# Accepting Generative Artificial Intelligence in Consulting Services – An Analysis of Success Factors

Inessa Herzog

Dissertation written under the supervision of professor Filipa Lancastre

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## Abstract

**Title:** Accepting Generative Artificial Intelligence in Consulting Services – An Analysis of Success Factors

**Author:** Inessa Herzog

The present study examines the success factors that influence the acceptance of Generative Artificial Intelligence (GenAI) among business consultants. While numerous research studies have developed and expanded models for general technology acceptance, there are still few studies that address the acceptance of GenAI in specific professional contexts such as the consulting industry. This work fills this research gap by developing a new model to investigate the acceptance factors of GenAI among business consultants.

The model is based on established theories such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Task-Technology-Fit (TTF) model, which have been combined into a new conceptual framework. For empirical verification, a quantitative study was conducted with 147 business consultants to identify key success factors on the intention to use and acceptance of GenAI.

The results show that the fit between technology and tasks (Task-Technology Fit, TTF), the expected performance improvement (Performance Expectancy, PE) and the Behavioural Intention (BI) play a crucial role in the acceptance of GenAI in the business consulting context.

The study highlights the need amongst companies for targeted training, practical use cases, and a strategic integration of GenAI into existing workflows to promote sustainable acceptance. The results provide both theoretical and practical implications for consulting firms to support the successful implementation of GenAI.

**Key words:** Generative Artificial Intelligence, Technology Acceptance, Consulting, Task-Technology Fit, Performance Expectancy, Structural Equation Modelling

## Abstrato

**Título:** Aceitação da Inteligência Artificial Generativa nos serviços de consultoria – uma análise dos fatores de sucesso

**Autor:** Inessa Herzog

O presente estudo analisa os fatores de sucesso que influenciam a aceitação da Inteligência Artificial Generativa (GenAI) entre consultores empresariais. Embora numerosos estudos de investigação tenham desenvolvido e expandido modelos para a aceitação geral de tecnologia, ainda existem poucos estudos que abordam a aceitação da GenAI em contextos profissionais específicos, como a indústria da consultoria. Este trabalho preenche esta lacuna de investigação ao desenvolver um novo modelo para analisar os fatores de aceitação da GenAI entre consultores empresariais.

O modelo baseia-se em teorias estabelecidas, como o Modelo de Aceitação de Tecnologia (TAM), a Teoria Unificada de Aceitação e Uso da Tecnologia (UTAUT) e o modelo de Ajuste Tarefa-Tecnologia (TTF), que foram combinados num novo quadro conceptual. Para a verificação empírica, foi realizado um estudo quantitativo com 147 consultores empresariais, a fim de identificar os principais fatores de sucesso na intenção de uso e aceitação da GenAI.

Os resultados mostram que o ajuste entre a tecnologia e as tarefas (Ajuste Tarefa-Tecnologia, TTF), a expectativa de melhoria do desempenho (Expectativa de Desempenho, PE) e a Intenção Comportamental (BI) desempenham um papel crucial na aceitação da GenAI no contexto da consultoria empresarial.

O estudo destaca a necessidade, por parte das empresas, de formação direcionada, casos de uso práticos e uma integração estratégica da GenAI nos fluxos de trabalho existentes para promover uma aceitação sustentável. Os resultados fornecem implicações tanto teóricas como práticas para as empresas de consultoria, apoiando a implementação bem-sucedida da GenAI.


**Palavras-chave:** Inteligência Artificial Generativa, Aceitação de Tecnologia, Consultoria, Ajuste Tarefa-Tecnologia, Expectativa de Desempenho, Modelação de Equações Estruturais

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## List of Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| AVE | Average variance extracted |
| BI | Behavioural Intention |
| AIDUA | Artificial Intelligent Device Use Acceptance Model |
| CR | Composite reliability |
| CONT | Consultant Tasks |
| GAIC | GenAI Characteristics |
| GenAI | Generative Artificial Intelligence |
| PE | Performance Expectancy |
| PEOU | Perceived ease of use |
| PLS-SEM | Partial Least Squares Structural Equation |
| PU | Perceived usefulness |
| SEM | Structural Equation Model |
| TAM | Technology Acceptance Model |
| TPC | Technology-to-Performance Chain |
| TTF | Task-Technology Fit |
| UTAUT | Unified Theory of Acceptance and Use of Technology |

# 1 Introduction

Generative Artificial Intelligence (GenAI) has developed into one of the most discussed technological advancements in recent years and is increasingly influencing society, the economy, and businesses. Since the release of OpenAI's ChatGPT in November 2022, the technology has gained significant attention worldwide. According to Gartner (2025), GenAI is currently experiencing the peak of inflated expectations in the hype cycle. While the technology is considered groundbreaking, there is a risk that inflated expectations may not be immediately met. This highlights the need to critically examine not only technological possibilities but also acceptance and actual areas of application (Gartner, 2025). While previous technological innovations primarily aimed at automating repetitive tasks, GenAI marks a paradigm shift as it increasingly affects knowledge-intensive professions and thus also the consulting industry (Manyika & Spence, 2023).

Management consultancy, characterized by a high degree of industry expertise, complex problem-solving, and tailored client strategies, is particularly in the spotlight of this technological development. Studies show that up to 62 percent of tasks performed by business professionals including consultants could be automated if GenAI is used strategically (McKinsey & Company, 2023). Oliver Wyman (2024) assumes that 95 to 98 percent of all knowledge workers could benefit from using GenAI in their daily work. According to the same report, banks such as JPMorgan Chase & Co. have already integrated AI-powered tools into their workflows. At JPMorgan Chase & Co., debt analysts and lawyers spend a significant portion of their time reviewing financial documents. By leveraging AI for the automated analysis of credit contracts, the company could save up to 360,000 working hours annually (Capgemini Research Institute, 2017). These developments illustrate the enormous potential of GenAI to increase efficiency and improve decision-making in knowledge-based professions.

Despite these promising possibilities, it appears that not all professionals are ready to accept GenAI (Kim, 2019). Studies suggest that many users have little confidence in their own ability to use the technology effectively, which in turn negatively impacts their willingness to adopt it (Oliver Wyman, 2024). Media coverage also influences the perception of GenAI, as it often highlights the challenges and risks of the technology (Schepman & Rodway, 2023). In some cases, AI failures have already caused significant reputational damage to companies, for example when Google's AI chatbot Bard spread false accusations against leading consulting firms (Bloomberg Law, 2023). Such incidents increase scepticism towards the technology and can hinder its widespread adoption in the consulting industry.

Another obstacle to acceptance is the fear of job losses. While GenAI is officially promoted as a supportive tool, there are concerns that companies might use the technology in the long term to cut costs and replace human consultants (Ernst & Young, 2023). These uncertainties highlight that the availability of innovative AI technologies such as GenAI does not automatically lead to their acceptance, but that individual and organizational factors play a crucial role.

Therefore, the question arises, which success factors mainly influence the acceptance of GenAI. As Kelly et al. (2023) emphasize, low acceptance of technology can limit its long-term use and leave innovation potential untapped. While existing technology acceptance models such as Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) provide general insights into the introduction of new technologies, they do not consider the specific challenges of using GenAI in knowledge-intensive professions. This study addresses this research gap by examining which success factors influence the acceptance of GenAI among consultants. The study focuses on the perceived technological performance of GenAI, the Task-Technology Fit (TTF), and the expected performance improvements (Performance Expectancy, PE). The results of this investigation are intended not only to provide theoretical insights but also to offer practical recommendations for consulting firms, to promote the successful integration of GenAI into everyday work. This study aims to answer the following research question:

***What success factors influence user acceptance of GenAI among business consultants?***

## 2 Literature Review

### 2.1 Characteristics of (Generative) Artificial Intelligence

Artificial Intelligence (AI) aims to achieve two primary objectives. Firstly, AI seeks to comprehend and replicate human cognitive processes and actions. Secondly, AI seeks to utilize acquired information to create systems capable of executing diverse cognitive tasks independently of human involvement (Antonov, 2011). Past studies emphasize the significance of the two objectives, including the aim of replacing humans in intellectual endeavours with computers (Antonov, 2011). However, recent literature underscores that the utilization of AI by governments, corporations, and researchers should not replace human abilities, but rather enhance human capabilities (Manyika & Spence, 2023).

AI encompasses numerous subcategories and types. This study specifically focuses on GenAI. The introduction of ChatGPT has raised the significance of GenAI in recent years (Fosso Wamba et al., 2024; Peres et al., 2023). The media has particularly highlighted the emerging capability to imitate and exceed human intelligence. GenAI has demonstrated its efficacy in previous instances. For instance, ChatGPT successfully passes examinations like the United States Medical Licensing Exam at the university level (Fosso Wamba et al., 2024; Kung et al., 2023). GenAI technologies, like ChatGPT, facilitate both simple and complex user interactions (Fosso Wamba et al., 2024; Rožanec et al., 2023), thereby promoting quicker and wider acceptance relative to conventional programming-based solutions (Fosso Wamba et al., 2024). GenAI operates via algorithms capable of producing films, photos, documents, and sounds based on the data on which they have been taught (Dwivedi et al., 2023; Fosso Wamba et al., 2024; Peres et al., 2023). The distinction between GenAI and AI lies in GenAI's capability to develop novel material rather than only analysing existing data (Fosso Wamba et al., 2024; Gozalo-Brizuela & Garrido-Merchan, 2023). Moreover, traditional AI requires explicit programming to execute tasks, while GenAI can produce material based on interactions between humans and machines (Fosso Wamba et al., 2024). GenAI is founded on AI technology, including deep learning algorithms and neural networks, including large-scale language models (Fosso Wamba et al., 2024). ChatGPT utilizes extensive language models that identify correlations among data through numerous parameters and forecast the appropriate content to be generated (Fosso Wamba et al., 2024). GenAI requires substantial data access, primarily sourced from the Internet (Fosso Wamba et al., 2024; Huang et al., 2023). In conclusion, it must be emphasized that Generative AI presents significant operational and strategic possibilities.

## 2.2 Consultancies and the Role of (Business) Consultants

The lack of a standardized definition for management consultancy complicates the characterization of this institution or profession (Banai & Tulimieri, 2013). It is important to highlight that management consultancy, whether as an institution or a professional endeavour, is challenging to define given the absence of regulatory protection for the phrase, allowing any entity to adopt it. Management consulting is defined in academic literature as a professional service delivered by specially trained and skilled employees who identify and resolve managerial and operational issues in diverse organizations (Kipping & Clark, 2012). This service is therefore focused on enhancing the managerial, operational, and economic performance of these institutions (Kipping & Clark, 2012). Two distinct participants can be identified in this service: particularly trained and experienced individuals, as well as varied institutions, both categorized as consultants and clients (Kipping & Clark, 2012). The term ‘consultant’ is often used by individuals who do not possess the appropriate training or qualifications (Banai & Tulimieri, 2013). Consequently, organizations approach consultants with a certain degree of scepticism and caution (Banai & Tulimieri, 2013; Mitchell, 1995). According to Loukus & Dixon (2014), a consultant is a person who exerts influence on individuals, groups, or organizations but does not have direct decision-making authority to implement changes. This definition emphasizes the advisory role of consulting, which focuses on influencing rather than direct decision-making authority (Loukus & Dixon, 2014). According to Wickham & Wilcock (2020), consultants are specialists who use their analytical, problem-solving, and strategic skills to assist clients in overcoming challenges, seizing opportunities, and enhancing their competitiveness.

The term ‘business consultant’ requires a clear definition in the context of this thesis. A specific definition of this term could not be found. Therefore, this paper uses the concept of ‘Business Consulting’, from which the definition of ‘business consultant’ can be derived. A business consultant is a specialist who helps organizations improve their performance. This is done by analysing business problems based on previous assessments and developing strategies for optimization (Banai & Tulimieri, 2013). The difference between a consultant and a business consultant is that a consultant advises individuals and takes on roles similar to those of a doctor or architect. A business consultant, on the other hand, focuses on improving individuals, processes, and organizational structures (Banai & Tulimieri, 2013).

Academic research on the knowledge, skills, abilities and personality traits of management consultants has so far been limited (Banai & Tulimieri, 2013). Critics call for a more intensive academic and critical examination of this topic (Banai & Tulimieri, 2013). This chapter is therefore largely based on findings from organizational development and educational science. A business consultant must possess diverse talents and personality qualities (Van Leusen et al., 2016) to assist clients' enterprises, which are increasingly confronted with several external and internal factors, including technology advancements (Banai & Tulimieri, 2013). For a business consultant to enhance a client's performance, they must possess a variety of capabilities, including communication, content development, and analytical abilities (Banai & Tulimieri, 2013).

