059	,057	1,042	,297
AIT	<-->	FC	-,081	,070	-1,162	,245
AIT	<-->	PExAIT	-,122	,085	-1,442	,149
AIT	<-->	SIxAIT	-,090	,083	-1,081	,280
SI	<-->	FCxAIT	,092	,073	1,266	,205
AIT	<-->	CSE	,027	,050	,548	,584
AIT	**<-->**	**EExAIT**	**-,006**	**,091**	**-,061**	**,951**
CSE	<-->	FCxAIT	-,011	,047	-,242	,809
e21	<-->	e23	,389	,076	5,124	***

*** $p < 0.001$

Note. Table extracted from Covariance Estimates in SPSS Amos 26.

Step 2.2: Removal of nonsignificant paths based on results from Table F3. Path from CSE and FCxAIT was removed.

Table F3

Covariance Estimates Second Result

			Estimate	SE	C.R.	P
SIxAIT	<-->	EExAIT	,416	,085	4,923	***
PExAIT	<-->	EExAIT	,341	,084	4,067	***
EExAIT	<-->	FCxAIT	,988	,109	9,089	***
PExAIT	<-->	SIxAIT	,878	,095	9,242	***
SIxAIT	<-->	FCxAIT	,207	,079	2,617	,009
PExAIT	<-->	FCxAIT	,187	,080	2,351	,019
FC	<-->	FCxAIT	,229	,067	3,416	***
CSE	<-->	SI	-,140	,043	-3,271	,001
CSE	<-->	FC	,086	,037	2,310	,021
AIT	<-->	SI	-,357	,082	-4,352	***
AIT	<-->	FCxAIT	,109	,055	1,990	,047
CSE	<-->	PExAIT	-,093	,045	-2,071	,038
CSE	<-->	SIxAIT	-,147	,046	-3,233	,001
CSE	<-->	EExAIT	-,082	,049	-1,681	,093
SI	<-->	PExAIT	,186	,070	2,655	,008
SI	<-->	SIxAIT	,215	,069	3,095	,002
SI	<-->	EExAIT	,216	,073	2,977	,003
FC	<-->	EExAIT	,194	,068	2,859	,004
FC	<-->	PExAIT	,110	,062	1,771	,077
FC	<-->	SIxAIT	,072	,061	1,183	,237
SI	<-->	FC	,059	,056	1,041	,298
AIT	<-->	FC	-,080	,068	-1,173	,241
AIT	<-->	PExAIT	-,121	,081	-1,487	,137
AIT	<-->	SIxAIT	-,088	,078	-1,134	,257
SI	<-->	FCxAIT	,091	,071	1,287	,198
AIT	<-->	CSE	,027	,050	,544	,586
CSE	**<-->**	**FCxAIT**	**-,011**	**,047**	**-,241**	**,809**
e21	<-->	e23	,389	,076	5,124	***

*** $p < 0.001$

Note. Table extracted from Covariance Estimates in SPSS Amos 26.

Step 2.3: Removal of nonsignificant paths based on results from Table F4. Path from AIT and CSE was removed.