Business consultants require the ability to conduct quantitative and qualitative evaluations based on client and project-specific data. These analyses can vary in complexity, encompassing both simple, repetitive operations and complex financial models (Banai & Tulimieri, 2013). The necessary consistency of the business consultant in executing these analyses enhances the trustworthiness of the outcomes and augments the perceived expertise of the business consultant (Banai & Tulimieri, 2013).

A business consultant must possess the capability to speak effectively and efficiently inside business dialogues (Glückler, 1999). Effective communication is evaluated by the capacity to attentively listen to the client, articulate the issue under examination using suitable terminologies, ask questions, and confirm information to mitigate the potential for misconceptions (Canato & Giangreco, 2011; Van Leusen et al., 2016). Effective communication skills entail that a business consultant can clarify tasks and responsibilities and allocate them within the client organization and the project team (Buono & Jamieson, 2010). Communication failures may result in divergent interpretations between the consultant and all project stakeholders, leading to knowledge asymmetries and conflicting interests within collaboration (Bronnenmayer et al., 2016). This may result in issues such as litigation, penalties, and financial difficulties (Van Leusen et al., 2016). Due the increasing complexity of issues, it is essential for a business consultant to exhibit creativity to devise novel solutions and effectively address these challenges (Banai & Tulimieri, 2013; Canato & Giangreco, 2011). To exhibit creativity, the business consultant must possess current academic knowledge alongside extensive expertise in particular organizational roles and industries (Banai & Tulimieri, 2013). The ability to imagine future scenarios through strategic thinking and planning is crucial and complements creativity. The resulting strategy must correspond with the client's objectives and assist the organization in identifying a sustainable solution (Buono & Jamieson, 2010). Another activity entails business consultants assisting management in decision-making by providing information regarding markets and trends (Canato & Giangreco, 2011). Consequently, content generation emerges as a primary responsibility. They share and transfer the insights acquired from prior projects to subsequent clients, enabling them to profit from the accumulated knowledge (Canato & Giangreco, 2011).

GenAI can serve as a substitute, supplement, or extension of tasks in consulting (Ernst et al., 2019). The advantages that GenAI can provide to business consultants differ based on their daily tasks. According to McKinsey & Company, IT consulting, particularly within software engineering, stands to gain significant advantages from GenAI implementation (McKinsey & Company, 2023). In contrast, consulting with a strategic focus is expected to see only limited benefits from its use. Moreover, McKinsey & Company predicts that knowledge professionals, such as consultants, allocate roughly 20 percent of their working hours to information research (McKinsey & Company, 2023). GenAI streamlines this process by enabling rapid and efficient database searches for relevant data. Additionally, it demonstrates greater reliability than humans, reducing errors commonly associated with human-driven tasks (Capgemini Research Institute, 2017).

In consulting, established methodologies are frequently employed to attain optimal outcomes (Barthélemy, 2017). Nonetheless, certain limitations have been identified in this situation. Consulting services cannot be standardized but must be tailored to the specific client and industry. Moreover, best practices are less distinctive than tailored solutions and hence do not result in significant performance enhancements (Barthélemy, 2017). It is important to acknowledge that GenAI can also be utilized for non-routine tasks. Generative AI offers business advisors innovative concepts for diverse industries and operational activities. This encompasses the formulation of innovative business models and the generation of customized content for marketing and sales (Ernst & Young, 2023). It is important to acknowledge that GenAI cannot deliver a comprehensive response and should be regarded solely as a preliminary guide (Monod et al., 2024). It is important to acknowledge that GenAI applications in consulting are mainly theoretical and have not been empirically evaluated by business consultants.

Finally, it should be noted that, for the sake of simplicity, the term 'consultant' will be used instead of 'business consultant' throughout the following text.

## 2.3 Critical Assessment of Key Acceptance Models

### 2.3.1 Technology Acceptance Model

The acceptance of novel technologies is crucial for their successful implementation (Davis, 1989; Kelly et al., 2023). In this setting, insufficient acceptance of these technologies results in inadequate AI adoption, causing resources to be ineffectively utilized and leading to a decrease in technological innovation, consequently disadvantaging customers (Kelly et al., 2023). Numerous models have been developed previously to evaluate this acceptability.

The Technology Acceptance Model (TAM), developed by Davis in 1985 and 1989, is grounded in the Theory of Reasoned Action by (Fishbein & Ajzen, 1975) and differentiates between two external variables: 'perceived usefulness' (PU) and 'perceived ease of use' (PEOU), which influence the ‘behavioural intentions’ that lead to ‘actual system use’ (see Figure one).

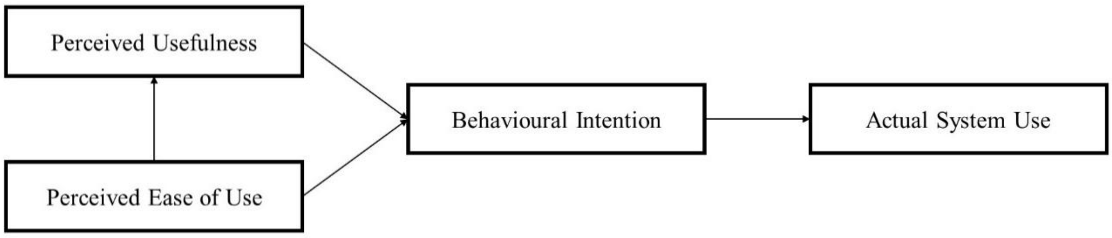


*Figure 1: Technology Acceptance Model*

The PEOU variable reflects how easily users perceive they can use this technology (Davis, 1989). PEOU is influenced by elements like the user's self-efficacy in computer usage, their perception of control and capacity to learn the system, overall negative attitudes towards computers, and possible enjoyment and intrinsic motivation associated with system use. The variable 'PU' denotes the extent to which the user considers this technology as beneficial in their daily life (Davis, 1989). PU is influenced by elements like usability, organizational usage norms, overall work relevance, and enhanced result quality (Vorm & Combs, 2022). The PU is the predominant determinant affecting an individual's behavioural intentions to utilize the technology (Davis, 1989; Kelly et al., 2023; Rafique et al., 2020; P.-J. Wu et al., 2021). Variables such as trust and knowledge are frequently incorporated into the TAM to enhance the model's predictive capability (Kelly et al., 2023; Lin & Xu, 2022). Numerous empirical research on the TAM reveal that PU continuously emerges as the most influential variable affecting usage intentions (Davis, 1989; Kelly et al., 2023; Rafique et al., 2020; P.-J. Wu et al., 2021). In contrast, perceived ease of use generally assumes a reduced significance in the assessment of usage intentions, mostly due to its pronounced emphasis on technological attributes and individual experiences (Venkatesh et al., 2012). Further literature reveals that the model exhibits deficiencies stemming from the misalignment between task and technological features (Dishaw & Strong, 1998). The rapid advancement of AI has prompted criticism about the reliability of traditional TAM. AI systems are typically engineered for user-friendliness, requiring users to input instructions to obtain responses. Consequently, it can be inferred that perceived user-friendliness has diminished in significance (Mogaji et al., 2024). Research on user acceptance indicates that elements such as social influences and hedonistic motivations significantly affect technology adoption. In the hotel and catering sector, it has been determined that technological acceptance is mostly influenced by an individual's intrinsic enjoyment. Service robots are essential in this context, as they execute jobs with more efficiency; nonetheless, users may express disagreement due to the absence of human-like interactions (Chi et al., 2023).

Consequently, it can be inferred that the TAM is lacking in industry-specific elements and is not enough for the implementation of AI.

### 2.3.2 Unified Theory of Acceptance and Use of Technology

In the early 2000s, Venkatesh et al. (2003) have developed and have empirically evaluated a further model. The 'Unified Theory of Acceptance and Use of Technology' (UTAUT) model has emerged as one of the most common acceptance frameworks in information systems research (Kelly et al., 2023). Eight established models were analysed in the study by (Venkatesh et al., 2003). The results of the study were used to develop the UTAUT model. The following theories were used for this purpose: Theory of Reasoned Action (Fishbein & Ajzen, 1975), TAM (Davis, 1989), Motivational Model (Davis et al., 1992), Theory of Planned Behaviour (Ajzen, 1991), Combined Technology Acceptance Model and Theory of Planned Behaviour (Taylor & Todd, 1995), Model of Personal Computer Utilization (Thompson et al., 1991), Innovation Diffusion Theory (Moore & Benbasat, 1991), and Social Cognitive Theory (Bandura, 1986). The investigation revealed that the UTAUT model was predicated on four determinants: Effort Expectancy, Performance Expectancy, Social Influence, and Facilitating Conditions.

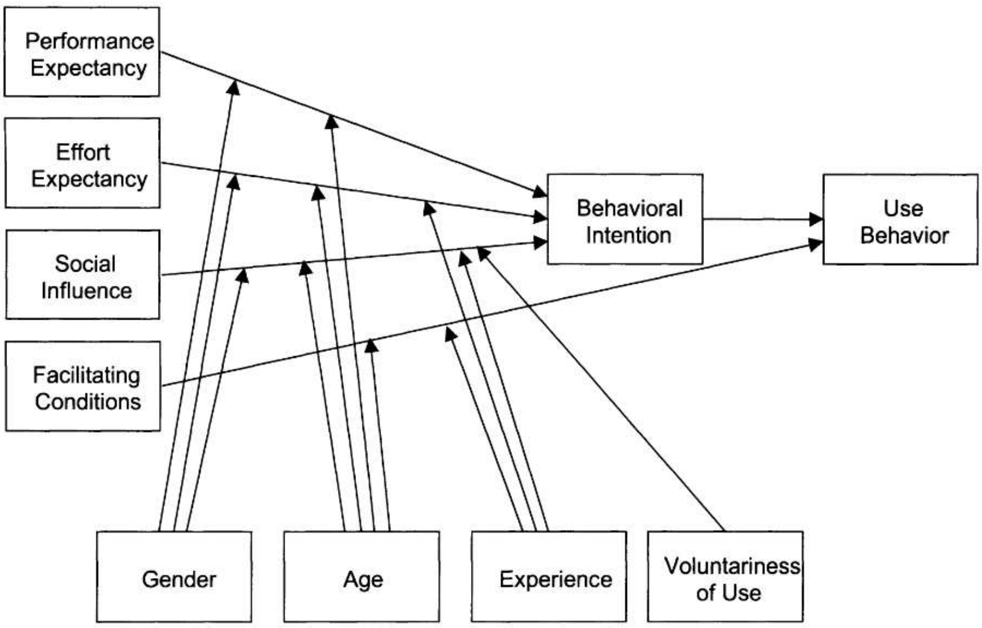


*Figure 2: Unified Theory of Acceptance and Use of Technology Model*

It is presumed that factors such as self-efficacy and anxiety have no direct impact on the user's intention to utilize the specific technology. However, gender, age, experience, and voluntary usage function as moderators (Venkatesh et al., 2003). The determinant 'Effort Expectancy' refers to the degree to which this technology facilitates job performance (Venkatesh et al., 2003). The determinant 'Effort Expectancy' parallels the factor Perceived Ease of Use from the

TAM model (Davis, 1989). Performance Expectancy describes the extent to which the use of a particular technology offers advantages that can support users in completing tasks (Brown & Venkatesh, 2005; Venkatesh et al., 2003, 2012). Social Influence refers to the influence of the social environment on the decision to use a technology (Brown & Venkatesh, 2005; Venkatesh et al., 2003, 2012). Facilitating conditions comprise the perceived resources and support structures that are considered necessary to be able to use a technology successfully (Brown & Venkatesh, 2005; Venkatesh et al., 2003, 2012). The determinants ‘Performance Expectancy’, ‘Effort Expectancy’ and ‘Social Influence’ influence the behavioural intention to use a technology. In contrast, ‘Behavioural Intention’ and ‘Facilitating Conditions’ have a direct effect on the ‘Use Behaviour’ of the technology (Venkatesh et al., 2012). The use of the UTAUT explains 60 to 70 percent of the variance in Behavioural Intention, hence serving as a robust model for forecasting technological acceptance (Kelly et al., 2023; Thomas et al., 2013; Venkatesh et al., 2003). About a decade later, the UTAUT model was reassessed, resulting in the development of a second version. The initial concept concentrated on individual acceptance within an organizational framework. The TAM model emphasized user assessment of technology, while the UTAUT model concentrated on corporate strategies and actions to enhance technology acceptance and use (Venkatesh et al., 2003). Scientists criticized that the UTAUT model was not intended for end consumers in an unorganized situation. Consequently, Venkatesh et al. (2012) developed an enhanced model approximately a decade later, relevant to the consumer market. The following determinants were added: hedonic motivation, price-performance ratio, and habits (Venkatesh et al., 2012).

The UTAUT is an expansion of the TAM model. The TAM and UTAUT have faced criticism for their oversimplification of the mechanisms and fundamental conceptions that drive technology adoption (Shachak et al., 2019). The UTAUT model has been criticized for its limited reach and for overlooking socio-technical, cultural, technical factors, and individual characteristics (Shachak et al., 2019). The original intent of TAM and UTAUT, which was to forecast the acceptance of non-intelligent information technologies (Gursoy et al., 2019), warrants criticism, as these frameworks are not applicable to GenAI. The complex introduction of GenAI in the advisory sector raises doubts about the suitability of the UTAUT model in this specific context. In addition, the applicability of this model has yet to be validated.

### 2.3.3 Task-Technology Fit

The Task-Technology Fit (TTF) model, developed by Goodhue & Thompson (1995), focuses on task support, in contrast to the TAM (Goodhue & Thompson, 1995; Lee & Lehto, 2013). It describes to what extent an information system can support the completion of tasks (Dishaw & Strong, 1998; Goodhue & Thompson, 1995; Lee & Lehto, 2013; Strong et al., 2006). The basic version of the TTF model consists of four main variables: task characteristics, technology characteristics, the fit between task and technology, and the resulting variable utilization.

At the centre is the variable ‘Task-Technology Fit’, which describes the extent to which a technology provides functions and support that meet the requirements of a task and can facilitate its completion (Goodhue & Thompson, 1995; Lee & Lehto, 2013). The model explains how both the characteristics of a task and the features of a technology can influence the acceptance and use of the technology (Pagani, 2006; Strong et al., 2006).

The TTF model provides the basis to assess whether a good match between the characteristics of a technology and the requirement of the task leads to a high user adoption rate (Lee & Lehto, 2013). It has been applied in numerous contexts, for example, in the study of user acceptance of YouTube for procedural learning (Lee & Lehto, 2013). In the context of this thesis, which examines the user acceptance of GenAI among consultants, there are no specific studies to the best of my knowledge.

In recent years, the established model has been further developed to account for current technological advancements. A significant addition is the variable ‘Performance Impacts’ (Goodhue & Thompson, 1995) (see Figure three). The extended version of the TTF model, also known as the Technology-to-Performance Chain (TPC), is based on two central findings. On the one hand, a user's attitude is considered a predictor of usage, and on the other hand, the match between task and technology is regarded as a predictor of performance. (Goodhue & Thompson, 1995). ‘Performance impacts’ describes a person's ability to handle a portfolio of tasks. A high performance can be reflected in improved efficiency, increased effectiveness, and/or higher quality of work. Thus, a high alignment between task and technology not only leads to a higher likelihood of use but also to a significant improvement in performance (Goodhue & Thompson, 1995).

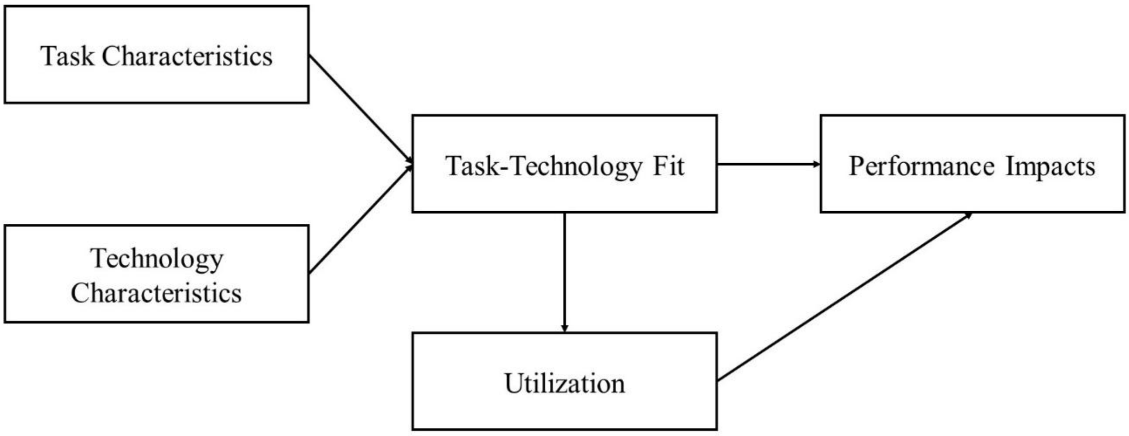


*Figure 3: Task-Technology Fit Model, also known as Technology-to-Performance Chain*

### 2.3.4 Artificial Intelligent Device Use Acceptance Model

The Artificial Intelligent Device Use Acceptance Model (AIDUA), developed by Gursoy et al. (2019), represents the latest framework for forecasting user acceptability of AI technologies within the consumer market. Gursoy et al. (2019) reject conventional models like the TAM and UTAUT, as they concentrate on the acceptance of non-intelligent systems and are thus inapplicable to AI systems. The AIDUA model is founded on Cognitive Appraisal Theory (Lazarus, 1991) and Cognitive Dissonance Theory (Festinger, 1962). The model defines the multi-stage process of customer willingness to utilize AI applications once recognizing a service. AIDUA operates through three phases of acceptance generation based on cognitive evaluation theory: primary evaluation, secondary evaluation, and the outcome stage (see Figure four). AIDUA contains six antecedents that influence the outcome stage: ‘Social Influence’, ‘Hedonic Motivation’, ‘Anthropomorphism’, ‘Performance Expectancy’, ‘Perceived Effort Expectancy’, and ‘Emotion’. The outcome stage consists of two Behavioural Intentions: ‘Willingness to Accept the Use of AI Devices’ and ‘Objection to the Use of AI Devices’ (Gursoy et al., 2019). This model is applicable mostly to the service sector and customer acceptability, as mentioned by Gursoy et al. (2019). Consequently, it is less appropriate for evaluating the acceptance of consultants.

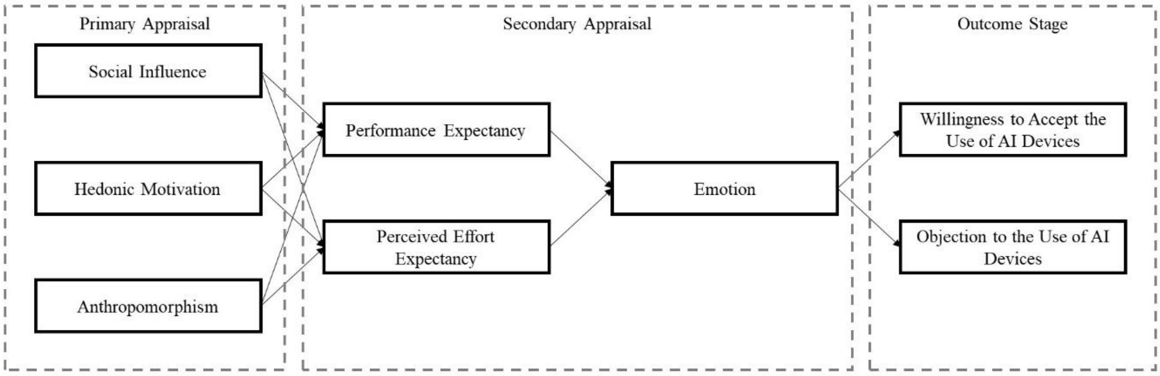


*Figure 4: Artificial Intelligent Device Use Acceptance Model*

## 2.4 Development of a GenAI Acceptance Model among Consultants

### 2.4.1 Relevance and Purpose

The analysis of current acceptance models revealed that a new model needed to be created. Previous models have shown two major weaknesses: lack of focus on the consulting sector and insufficient focus on intelligent systems. Prior research indicates the necessity of technology- and industry-specific attributes in evaluating user acceptance (Goodhue & Thompson, 1995; Mogaji et al., 2024; Venkatesh et al., 2011). Specifically, this means that the model should relate to industry-specific aspects such as general characteristics of an industry and specific requirements for the people working in it. The comparison between the consulting industry and the healthcare system suggests that the responsibilities of a consultant significantly diverge from those of a medical professional. The adoption of AI is profoundly affected by the context in which it is utilized (Kelly et al., 2023). As of December 2024, there is no acceptance model explicitly tailored for the consulting industry. The conventional models such as TAM, UTAUT, AIDUA and their underlying theories (Theory of Reasoned Action, Theory of Planned Behaviour, etc.) are less suited for assessing AI acceptance, because they have their limitations. These models are intended to evaluate the acceptance of non-intelligent, functional technologies and self-service systems (Chow et al., 2023). The numerous extended models, particularly the TAM, indicate a necessity for innovation and specification of these models (Mogaji et al., 2024). The rapid evolution of GenAI since the launch of ChatGPT demands further development of these models to better comprehend the complexity of GenAI and its acceptability. The mixed model technique is used for the development of the new model to overcome the limitations of the appropriate models, as it facilitates the evaluation of exact acceptance criteria. Research indicates that a mixed modelling strategy yields optimal outcomes (Cai et al., 2023; Dishaw & Strong, 1998; Oliveira et al., 2014; Zhou et al., 2010).

### 2.4.2 Conceptual Framework

Based on previous models, a new model was designed that combines the relevant variables of the TAM, UTAUT, TTF and AIDUA models. This model enables the specific investigation of GenAI acceptance among consultants. In the following section, this model is referred to as the 'new model'. The effectiveness of this new model is tested based on six hypotheses.

Models of user acceptance generally distinguish between productivity-orientated (utilitarian) and pleasure-orientated (hedonic) information systems (van der Heijden, 2004; J. Wu et al., 2013). This classification helps to distinguish whether information systems are used in a work or school context or in a private, entertaining context (J. Wu et al., 2013).

Regarding the TAM, initial UTAUT and TTF models, these are predominantly utilitarian models that focus on improving work performance. In contrast, the AIDUA model and the extended UTAUT model focus on the hedonic use of technology. The term 'hedonic' is derived from hedonism and focuses on pleasure and personal well-being (van der Heijden, 2004). Hedonistic information systems offer the user self-fulfilling added value, while utilitarian information systems provide instrumental value (van der Heijden, 2004).

The new model suggests a stronger focus on task-orientated, utilitarian constructs. It is primarily based on the TAM, UTAUT and TTF models and supplements these with consulting-specific and GenAI-specific characteristics.

The TTF model plays a central role in the development of the new model as it provides a solid basis for the conceptualisation of a task-oriented, utilitarian construct due to its task-oriented approach. The TTF model describes the extent to which task and technology characteristics influence the utilization of a technology (see Figure three, p.11) (Lee & Lehto, 2013). It states that a high match between the characteristics of technology and task (See variable Task-Technology Fit) leads to an increased utilisation rate (Lee & Lehto, 2013). By integrating the GenAI Characteristic and Consultant Task variables, technology- and consulting-specific characteristics can be considered. As a result, the new model is specifically geared towards the acceptance of GenAI among consultants.

Therefore, the following hypotheses based on the TTF model (see Figure three, p.11) are tested in the new model:

***H1: GenAI Characteristics (GAIC) positively impact Task-Technology Fit (TTF).***

***H2: Consultant Tasks (CONT) positively impact Task-Technology Fit (TTF).***

According to the TTF model, the TTF variable leads to the variables ‘Utilization’ and ‘Performance Impacts’ (see Figure three, p. 11). The variable ‘Performance Impacts’ describes a person's ability to efficiently manage a portfolio of tasks (Goodhue & Thompson, 1995). High ‘Performance Impacts’ can lead to improved efficiency, increased effectiveness, and higher work quality (Goodhue & Thompson, 1995). Accordingly, a strong alignment between task and technology does not only lead to a higher likelihood of technology use (See variable Utilization) but also improves work performance (See variable Performance Impacts) (Goodhue & Thompson, 1995). A comparison with other models shows similarities and overlaps between the TTF and UTAUT models. Both models analyse how the use of technology affects performance: Performance Impact in the TTF model and Performance Expectancy in the UTAUT model. In the UTAUT model, this is represented by the variable ‘Performance Expectancy,’ which describes the extent to which the use of a technology provides benefits and supports the user in completing their tasks (Brown & Venkatesh, 2005; Venkatesh et al., 2003, 2012). This variable ‘Performance Expectancy’ is the strongest predictor for ‘Behavioural Intention’ in the UTAUT model and is the basis for hypothesis four (H4). ‘Performance Expectancy’ has been examined in various models, including ‘Perceived Usefulness’ (Davis, 1989), ‘Extrinsic Motivation’ (Davis et al., 1992), ‘Job-Fit’ (Thompson et al., 1991), ‘Relative Advantage’ (Moore & Benbasat, 1991), and ‘Outcome Expectations’ (Compeau & Higgins, 1995). Both, ‘Performance Impacts’ in the TTF Model and ‘Performance Expectancy’ in the UTAUT Model, pursue the same goals in the study of technology acceptance. In this study, the term 'Performance Expectancy' is used for the analysis, which has the same meaning as 'Performance Impact'. This leads to the following hypotheses:

***H3: Task-Technology Fit (TTF) positively influences Performance Expectancy (PE).***

As part of the TTF model, it was investigated whether TTF influences the ‘Performance Expectancy’ and ‘Utilization’ (see Figure three, p.11) (Goodhue & Thompson, 1995). As Performance Expectancy is a central variable in the UTAUT model and is considered the strongest predictor of ‘Behavioural Intention’, this path (PE → BI) was also included in the new model. The path without PE (TTF → BI) was also tested to check whether PE as a mediator significantly influences Behavioural Intention.