Table F4

Covariance Estimates Third Result

			Estimate	SE	C.R.	P
SIxAIT	<-->	EExAIT	,412	,083	4,979	***
PExAIT	<-->	EExAIT	,339	,083	4,077	***
EExAIT	<-->	FCxAIT	,986	,108	9,116	***
PExAIT	<-->	SIxAIT	,877	,095	9,251	***
SIxAIT	<-->	FCxAIT	,202	,077	2,634	,008
PExAIT	<-->	FCxAIT	,185	,079	2,342	,019
FC	<-->	FCxAIT	,231	,066	3,496	***
CSE	<-->	SI	-,139	,043	-3,263	,001
CSE	<-->	FC	,088	,036	2,434	,015
AIT	<-->	SI	-,358	,082	-4,355	***
AIT	<-->	FCxAIT	,109	,055	1,997	,046
CSE	<-->	PExAIT	-,092	,044	-2,061	,039
CSE	<-->	SIxAIT	-,145	,045	-3,244	,001
CSE	<-->	EExAIT	-,072	,030	-2,421	,015
SI	<-->	PExAIT	,185	,070	2,649	,008
SI	<-->	SIxAIT	,214	,069	3,090	,002
SI	<-->	EExAIT	,213	,071	2,995	,003
FC	<-->	EExAIT	,196	,067	2,901	,004
FC	<-->	PExAIT	,109	,062	1,769	,077
FC	<-->	SIxAIT	,071	,061	1,178	,239
SI	<-->	FC	,058	,056	1,032	,302
AIT	<-->	FC	-,080	,068	-1,168	,243
AIT	<-->	PExAIT	-,121	,081	-1,490	,136
AIT	<-->	SIxAIT	-,089	,078	-1,139	,255
SI	<-->	FCxAIT	,087	,069	1,268	,205
AIT	**<-->**	**CSE**	**,028**	**,050**	**,565**	**,572**
e21	<-->	e23	,389	,076	5,124	***

*** $p < 0.001$

Note. Table extracted from Covariance Estimates in SPSS Amos 26.

Appendix G: Disclosure of AI Usage

We used GPT-4 during this work for its creative ability to provide novel and appropriate content. Specifically, we utilized it to receive conversational, constructive feedback for our thesis topic and theoretical framework during the ideation phase and to receive suggestions for improving the clarity and flow of our text during the writing process.

Application of GPT-4

At the start of our work, GPT-4 helped us in the brainstorming phase by supporting us in creating drafts of research questions and thesis topics. This acted as a foundational phase, allowing us to pinpoint our exact research topic. We discussed our ideas on the theoretical framework in dialogue with GPT-4 and received detailed feedback, e.g., on the differences of including AIT as a moderator vs. as a predictor. In addition, we utilized GPT-4 to refine the coherence and structural clarity of the thesis. This included compiling our notes, restructuring our text drafts, and improving the narrative flow of the text. To do this, we prompted GPT-4 to act as an academic researcher of a journal who reviews our text for academic quality characteristics such as academic language and clarity.

Enhancement of Thesis Quality

The research process was improved by GPT-4 from the earliest stages. With GPT-4's help, we were able to explore a larger number of different topics and understood our theoretical framework and its implications in detail, which had a positive impact on the further course of the work, especially the discussion. In addition, its ability to provide accurate suggestions for improving our text for clarity and academic language greatly simplified the editing process and ensured consistency and smooth transitions in the text. Altogether, GPT-4 improved the readability and overall academic presentation of our thesis.

Mitigation of Potential Risks

We are aware of the potential risks of using GPT-4, especially concerns regarding the accuracy of its content. To mitigate these risks, we emphasize that we have never used GPT-4 to generate citations, reference materials, or factual information, nor did we use it as a substitute for analytical tasks. The role of GPT-4 was therefore limited to preliminary idea generation/discussion and in supporting the academic presentation of the thesis. In addition, we thoroughly reviewed all text and ideas generated by the AI to ensure it matched the original input text. We interacted with GPT-4 in a turn-based mode to further elaborate its

suggestions. In most cases, we could not incorporate suggestions from the text revision one-to-one, but only used parts of it that really matched with the nuances of the content we wanted to convey.

Insights Gained from Using GenAI

The use of GenAI in developing this thesis showed us both the advantages and disadvantages of applying AI to academia. Although GPT-4 was very helpful in improving textual consistency and clarity and in developing new ideas, it occasionally deviated from the given instructions, which demonstrates the need for close supervision and a human-in-the-loop. These experiences showed us the value of AI as a complementary tool that enhances but does not replace the critical analytical capabilities of us, the researchers. Considering the overarching theme of our thesis, our hands-on experience with GPT-4 in the special context of academia confirms that we used and viewed GenAI as an *ally*, not a *competitor.*