Additionally, the UTAUT model is based on the fundamental concept of user acceptance and includes three central predictors (see Appendix A): ‘Individual reactions to using information technology (1)’, ‘Intentions to use information technology (2)’, and ‘Actual use of information technology (3)’. These predictors build on each other, as individual reactions (1) influence intentions (2), which in turn govern actual usage (3). Accordingly, BI is followed by the 'Actual Use of Information Technology'. As acceptance is generally also interpreted as 'actual use of technology', the variable Acceptance is examined in this paper (Naneva et al., 2020).

***H4: Performance Expectancy (PE) positively influences Behavioural Intention (BI).***

***H5: Task-Technology Fit (TTF) positively influences Behavioural Intention (BI).***

***H6: Behavioural Intention (BI) positively influences Acceptance (ACT).***

By combining each hypothesis, we arrive at the following model (see Figure five):

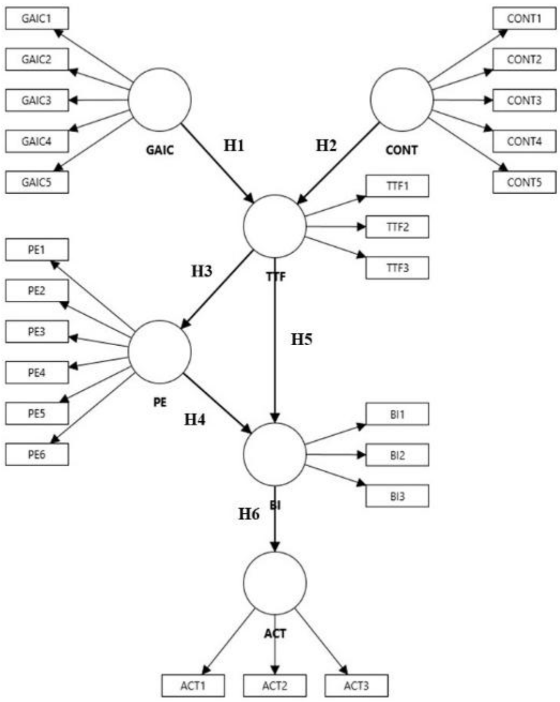


*Figure 5: New Model*

# 3 Research methodology and data analysis

## 3.1 Survey Design and Data Collection

Both qualitative and quantitative approaches were considered for the selection of a suitable research method. The acceptance models described in the literature review are based exclusively on quantitative methods. Quantitative methods enable the collection of extensive structured data within a short period of time and are particularly suitable for analysing data, identifying patterns, and testing causal relationships (Rana et al., 2021). In the previous chapter, the hypotheses to be tested were formulated based on the literature review. Similarly, the latent variables used and their corresponding items were determined, building the foundation of the survey (see Appendix B).

A survey was developed to answer the research question ‘What success factors influence user acceptance of GenAI among consultants?’ and to test the defined hypotheses. To ensure a stronger focus on the consulting sector and GenAI, linguistic adjustments were made to some variables. Each latent variable comprises at least three items (see Appendix B). Each item corresponds to a question from the survey, which was answered using a five-point Likert scale (1 = ‘strongly disagree’, 5 = ‘strongly agree’) (see Appendix D).

The survey was also translated into German, as the researcher's location encouraged many German consultants to participate. The translation lowered the participation threshold. Before publication, the questionnaire was made available to five people for testing. These test subjects included both people with a consulting background and those without consulting experience. This pre-test procedure enabled the identification and elimination of misunderstandings and ambiguities in the survey.

The survey, hosted online, consisted of two parts (see Appendix F). The first part included an introductory question that excluded people without any consulting experience and 25 questions (items) related to the six latent variables. The second part focused on demographic data such as age, gender, technical skills, consulting experience, use of GenAI and the context of this use. This section also included a control question to ensure that respondents completed the survey attentively. One person was excluded due to inattentive responses. A total of 147 responses were collected over a period of roughly three weeks. Of these, 14 responses had to be excluded as the respondents either had no consulting experience or were not attentive to the survey. Due to the focus on GenAI in the consulting environment and the researcher's location, the survey was primarily distributed to German consulting firms. In addition, social media networks such as LinkedIn were used to reach international participants.

Table one shows an overview of the demographic data of the participants. At 66 percent, significantly more men than women took part. This reflects the generally higher proportion of men in the consulting industry. According to the Federal Association of German Management Consultants (BDU), the proportion of women in the industry in Germany is 39 percent (Federal Association of German Management Consultants, 2025). Since mainly German consultants were surveyed due to the location of the researcher, the proportion of women in management consulting in Germany was considered.

| Demographics | Category | Frequency | Distribution |
|---|---|---|---|
| Gender | Female | 42 | 34% |
| | Male | 83 | 66% |
| | Non-binary | 0 | 0% |
| Age | 18-23 | 4 | 3% |
| | 24-29 | 64 | 51% |
| | 30-39 | 38 | 30% |
| | 40-49 | 10 | 8% |
| | 50 years or older | 9 | 7% |
| Technical skills | Beginner | 2 | 2% |
| | Basic | 42 | 34% |
| | Advanced | 71 | 57% |
| | Professional | 0 | 8% |
| Consulting experience | 0-3 years | 71 | 57% |
| | 4-7 years | 28 | 22% |
| | 8 years or more | 26 | 21% |
| GenAI usage | Regularly | 77 | 62% |
| | Occasionally | 45 | 36% |
| | No experience so far | 3 | 2% |
| Context of GenAI usage | Consulting context | 113 | 90% |
| | Personal context | 111 | 89% |
| | In another working context | 53 | 42% |
| | No context | 2 | 2% |

Table 1: Distribution of Survey Participants

To verify the measurement model, various scales were used to assess both the reliability and validity of the construct. The construct reliability was verified using Cronbach's Alpha as well as Composite Reliability (rho_a and rho_c). Values above 0.7 are considered acceptable in this context (Sarstedt et al., 2021). The convergent validity was tested using the Average Variance Extracted (AVE). A value above 0.5 indicates that a construct is sufficiently explained by its indicators (Fornell & Larcker, 1981). Discriminant validity was verified using cross-loadings, the Fornell-Larcker criterion, and the Heterotrait-Monotrait Ratio (HTMT). The Fornell-Larcker criterion ensures that the squared AVE of a construct is higher than its highest correlation with other constructs. The HTMT analysis checks whether the similarity between two constructs remains below 0.90 to ensure sufficient discriminant validity. These methods were chosen because they are widely used in empirical research and allow for a well-founded evaluation of measurement models within the framework of structural equation modelling (F. Hair Jr et al., 2014).

### 3.2 Measurement Model Assessment

The new model was examined using a two-step approach. First, the construct reliability, convergent validity, and discriminant validity of the variables and their corresponding items were examined. The structural equation model (SEM) was then analysed using SmartPLS, a software specialized in Partial Least Squares Structural Equation Modelling (PLS-SEM) for statistical and path analysis.

The descriptive statistics (see Table two, p.19) provide an overview of the means, standard deviations, skewness, and excess kurtosis of the variables and their items. The model consists of both reflective (PE, BI, ACT) and formative (CONT, GAIC, TTF) latent variables. For formative variables, it is important to note that a direct interpretation of their mean values is not appropriate, as the individual items represent distinct aspects of the construct rather than forming a unified whole. The varying nature of these indicators means that they cannot be aggregated in a meaningful way.

Regarding the reflective variables**,** PE shows a moderate average, with PE4 (Competence perception by colleagues) and PE6 (Work facilitation) standing out with slightly lower mean values, indicating that these aspects are perceived less favourably. BI presents an overall strong agreement, with BI1 (Good idea) achieving a particularly high mean (4.484), whereas BI2 (More interesting work) shows greater variability in responses, as indicated by its higher standard deviation (1.122). Finally, ACT exhibits a high overall mean (4.309), signalling strong agreement with GenAI acceptance in the consulting context.

The standard deviations highlight varying response patterns. Notably, BI2 (More interesting work) and TTF3 (Creativity-related tasks) show a wider spread, indicating heterogeneous perceptions in these areas. In contrast, items like CONT1 and BI1 exhibit low variability, suggesting a more consistent agreement among respondents.

Regarding the distribution of responses, most items show negative skewness, particularly GAIC1 (-1.619), CONT2 (-2.030), and BI1 (-1.795), indicating that the majority of responses are in the upper range of the Likert scale. Additionally, high excess kurtosis values, such as CONT1 (4.411) and BI1 (4.413), suggest a peaked distribution with responses clustered near the mean.

Finally, missing values are present in CONT, TTF, PE, BI, and ACT, ranging from 6 to 9 cases per item, corresponding to approximately four to six percent of the 147 responses. Given the relatively low number of missing values, they were imputed using the mean replacement method**,** with missing values marked as ‘-99’ in the dataset.

| Item | Missings | Mean | Median | Standard deviation | Excess kurtosis | Skewness |
|---|---|---|---|---|---|---|
| **GAIC1** | 0 | 4.459 | 5 | 0.761 | 3.218 | -1.619 |
| **GAIC2** | 0 | 3.045 | 3 | 0.900 | 0.193 | 0.036 |
| **GAIC3** | 0 | 3.594 | 4 | 0.950 | -0.264 | -0.539 |
| **GAIC4** | 0 | 3.805 | 4 | 1.007 | -0.686 | -0.446 |
| **GAIC5** | 0 | 4.143 | 4 | 0.902 | 0.470 | -0.847 |
| **CONT1** | 6 | 4.512 | 5 | 0.741 | 4.411 | -1.862 |
| **CONT2** | 6 | 4.520 | 5 | 0.812 | 4.255 | -2.030 |
| **CONT3** | 6 | 4.465 | 5 | 0.849 | 2.518 | -1.683 |
| **CONT4** | 6 | 4.252 | 4 | 0.939 | 1.870 | -1.451 |
| **CONT5** | 6 | 4.276 | 5 | 0.902 | 1.288 | -1.293 |
| **TTF1** | 7 | 3.929 | 4 | 0.856 | -0.374 | -0.476 |
| **TTF2** | 7 | 3.944 | 4 | 0.954 | 0.024 | -0.777 |
| **TTF3** | 7 | 3.556 | 4 | 0.988 | -0.295 | -0.506 |
| **PE1** | 8 | 4.320 | 5 | 0.926 | 2.160 | -1.540 |
| **PE2** | 8 | 3.904 | 4 | 0.933 | 0.752 | -0.823 |
| **PE3** | 8 | 4.248 | 4 | 0.816 | 1.465 | -1.115 |
| **PE4** | 8 | 3.488 | 4 | 0.968 | -0.521 | -0.206 |
| **PE5** | 8 | 4.096 | 4 | 0.889 | 0.685 | -0.951 |
| **PE6** | 8 | 4.240 | 4 | 0.804 | 0.104 | -0.840 |
| **BI1** | 9 | 4.484 | 5 | 0.735 | 4.413 | -1.795 |
| **BI2** | 9 | 3.734 | 4 | 1.122 | -0.411 | -0.600 |
| **BI3** | 9 | 4.105 | 4 | 0.869 | 0.614 | -0.878 |
| **ACT1** | 9 | 4.266 | 5 | 0.960 | 2.339 | -1.501 |
| **ACT2** | 9 | 4.371 | 5 | 0.929 | 2.986 | -1.726 |
| **ACT3** | 9 | 4.290 | 5 | 0.840 | 0.985 | -1.091 |

*Table 2: Descriptive Statistics of the Dataset*

The items used in the new model were subjected to a Confirmatory Factor Analysis (CFA) in their original studies (see Table three, p. 20). Since the items were specifically adapted for the consulting industry, a re-evaluation was necessary. To assess convergent validity, the outer loadings were first analysed. Outer loading values higher than 0.7 indicate that at least 50 percent of the variance of an item is explained by the underlying latent variable, which suggests satisfactory item reliability (Sarstedt et al., 2021).

Many of the items achieved an outer loading above 0.7. Seven items (CONT2, GAIC1, GAIC3, GAIC5, PE1, TTF2, TTF3) were just below, while GAIC2 stood out significantly with a value of 0.458. Accordingly, this item GAIC2 was removed. The additional removal of GAIC3 (Outer Loading = 0.458; Value before removal of GAIC2) only led to minimal changes in the Outer Loadings ($\Delta \leq 0.054$) and the path coefficients ($\Delta \leq 0.018$). Therefore, the additional removal of GAIC3 was not recommended.

Convergent validity was also tested using the Average Variance Extracted (AVE), which measures the proportion of explained variance by the latent variable. Values above 0.5 are considered acceptable (Fornell & Larcker, 1981). Five of the six latent variables achieved an AVE higher than 0.5, only GAIC remained below at 0.457, indicating weaker convergent validity.

Construct reliability can be verified using Cronbach's Alpha and composite reliability (rho_a or rho_c). Cronbach's Alpha measures the internal consistency of the items, with values above 0.7 being acceptable (Sarstedt et al., 2021). Since the model exhibits different outer loadings, rho_c was preferred as it takes into account the weights of the items and provides a more accurate assessment (F. Hair Jr et al., 2014). All latent variables achieved acceptable to good values for rho_c, which ranged between 0.754 and 0.893.

| Latent variable | Item | Outer loadings | Cronbach's Alpha | CR (rho_a) | CR (rho_c) | AVE |
|---|---|---|---|---|---|---|
| **ACT** | **ACT1** | 0.716 | 0.623 | 0.63 | 0.799 | 0.571 |
| | **ACT2** | 0.728 | | | | |
| | **ACT3** | 0.819 | | | | |
| **BI** | **BI1** | 0.857 | 0.82 | 0.825 | 0.893 | 0.735 |
| | **BI2** | 0.866 | | | | |
| | **BI3** | 0.849 | | | | |
| **CONT** | **CONT1** | 0.757 | 0.819 | 0.849 | 0.869 | 0.572 |
| | **CONT2** | 0.643 | | | | |
| | **CONT3** | 0.849 | | | | |
| | **CONT4** | 0.779 | | | | |
| | **CONT5** | 0.738 | | | | |
| **GAIC** | **GAIC1** | 0.677 | 0.607 | 0.623 | 0.769 | 0.457 |
| | **GAIC3** | 0.570 | | | | |
| | **GAIC4** | 0.769 | | | | |
| | **GAIC5** | 0.674 | | | | |
| **PE** | **PE1** | 0.675 | 0.846 | 0.847 | 0.887 | 0.567 |
| | **PE2** | 0.797 | | | | |
| | **PE3** | 0.742 | | | | |
| | **PE4** | 0.766 | | | | |
| | **PE5** | 0.809 | | | | |
| | **PE6** | 0.721 | | | | |
| **TTF** | **TTF1** | 0.810 | 0.531 | 0.563 | 0.754 | 0.508 |
| | **TTF2** | 0.640 | | | | |
| | **TTF3** | 0.676 | | | | |

*Table 3: Item loadings, Cronbach's Alpha, CR, and AVE*

Discriminant validity was tested through cross-loadings (see Appendix G), the Fornell-Larcker criterion (FLC) (see Appendix H), and the heterotrait-monotrait ratio (HTMT) (see Appendix I). In the cross-loadings, it was found that most items had higher loadings on their own latent variable than on others, indicating good discriminant validity. Some items of the variables CONT, GAIC, PE, and TTF, however, showed weaker loadings (< 0.7), indicating possible overlaps. The Fornell-Larcker criterion showed that discriminant validity was established for five of the six latent variables. For GAIC, however, the square root of the AVE (0.637) was below the correlation with PE (0.644), indicating that GAIC and PE are not clearly distinguishable from each other. The HTMT analysis confirmed another overlaps. The HTMT value between GAIC and TTF was 0.933, clearly above the threshold of 0.9, indicating a lack of discriminant validity between these variables. Similarly, ACT and BI had a value of 0.932 and BI and TTF had a value of 0.908.

The analysis of construct reliability shows acceptable to good results overall, as the composite reliability was satisfactory for all latent variables, ranging from 0.754 to 0.893. Convergent validity was confirmed for five of the six latent variables, while GAIC showed weaknesses due to a low AVE value of 0.457. When testing discriminant validity, five of the six variables met the criteria of the Fornell-Larcker criterion. However, weaknesses were found in GAIC, as its square root of AVE (0.637) was lower than its correlation with PE (0.644), indicating a lack of clear differentiation. Additionally, the HTMT values show that GAIC and TTF (0.933), BI and TTF (0.908) as well as ACT and BI (0.932) exceeded the recommended threshold of 0.90, further suggesting insufficient discriminant validity. GAIC remains the focus of potential revision due to its low AVE and high correlations with PE and TTF. In summary, the model is robust, but there are weaknesses in the separation of certain constructs, indicating content overlaps that require optimization of the measurement instruments.

The analysis of the structural model shows that all of the tested hypotheses could be supported by significant results.

| **Hypothesis** | **Path** | **Path coefficients** | **T statistics (\|O/STDEV\|)** | **P values** | **$f^2$** | **Supported?** |
|---|---|---|---|---|---|---|
| **H6** | **BI -> ACT** | 0.673 | 10.274 | 0.000 | 0.826 | Yes |
| **H2** | **CONT -> TTF** | 0.188 | 2.771 | 0.006 | 0.056 | Yes |
| **H1** | **GAIC -> TTF** | 0.569 | 10.034 | 0.000 | 0.511 | Yes |
| **H4** | **PE -> BI** | 0.626 | 7.686 | 0.000 | 0.546 | Yes |
| **H5** | **TTF -> BI** | 0.179 | 1.974 | 0.048 | 0.045 | Yes |
| **H3** | **TTF -> PE** | 0.627 | 13.377 | 0.000 | 0.647 | Yes |

*Table 4: Path Coefficients, T Statistics, and p-values*

Overall, all six tested hypotheses were fully supported. The relationship between BI and ACT (H6) shows a strong and significant connection with a path coefficient of 0.673 and a T-value of 10.274 (p < 0.001). This confirms that an increased BI has a direct positive impact on ACT.

The analysis of the relationship between CONT and TTF (H2) shows a path coefficient of 0.188 (T-value = 2.771, p = 0.006). This connection is significant but shows a lower effect size ($f^2$ = 0.056) compared to other variables. In contrast, GAIC shows a strong and significant connection to TTF (H1), with a path coefficient of 0.569 and a T-value of 10.034 ($p < 0.001$). This underlines the importance of GAIC on TTF.

The relationship between PE and BI (H4) is also supported, with a path coefficient of 0.626 and a T-value of 7.686 ($p < 0.001$). This illustrates that PE has a significant impact on BI. Similarly, the connection between TTF and PE (H3) shows a strong and significant relationship, with a path coefficient of 0.627 and a T-value of 13.377 ($p < 0.001$), which also confirms the hypothesis. The connection between TTF and BI (H5), on the other hand, shows a path coefficient of 0.179 (T-value = 1.974, p = 0.048) and is thus confirmed as significant, but with a lower effect size ($f^2$ = 0.045).

To investigate the mediation effects, the indirect effects were analysed (see Table five). The results show several significant mediation effects, particularly with PE as the central mediator. The path TTF → PE → BI ($p < 0.001$) confirms that a higher fit between tasks and technology (TTF) increases PE, which in turn raises the intention to use (BI). Similarly, a significant indirect effect is observed in the path PE → BI → ACT ($p < 0.001$), whereby PE also indirectly influences the Acceptance (ACT) of GenAI. A serial mediation effect occurs in the path TTF → PE → BI → ACT ($p < 0.001$), extending the effect of TTF through PE and BI on Acceptance. Also, GAIC → TTF → PE → BI → ACT ($p < 0.001$) as well as GAIC → TTF → PE → BI ($p < 0.001$) are significant, highlighting the central role of PE in the perception of GenAI quality. Similarly, CONT → TTF → PE → BI (p = 0.012) indirectly conveys the use of GenAI. Not all indirect effects are significant. TTF → BI → ACT (p = 0.058), GAIC → TTF → BI → ACT (p = 0.070), and CONT → TTF → BI → ACT (p = 0.149) show no strong statistical evidence for an indirect effect. This suggests that the direct connection between TTF and BI is less crucial than the indirect effect through PE. The results confirm the central role of PE as a mediator: PE not only mediates the effect of TTF on BI but also contributes to Acceptance (ACT) through BI. Thus, the perceived performance enhancement (PE) through GenAI is a key driver for its acceptance in the consulting industry.

| Path | P values |
|---|---|
| **CONT -> TTF -> PE** | 0.008 |
| **GAIC -> TTF -> PE -> BI -> ACT** | 0.000 |
| **GAIC -> TTF -> PE** | 0.000 |
| **TTF -> PE -> BI** | 0.000 |

| | |
|---|---|
| **PE -> BI -> ACT** | 0.000 |
| **TTF -> BI -> ACT** | 0.058 |
| **CONT -> TTF -> BI -> ACT** | 0.149 |
| **CONT -> TTF -> PE -> BI -> ACT** | 0.019 |
| **GAIC -> TTF -> BI -> ACT** | 0.070 |
| **CONT -> TTF -> PE -> BI** | 0.012 |
| **GAIC -> TTF -> PE -> BI** | 0.000 |
| **TTF -> PE -> BI -> ACT** | 0.000 |
| **CONT -> TTF -> BI** | 0.133 |
| **GAIC -> TTF -> BI** | 0.059 |

*Table 5: Indirect effects (Identification of mediators)*

The explained variances ($R^2$) of the dependent variables range from 0.393 to 0.565, indicating a moderate to good model fit (see Appendix J). The highest variance explanation is shown in BI with an $R^2$ of 0.565, followed by ACT with an $R^2$ of 0.452. PE and TTF have $R^2$ values of 0.393 and 0.424, respectively, which also demonstrate a satisfactory explanatory power of the model.

The effect sizes ($f^2$) indicate which independent variables have the greatest impact on a dependent variable and help to understand the relative importance of these influences (Selya et al., 2012). The strongest effect is observed between BI and ACT (H6) with an $f^2$ value of 0.826, indicating a large impact. The relationships TTF → PE (H3, $f^2 = 0.647$) and PE and BI (H4, $f^2 = 0.546$) also show strong effect sizes. The relationship between GAIC → TTF (H1) shows a medium effect size with an $f^2$ value of 0.511. In contrast, the relationships CONT → TTF (H2, $f^2 = 0.056$) and TTF → BI (H5, $f^2 = 0.045$) are relatively weak, indicating a lower relative influence. In summary, the model provides a robust explanation for the Acceptance of GenAI in the consulting industry. The results highlight the central role of BI for ACT and TTF for PE.

Finally, a multigroup invariance analysis was conducted to gain further insights from the structural model. The demographic ‘gender’ was divided into the category’s women (n=42) and men (n=83). The category ‘diverse’ was not considered, as none of the respondents made this selection. The measurement invariance of composition (MICOM) includes three hierarchical steps: (1) configural invariance, (2) compositional invariance, and (3) the equality of means and variances of the composites (Hair et al., 2021).

Configuration invariance ensures that the model is structured the same way in both groups and is automatically fulfilled in SmartPLS. Composition invariance checks using permutation tests whether the latent variables in both groups are composed in the same way. It is considered fulfilled if the p-value is greater than 0.05, as this indicates the absence of significant differences. In the third stage, it is checked whether the means and variances between the groups differ significantly (Hair et al., 2021).

If complete measurement invariance is present, the groups can be directly compared, as differences in the results are indeed attributable to group differences. If only partial invariance is present, further MGA analyses are required to exclude biases. The investigation of the Measurement Invariance of Composites (MICOM) proves that the latent variables are comparable for women and men. The correlations between the original values and the permuted values for all variables (ACT, BI, CONT, GAIC, PE, TTF) are at least 0.96. The permutation p-values are not significant (all > 0.05). This suggests that compositional invariance is present for all variables (see Appendix K).

Regarding the means, however, significant differences are observed in ACT, BI, and TTF, while CONT, GAIC, and PE do not show significant differences. Above all, ACT (difference = 0.424, p = 0.021), BI (difference = 0.457, p = 0.020) and TTF (difference = 0.413, p = 0.033) show significant deviations. The results suggest that women and men exhibit different means for certain latent variables, indicating that mean invariance is not present for all variables (see Appendix L).

The variability of the variables is largely comparable in the groups, except for PE, where the threshold of p > 0.05 is only slightly exceeded (p = 0.057). This suggests that the variability of PE may slightly differ by gender (see Appendix M).

When examining the paths in the multigroup analysis, it becomes clear that most relationships between the variables do not show significant differences between women and men. This includes, among others, the paths BI → ACT, GAIC → TTF, PE → BI, TTF → BI, and TTF → PE, which are all invariant. However, a difference becomes apparent in the CONT → TTF path: Men exhibit a stronger connection (path coefficient = 0.187, p = 0.024) than women (path coefficient = 0.119, p = 0.285). This suggests that the perception of the relationship between CONT and TTF may vary based on gender (see Appendix N).

The results indicate that most latent variables for women and men are comparable in terms of their composition as well as the relationships in the model. However, significant differences were found in the means of ACT, BI, and TTF, indicating that these variables are perceived differently between genders. Additionally, a marginally significant difference in the variability of PE suggests that its distribution may slightly differ by gender. The only significant difference in path coefficients was observed in the CONT → TTF relationship, where men exhibit a stronger association than women. These results suggest that gender-specific factors can influence technology acceptance and use. To ensure that the results of the multi-group analysis are not coincidental, further investigations must be conducted, as no hypotheses involving the gender variable were examined in the model. Accordingly, these results should not be interpreted as definitive, but rather as an indication of the need for further examinations within the model.

The final model (see Figure six) was developed based on all analyses, with all tested paths supported. Only GAIC2 was removed due to low reliability. The model illustrates the relationships between formative (GAIC, CONT, TTF) and reflective (PE, BI, ACT) latent variables, confirming key drivers of GenAI acceptance among consultants.

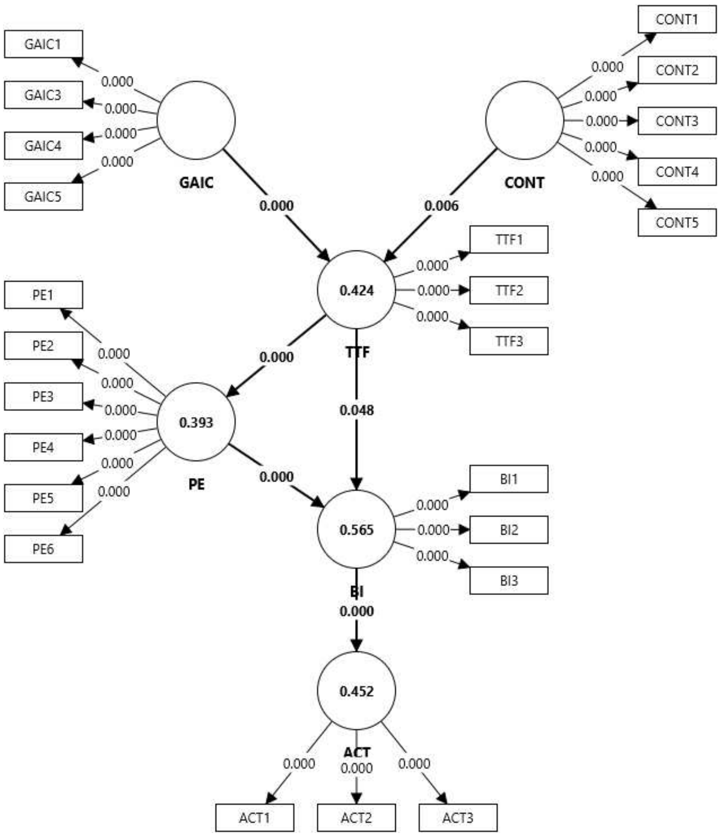


*Figure 6: Results of the Proposed Conceptual Model for GenAI Acceptance among Consultants (Construct with P-values and $R^2$)*

# 4 Discussion

## 4.1 Results

The results of this study confirm the proposed conceptual model and underscore its relevance for explaining the acceptance of Generative Artificial Intelligence (GenAI) in the consulting industry. By integrating established acceptance models such as UTAUT and TTF, a comprehensive framework was developed that captures the key success factors of GenAI acceptance among consultants. The results validate all proposed hypotheses and particularly highlight the key role of Behavioral Intention (BI) in the acceptance and integration of GenAI. At the same time, the study reveals challenges and complex interrelationships that should be critically reflected upon. Particularly noteworthy is the strong mediating effect of Performance Expectancy in the relationship between TTF and BI, which underscores the central importance of PE for the acceptance of GenAI. Furthermore, overlaps between individual constructs are evident, which should be methodically differentiated in future studies.

The latent variable GAIC has a significant impact on TTF (H1: path coefficient = 0.569, $p < 0.001$). This confirms GAIC as a central influencing variable on TTF. At the same time, however, GAIC shows weaknesses in item reliability and convergent validity. Although GAIC2 has already been removed, GAIC remains methodologically challenging overall, necessitating further refinement and validation of the measurement instruments.

The comparatively low mean values of the GAIC items – particularly 3.045 for GAIC2 (GenAI can generate audio files) and 3.594 for GAIC3 (Visual content) – indicate that consultants primarily associate GenAI with text-based applications, data analysis, or code generation, while underestimating its capabilities in other areas. This contradicts the technological capabilities of GenAI, which can already generate realistic music pieces or images (e.g., OpenAI MuseNet, AIVA). A possible explanation for this discrepancy could be the recency bias: consultants who have primarily worked with text-based GenAI applications may be less familiar with advancements in other areas.

The analysis also shows that the type of consulting tasks (Consultant Tasks, CONT) influences the TTF (H2, path coefficient = 0.188, $p = 0.006$, $f^2 = 0.056$). The mean values of the items for CONT range between 4.252 and 4.520, thus confirming that the captured consulting tasks largely align with the perceptions of the surveyed consultants. In comparison, the mean values of the items for TTF are lower (3.556 to 3.944), particularly for the item TTF3 (Creativity-related tasks), which received the least agreement. This suggests that analytical and communicative tasks are perceived to be particularly well supported by GenAI, while creative tasks appear to be less compatible.

The strong connection between TTF and PE confirms hypothesis three (H3, path coefficient = 0.627, $p < 0.001$). A high fit between a consultant's tasks and the capabilities of GenAI significantly enhances PE. The perception that GenAI leads to higher efficiency and productivity consequently increases the willingness to use the technology. This underscores that not only the availability of the technology but particularly the assessment of its concrete benefits for work is decisive.

PE has a significant impact on BI (H4) with a path coefficient of 0.626 ($p < 0.001$). This illustrates that consultants consider PE as a crucial factor for their Behavioural Intention. All items of PE – 'Time-saving on routine tasks', 'Task quality', 'Higher productivity', 'Competence perception by colleagues', 'Job performance improvement', and 'Work facilitation' – directly affect Behavioural Intention.

To validate the hypothesis PE → BI (H4), the direct influence of TTF on BI was also analysed. The direct effect of TTF on BI (H5) is weaker with a path coefficient of 0.179 ($p = 0.048$, $f^2 = 0.045$) than the indirect effect through PE (H3: path coefficient = 0.627, $p < 0.001$). This illustrates the strong mediating role of PE: The acceptance of GenAI does not solely depend on whether the technology fits the task (TTF), but primarily on how strongly consultants assess the actual benefits of GenAI (PE) for their work.

The study confirms the relevance of BI for the acceptance (Acceptance, ACT) of GenAI (H6). The high path coefficient of 0.673 ($p < 0.001$) as well as the strong effect size ($f^2 = 0.826$) demonstrate that an increased BI significantly influences the acceptance and integration of GenAI into work processes. As in the UTAUT model(Venkatesh et al., 2003), BI is a central predictor of technology acceptance.

The multigroup analysis shows gender-specific differences in the variables ACT, BI, PE, and TTF. Women tend to show lower values for BI and ACT, indicating that they have a lower intention to accept and integrate GenAI into their daily work. These differences are reflected in both the means and the strength of certain paths. However, these results should be interpreted with caution, as no specific hypothesis regarding gender-specific technology acceptance was formulated. Therefore, it is recommended that future studies integrate the moderator 'gender' into models of GenAI acceptance among consultants. This is in line with the UTAUT model, which also examines gender-specific differences in technology acceptance.

In summary, the study shows that perceived performance enhancement (PE), the fit between task and technology (TTF) and the Behavioural Intention (BI) are central factors for the acceptance of GenAI. While some hypotheses were strongly confirmed, challenges particularly arise in the creative application of GenAI and in methodological ambiguities between certain constructs. The results provide valuable insights for companies looking to successfully integrate GenAI into their consulting processes.

## 4.2 Implications for Practice

The successful acceptance and introduction of GenAI in the consulting industry depends not only on the technological capabilities of the systems. It also requires a targeted integration into existing workflows and a practical approach to familiarizing consultants with the technology. In addition to technological aspects, the perception of benefits, the adaptability of consultants, and the concrete applicability in various consulting scenarios play a crucial role. To ensure sustainable use and Acceptance, companies should take various measures that both leverage the efficiency potentials of GenAI and address potential reservations, facilitating its targeted application in the daily work of consultants.

A key finding of the study is the importance of TTF for the acceptance of GenAI. Companies should not primarily focus on the technology itself, but rather conduct a targeted analysis of the areas of activity where GenAI offers the greatest value. This means that consulting firms should reconsider their work processes to identify areas where GenAI can provide effective support—whether through the automation of repetitive tasks, the optimization of research and analysis processes, or assistance with content generation. One way to achieve better integration is the granular structuring of work processes. By breaking down complex consulting tasks into smaller work steps, it can be precisely analysed in which areas GenAI can be meaningfully employed and where human expertise is still necessary. An example of this would be a comprehensive market analysis, which is divided into several phases: data collection, pattern recognition, and result interpretation. While GenAI particularly supports the first two phases through rapid data aggregation and trend identification, the final analysis and derivation of strategic recommendations remain a core competency of the consultants.

A key success factor for the widespread use of GenAI is the practical experience of the consultants with the technology. Interactive workshops could prove to be particularly effective in this context to create initial touchpoints with the technology and make its potential tangible. A targeted training should not only convey theoretical knowledge about GenAI but also demonstrate concrete use cases. Hands-on workshops, where consultants try out GenAI in real consulting situations, strengthen trust in the technology and increase the willingness to use it. Particularly effective are small workshop groups that individually address industry-specific challenges and consider the specific issues faced by the consultants.

Another important aspect of this training is the creation of realistic expectations about the technology. It should be clearly communicated that GenAI is not a fully autonomous system, but rather should be used as a supportive tool. Often, there is a misunderstanding that GenAI can independently take over all tasks, while in many cases, it requires human review and correction. With the right expectations, frustration can be avoided, and the productive use of technology can be promoted.

In addition to individual acceptance, technical integration plays a crucial role. Consulting firms must strategically consider whether to use existing AI solutions like Microsoft Copilot or develop their own GenAI models to meet specific data protection and security requirements. While external solutions are quickly deployable, customized models offer the advantage of greater adaptation to company-specific processes. A hybrid solution could be sensible here: standard solutions for general tasks and proprietary models for specific, protected data analyses. The implementation process should also be accompanied by a seamless integration into existing applications. GenAI is only regularly used by consultants when it is directly integrated into their familiar workflows. For example, seamless access to AI-powered analytics within CRM systems could significantly facilitate usage.

The successful introduction of GenAI requires a structured and long-term implementation process. In addition to technical integration and training measures, it is crucial that companies pursue a clear strategy for scaling the technology. This means that after a successful testing phase, additional application areas should be specifically developed to make the technology more widely usable. The creation of an AI-friendly corporate culture can play a key role in this. Leaders should actively promote the use of GenAI and formulate clear guidelines for its use to avoid uncertainties. At the same time, success stories should be made visible – for example, through best practice examples or success stories of consultants who have achieved significant efficiency gains through GenAI.

In summary, it becomes clear that the successful implementation of GenAI is not just a technical challenge, but above all requires strategic change management. Companies that strategically invest in training their employees, optimize TTF, and pursue a clear adoption strategy can long-term increase the acceptance of GenAI and thereby secure a decisive competitive advantage.

## 4.3 Limitations and Future Research

The present study provides valuable insights into the acceptance of GenAI in the consulting industry, but it has some limitations that must be considered when interpreting the results. A key limitation concerns the sample size, its composition, and the generalizability of the results. Although the number of participants for analyses based on structural equation models is generally considered sufficient, a larger sample could further enhance the robustness of future studies. In addition, there is a gender imbalance in the sample (42 women, 83 men), which could limit the generalizability of the results. However, this partially reflects the gender distribution in the consulting industry, which is traditionally male-dominated (Federal Association of German Management Consultants, 2025). In particular, the identified gender-specific differences in the acceptance and use of GenAI should be further investigated in future studies with a more balanced gender distribution. It would be sensible to consider gender as a moderator in future acceptance models for GenAI in the consulting sector. This would allow for further validation of the results of the multigroup analysis.

Another methodological limitation lies in the measurement instruments used. In particular, the variable GAIC shows weaknesses in its convergent validity. There were conceptual overlaps with the variables TTF and PE. This could indicate that consultants have difficulty distinguishing between the technological features of GenAI (GAIC), its fit with their tasks (TTF), and the perceived performance improvements (PE). These overlaps make it difficult to clearly interpret the individual influencing factors, which is why future studies should develop more precise measurement instruments to enable a clearer separation of these constructs.

Another point that was not considered in this study is the duration of GenAI usage. The study focuses on Behavioural Intention as a central predictor of Acceptance but does not measure whether the surveyed consultants would integrate GenAI into their work routine over longer periods. The literature shows that an initial intention to use does not necessarily mean that a technology will be used permanently and intensively (Jasperson et al., 2005). To better understand this aspect, future studies could conduct a longitudinal analysis to capture which factors contribute to or hinder the long-term continuous use of GenAI.

In addition to individual acceptance factors, organizational influences were not systematically examined in this study. Factors such as corporate culture, training programs, and internal incentive structures could, however, play a significant role in whether and how intensively GenAI is used in consulting firms. For example, it could be investigated whether companies with a strongly technology-driven culture exhibit a higher acceptance rate than organizations where more traditional working methods dominate. The manner of introducing GenAI, for example through targeted training programs or gradual integration into existing systems, could also have a significant impact on how well the technology is accepted by consultants.

While this study adopted a quantitative approach, qualitative research could provide further valuable insights. Particularly the identified gender-specific differences raise questions that can only be partially answered by standardized measurement tools. Qualitative interviews or focus groups could help gain a deeper understanding of why women tend to show a lower BI and ACT towards GenAI. Additionally, a qualitative analysis could provide insights into the specific barriers or uncertainties that consultants experience when dealing with GenAI and what measures would be necessary to overcome them.

In addition to the conceptual and methodological challenges, technological development is also a factor that will influence future research. GenAI technologies are rapidly evolving, so the perception and use of these systems could change significantly in just a few years. Solutions like Microsoft Copilot or specialized GenAI models for the consulting sector could introduce new acceptance factors that have not yet been considered in this study. Regular updates to the research are therefore necessary to better understand the impact of new technologies on the consulting industry and to capture long-term trends in the use of GenAI.

In summary, this study shows that the acceptance of GenAI is influenced by a variety of factors, the relationships of which have not yet been conclusively clarified. Future studies could particularly explore the long-term use of GenAI as well as the influence of organizational structures. Qualitative studies could also provide valuable insights to better understand individual perceptions and challenges in dealing with GenAI. A continuous scientific engagement with these topics will be crucial to provide companies with a solid foundation for the successful integration of GenAI into the work processes of consultants.

## 4.4 Conclusion

The present study examines the factors that influence the Acceptance and integration of GenAI in the consulting industry. The results show that TTF, PE and BI play a central role for work processes. It is confirmed that the integration of GenAI is not only a technological challenge but is significantly shaped by individual and organizational factors.

A central finding of this work is that BI has a direct and significant impact on the acceptance of GenAI. This underscores the importance of training measures and change management strategies that can positively influence the Behavioural Intention to accept. At the same time, it becomes evident that PE has a significant impact on BI, indicating that consultants consider the expected added value of the technology in terms of efficiency, quality, and productivity as a decisive factor. The results are thus in line with existing technology acceptance models, but they extend these by specifically focusing on the consulting industry and the role of TTF, which has also been focused on the consulting industry with its variables GAIC and CONT.

The study also confirms that GAIC are not equally recognized. While text-based applications and data analysis receive high approval, the ability of GenAI to create visual and auditory content is viewed more sceptically. This could indicate that awareness of the full technological possibilities in the industry has not yet fully developed or that these application areas are still perceived as less relevant to everyday consulting.

Another significant finding concerns the role of TTF. The results show that a high alignment between the requirements of a task and the capabilities of GenAI significantly promotes the acceptance of the technology. Particularly analytical and communicative tasks are perceived as well-supported, while creative activities are still considered to be strongly human-centric. This underscores that GenAI should be understood as a complement to existing processes and not as a complete replacement for human expertise.

In addition to these individual factors, conceptual challenges also became apparent. The overlap between GAIC, TTF, and PE indicates that consultants have difficulty clearly separating technological characteristics, task-fit, and expected performance improvement. This makes it clear that future research should aim for a more precise separation of these constructs and pursue methodological advancements.

In summary, this study shows that the introduction and use of GenAI in the consulting industry does not solely depend on technological advancements. Individual acceptance factors TTF, PE and BI play a crucial role. Companies should therefore not only invest in technological development but also specifically develop strategies to promote its use. Important measures include training programs and a clear positioning of GenAI as support, not as a replacement for consultants. A thoughtful integration can help increase efficiency, promote innovation, and sustainably prepare the consulting industry for a technology-driven future.

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# 6 Appendix

## *Appendix A: Basic concept of the user acceptance models for the UTAUT model*

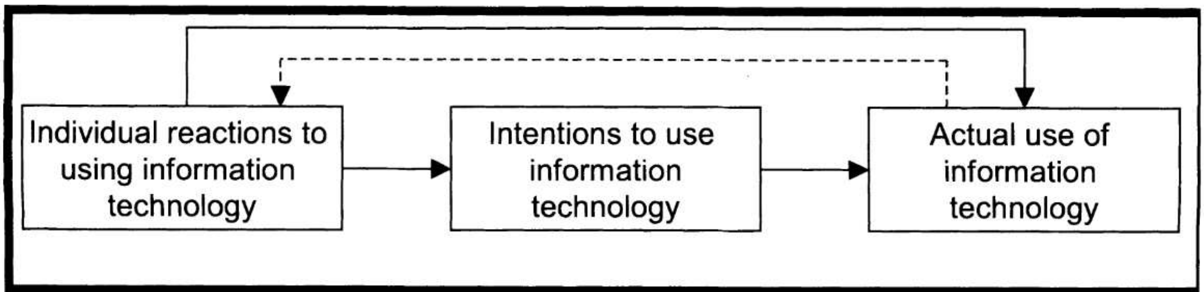


Figure 1. Basic Concept Underlying User Acceptance Models

## *Appendix B: Overview of the Latent Variables, Items and Variables Sources*

| No. | Latent variable | Source | Item | Abbreviation Questition | Source2 |
|---|---|---|---|---|---|
| 0 | | | | | |
| 1 | GenAI Characteristics (GAIC) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | GAIC1 | Text-based content | Nah et. Al. (2023) |
| 2 | GenAI Characteristics (GAIC) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | GAIC2 | Audio-based content | Nah et. Al. (2023) |
| 3 | GenAI Characteristics (GAIC) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | GAIC3 | Visual content | Nah et. Al. (2023) |
| 4 | GenAI Characteristics (GAIC) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | GAIC4 | Data analysis | Nah et. Al. (2023) |
| 5 | GenAI Characteristics (GAIC) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | GAIC5 | Softwarecodes | Nah et. Al. (2023) |
| 6 | Consultant tasks (CONT) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | CONT1 | Quantitative and qualitative evaluations | Canato & Giangreco (2011); Banai & Tulimieri (2013) |
| 7 | Consultant tasks (CONT) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | CONT2 | Customer communication | Canato & Giangreco (2011); Banai & Tulimieri (2013) |
| 8 | Consultant tasks (CONT) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | CONT3 | Industry-specific insights | Canato & Giangreco (2011); Banai & Tulimieri (2013) |
| 9 | Consultant tasks (CONT) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | CONT4 | Innovative solutions | Canato & Giangreco (2011); Banai & Tulimieri (2013) |
| 10 | Consultant tasks (CONT) | Goodhue and Thompson (1995); Brown, Dennis & Venkatesh (2014) | CONT5 | Transferring best practices | Canato & Giangreco (2011); Banai & Tulimieri (2013) |
| 11 | Task-Technology Fit (TTF) | Goodhue and Thompson (1995); Dishawa & Strong (1998) | TTF1 | Analytics-related tasks | Banai & Tulimieri (2013) |
| 12 | Task-Technology Fit (TTF) | Goodhue and Thompson (1995); Dishawa & Strong (1998) | TTF2 | Communication-related tasks | Banai & Tulimieri (2013) |
| 13 | Task-Technology Fit (TTF) | Goodhue and Thompson (1995); Dishawa & Strong (1998) | TTF3 | Creativity-related tasks | Banai & Tulimieri (2013) |
| 14 | Performance Expactancy (PE) | Vankatesh et al. (2003) | PE1 | Time-saving on routine tasks | Vankatesh et al. (2003) |
| 15 | Performance Expactancy (PE) | Vankatesh et al. (2003) | PE2 | Task quality | Vankatesh et al. (2003) |
| 16 | Performance Expactancy (PE) | Vankatesh et al. (2003) | PE3 | Higher productivity | Vankatesh et al. (2003) |
| 17 | Performance Expactancy (PE) | Vankatesh et al. (2003) | PE4 | Competence perception by colleagues | Vankatesh et al. (2003) |
| 18 | Performance Expactancy (PE) | Vankatesh et al. (2003) | PE5 | Job performance improvement | Vankatesh et al. (2003) |
| 19 | Performance Expactancy (PE) | Vankatesh et al. (2003) | PE6 | Work facilitation | Vankatesh et al. (2003) |
| 20 | Behavioral Intention (BI) | Venkatesh, Thong and Xu (2012) | BI1 | Good idea | Venkatesh, Thong and Xu (2012); Venkatesh et al. (2003) |
| 21 | Behavioral Intention (BI) | Venkatesh, Thong and Xu (2012) | BI2 | More interesting work | Venkatesh, Thong and Xu (2012); Venkatesh et al. (2003) |
| 22 | Behavioral Intention (BI) | Venkatesh, Thong and Xu (2012) | BI3 | Fun | Venkatesh, Thong and Xu (2012); Venkatesh et al. (2003) |
| 23 | Acceptance(ACT) | Gursoy et al. (2019); Ismatullaev and Kim (2024) | ACT1 | Integration into work | Gursoy et al. (2019) |
| 24 | Acceptance(ACT) | Gursoy et al. (2019); Ismatullaev and Kim (2024) | ACT2 | Already integrated | Gursoy et al. (2019) |
| 25 | Acceptance(ACT) | Gursoy et al. (2019); Ismatullaev and Kim (2024) | ACT3 | Further integration planned | Gursoy et al. (2019) |

## *Appendix C: Overview of all hypotheses*

| No. | Hypothesis |
|---|---|
| H1 | GenAI Characteristics (GAIC) positively impact Task-Technology Fit (TTF). |
| H2 | Consultant Tasks (CONT) positively impact Task-Technology Fit (TTF). |
| H3 | Task-Technology Fit (TTF) positively influences Performance Expectancy (PE). |
| H4 | Performance Expectancy (PE) positively influences Behavioural Intention (BI). |
| H5 | Task-Technology Fit (TTF) positively influences Behavioural Intention (BI). |
| H6 | Behavioural Intention (BI) positively influences Acceptance (ACT). |

***Appendix D: Overview of the Variables, Items, Survey Questions and Abbreviation***

| No. | Latent variable | Item | Abbreviation Questition | Question |
|---|---|---|---|---|
| 1 | GenAI Characteristics | GAIC1 | Text-based content | GenAI is very effective at creating new text-based content, such as emails or essays. |
| 2 | GenAI Characteristics | GAIC2 | Audio-based content | GenAI is very effective at creating new audio-based content, such as music or videos. |
| 3 | GenAI Characteristics | GAIC3 | Visual content | GenAI is very effective at creating new visual content, such as images or designs. |
| 4 | GenAI Characteristics | GAIC4 | Data analysis | GenAI is very effective at analysing data. |
| 5 | GenAI Characteristics | GAIC5 | Softwarecodes | GenAI is very effective at producing software codes. |
| 6 | Consultant Task | CONT1 | Quantitative and qualitative evaluatio | My role as consultant includes to perform quantitative and qualitative evaluations to provide meaningful |
| 7 | Consultant Task | CONT2 | Customer communication | My role as consultant includes clear and effective communication throughout the customer relationship. |
| 8 | Consultant Task | CONT3 | Industry-specific insights | My role as consultant includes providing industry-specific insights to support clients' strategic decision- |
| 9 | Consultant Task | CONT4 | Innovative solutions | My role as consultant includes designing innovative solutions focused on client challenges. |
| 10 | Consultant Task | CONT5 | Transferring best practices | My role as consultant includes helping clients transfer best practices from other industries or projects. |
| 11 | Task-Technology Fit | TTF1 | Analytics-related tasks | GenAI effectively executes analytics-related tasks. |
| 12 | Task-Technology Fit | TTF2 | Communication-related tasks | GenAI effectively executes communication-related tasks. |
| 13 | Task-Technology Fit | TTF3 | Creativity-related tasks | GenAI effectively executes creativity-related tasks. |
| 14 | Performance Expectancy | PE1 | Time-saving on routine tasks | If I use GenAI, I will save time on routine tasks. |
| 15 | Performance Expectancy | PE2 | Task quality | If I use GenAI, I will increase the quality of output of my tasks. |
| 16 | Performance Expectancy | PE3 | Higher productivity | If I use GenAI, I can produce more output with the same effort. |
| 17 | Performance Expectancy | PE4 | Competence perception by colleagues | If I use GenAI, my colleagues will perceive me as competent. |
| 18 | Performance Expectancy | PE5 | Job performance improvement | If I use GenAI, I will improve my job performance. |
| 19 | Performance Expectancy | PE6 | Work facilitation | If I use GenAI, it will make my work easier. |
| 20 | Behavioural Intention | BI1 | Good idea | Using GenAI is a good idea. |
| 21 | Behavioural Intention | BI2 | More interesting work | Using GenAI makes work more interesting. |
| 22 | Behavioural Intention | BI3 | Fun | Using GenAI is fun. |
| 23 | Acceptance | ACT1 | Integration into work | I would like to integrate GenAI into my work. |
| 24 | Acceptance | ACT2 | Already integrated | I already integrated GenAI into my work. |
| 25 | Acceptance | ACT3 | Further integration planned | I plan on integrating GenAI into my work even more. |

***Appendix F: Questionnaire***

# GenAI Consultant Acceptance (DEU/ENG)

Q1 Thank you for taking about **3 to 5 minutes** to answer the survey! This survey is part of my **Master's thesis** at **Católica** in Lisbon, supervised by Professor Filipa Lancastre. The study analyses **how consultants use generative artificial intelligence (GenAI)**, such as ChatGPT, **in their daily work** and **which factors influence their acceptance and use of GenAI**. Your answers will of course be treated **anonymously** and **confidentially**. By continuing with the survey, you confirm that you are participating in this survey voluntarily. If you have any questions, please contact me at **s-iherzog@ucp.pt**. Thank you for your time!

Inessa Herzog

Q2 Definition Consultant: *'In this survey, a consultant in management consulting is defined as an external expert who supports companies in solving problems, developing strategies, and implementing projects.'*

Q3 Have you ever been a consultant before, or are you still one?

- ○ Yes, I am currently a consultant. (1)
- ○ Yes, I have been a consultant at some point within the last three years. (2)
- ○ No, I have never been a consultant. (3)

Q4 Please check one option from 'completely disagree' to 'completely agree'. GenAI is very effective at...

| | 1 Completely disagree (1) | 2 Somewhat disagree (2) | 3 Neutral (3) | 4 Somewhat agree (4) | 5 Completely agree (5) |
|---|---|---|---|---|---|
| ...creating new text-based content, such as emails or essays. (1) | ○ | ○ | ○ | ○ | ○ |
| ...creating new audio-based content, such as music or videos. (2) | ○ | ○ | ○ | ○ | ○ |
| ...creating new visual content, such as images or designs. (3) | ○ | ○ | ○ | ○ | ○ |
| ...analysing data. (4) | ○ | ○ | ○ | ○ | ○ |
| ...producing software codes. (5) | ○ | ○ | ○ | ○ | ○ |

Q5 Please check one option from ‘completely disagree’ to ‘completely agree’. My role as consultant includes...

| | 1 Completely disagree (1) | 2 Somewhat disagree (2) | 3 Neutral (3) | 4 Somewhat agree (4) | 5 Completely agree (5) |
|---|---|---|---|---|---|
| ...to perform quantitative and qualitative evaluations to provide meaningful insights. (1) | ○ | ○ | ○ | ○ | ○ |
| ...clear and effective communication throughout the customer relationship. (2) | ○ | ○ | ○ | ○ | ○ |
| ...providing industry-specific insights to support clients’ strategic decision-making. (3) | ○ | ○ | ○ | ○ | ○ |
| ...designing innovative solutions focused on client challenges. (4) | ○ | ○ | ○ | ○ | ○ |
| ...helping clients transfer best practices from other industries or projects. (5) | ○ | ○ | ○ | ○ | ○ |

Q6 Please check one option from ‘completely disagree’ to ‘completely agree’. GenAI effectively executes...

| | 1 Completely disagree (1) | 2 Somewhat disagree (2) | 3 Neutral (3) | 4 Somewhat agree (4) | 5 Completely agree (5) |
|---|---|---|---|---|---|
| ...analytics-related tasks. (1) | o | o | o | o | o |
| ...communication-related tasks. (2) | o | o | o | o | o |
| ...creativity-related tasks. (3) | o | o | o | o | o |

Q7 Please check one option from ‘completely disagree’ to ‘completely agree’. If I use GenAI, ...

| | 1 Completely disagree (1) | 2 Somewhat disagree (2) | 3 Neutral (3) | 4 Somewhat agree (4) | 5 Completely agree (5) |
|---|---|---|---|---|---|
| ...I will save time on routine tasks. (1) | o | o | o | o | o |
| ...I will increase the quality of output of my tasks. (2) | o | o | o | o | o |
| ...I can produce more output with the same effort. (3) | o | o | o | o | o |
| ...my colleagues will perceive me as competent. (4) | o | o | o | o | o |
| ...I will improve my job performance. (5) | o | o | o | o | o |
| ...it will make my work easier. (6) | o | o | o | o | o |

Q8 Please check one option from ‘completely disagree’ to ‘completely agree’. Using GenAI...

| | 1 Completely disagree (1) | 2 Somewhat disagree (2) | 3 Neutral (3) | 4 Somewhat agree (4) | 5 Completely agree (5) |
|---|---|---|---|---|---|
| ...is a good idea. (1) | ○ | ○ | ○ | ○ | ○ |
| ...makes work more interesting. (2) | ○ | ○ | ○ | ○ | ○ |
| ...is fun. (3) | ○ | ○ | ○ | ○ | ○ |

Q9 Please check one option from ‘completely disagree’ to ‘completely agree’.

| | 1 Completely disagree (1) | 2 Somewhat disagree (2) | 3 Neutral (3) | 4 Somewhat agree (4) | 5 Completely agree (5) |
|---|---|---|---|---|---|
| I would like to integrate GenAI into my work. (1) | ○ | ○ | ○ | ○ | ○ |
| I already integrated GenAI into my work. (2) | ○ | ○ | ○ | ○ | ○ |
| I plan on integrating GenAI into my work even more. (3) | ○ | ○ | ○ | ○ | ○ |

Q10 Please select ‘GenAI’ to confirm you are paying attention.

○ GenAI (1)

○ Excel (2)

○ Word (3)

Q11 How old are you?

- ◯ 18-23 years (1)
- ◯ 24-29 years (2)
- ◯ 30-39 years (3)
- ◯ 40-49 years (4)
- ◯ 50 years or older (5)

Q12 What is your gender?

- ◯ Female (1)
- ◯ Male (2)
- ◯ Non-binary (3)

Q13 How would you describe your level of technical skills?

- ◯ Beginner (1)
- ◯ Basic (5)
- ◯ Advanced (2)
- ◯ Professional (3)

Q14 How many years of consulting experience do you have?

- ◯ 0-3 years (1)
- ◯ 4-7 years (2)
- ◯ 8 years or more (3)

Q15 Have you previously used GenAI?

- ◯ Regularly (1)
- ◯ Occasionally (2)
- ◯ No experience so far (3)

Q16 In which specific contexts have you used GenAI? (Multiple selection possible)

- ▢ Consulting context (1)
- ▢ Personal context (2)
- ▢ In another working context (3)
- ▢ No context (4)

## *Appendix G: Discriminant validity (Cross loadings)*

| Item | AC | | CON | GAI | I | TI |
|---|---|---|---|---|---|---|
| **ACT1** | **0,716** | 0,48 | 0,042 | 0,301 | 0,398 | 0,206 |
| **ACT2** | **0,728** | 0,487 | 0,153 | 0,217 | 0,415 | 0,396 |
| **ACT3** | **0,819** | 0,555 | 0,16 | 0,395 | 0,477 | 0,364 |
| **BI1** | 0,673 | **0,857** | 0,2 | 0,459 | 0,65 | 0,536 |
| **BI2** | 0,479 | **0,866** | 0,237 | 0,489 | 0,683 | 0,471 |
| **BI3** | 0,563 | **0,849** | 0,199 | 0,367 | 0,561 | 0,456 |
| **CONT1** | 0,225 | 0,258 | **0,757** | 0,241 | 0,3 | 0,354 |
| **CONT2** | 0,113 | 0,099 | 0,642 | 0,093 | 0,121 | 0,119 |
| **CONT3** | 0,052 | 0,197 | **0,849** | 0,206 | 0,188 | 0,224 |
| **CONT4** | 0,087 | 0,173 | **0,78** | 0,267 | 0,22 | 0,324 |
| **CONT5** | 0,08 | 0,14 | **0,738** | 0,241 | 0,238 | 0,218 |
| **GAIC1** | 0,324 | 0,377 | 0,205 | 0,657 | 0,482 | 0,47 |
| **GAIC2** | 0,218 | 0,292 | 0,07 | 0,458 | 0,301 | 0,143 |
| **GAIC3** | 0,169 | 0,26 | 0,236 | 0,602 | 0,317 | 0,286 |
| **GAIC4** | 0,266 | 0,37 | 0,222 | **0,763** | 0,501 | 0,497 |
| **GAIC5** | 0,302 | 0,336 | 0,173 | 0,665 | 0,395 | 0,402 |
| **PE1** | 0,44 | 0,57 | 0,272 | 0,512 | 0,675 | 0,457 |
| **PE2** | 0,49 | 0,549 | 0,201 | 0,489 | **0,797** | 0,564 |
| **PE3** | 0,353 | 0,563 | 0,222 | 0,478 | **0,742** | 0,455 |
| **PE4** | 0,364 | 0,558 | 0,194 | 0,383 | **0,766** | 0,381 |
| **PE5** | 0,445 | 0,556 | 0,326 | 0,563 | **0,809** | 0,476 |
| **PE6** | 0,474 | 0,536 | 0,142 | 0,473 | **0,721** | 0,484 |
| **TTF1** | 0,33 | 0,534 | 0,338 | 0,599 | 0,536 | **0,813** |
| **TTF2** | 0,313 | 0,357 | 0,289 | 0,269 | 0,37 | 0,636 |
| **TTF3** | 0,279 | 0,282 | 0,113 | 0,373 | 0,411 | 0,676 |

## *Appendix H: Fornell-Larcker criterion (discriminant validity)*

| Latent variable | AC | | CON | GAI | I | TI |
|---|---|---|---|---|---|---|
| **ACT** | **0,756** | | | | | |
| **BI** | 0,673 | **0,857** | | | | |
| **CONT** | 0,159 | 0,247 | **0,756** | | | |
| **GAIC** | 0,407 | 0,513 | 0,297 | **0,637** | | |
| **PE** | 0,571 | 0,738 | 0,301 | 0,644 | **0,753** | |
| **TTF** | 0,429 | 0,572 | 0,361 | 0,613 | 0,627 | **0,712** |

## *Appendix I: Discriminant validity (HTMT)*

| Latent variable | AC | I | CON | GA | I | T |
|---|---|---|---|---|---|---|
| ACT | | | | | | |
| BI | **0,932** | | | | | |
| CONT | 0,202 | 0,279 | | | | |
| GAIC | 0,621 | 0,688 | 0,368 | | | |
| PE | 0,782 | 0,884 | 0,337 | 0,828 | | |
| TTF | 0,742 | 0,819 | 0,482 | **0,933** | **0,908** | |

## *Appendix J: R-square of the Latent variables*

| Latent variables | R-square | R-square adjusted |
|---|---|---|
| ACT | 0.452 | 0.448 |
| BI | 0.565 | 0.558 |
| PE | 0.393 | 0.388 |
| TTF | 0.424 | 0.415 |

## *Appendix K: MGA for Gender (Female vs. Male) Step 2 (compositional invariance)*

| Latent variable | Original correlation | Correlation permutation mean | 5.0% | Permutation p value |
|---|---|---|---|---|
| ACT | 0.968 | 0.981 | 0.942 | 0.189 |
| BI | 0.999 | 0.999 | 0.996 | 0.466 |
| CONT | 0.986 | 0.960 | 0.883 | 0.702 |
| GAIC | 0.962 | 0.982 | 0.950 | 0.099 |
| PE | 0.998 | 0.997 | 0.993 | 0.516 |
| TTF | 0.959 | 0.982 | 0.948 | 0.098 |

## *Appendix L: MGA for Gender (Female vs. Male) Step 3a (mean invariance)*

| Latent variable | Original difference | Permutation mean difference | 2.5% | 97.5% | Permutation p value |
|---|---|---|---|---|---|
| ACT | 0.424 | 0.001 | -0.361 | 0.353 | 0.021 |
| BI | 0.457 | 0.001 | -0.382 | 0.366 | 0.020 |
| CONT | 0.225 | 0.002 | -0.412 | 0.371 | 0.250 |
| GAIC | 0.217 | -0.005 | -0.372 | 0.371 | 0.258 |
| PE | 0.324 | -0.000 | -0.392 | 0.383 | 0.100 |
| TTF | 0.413 | -0.002 | -0.390 | 0.372 | 0.033 |

## *Appendix M: MGA for Gender (Female vs. Male) Step 3b (variance invariance)*

| Latent variable | Original difference | Permutation mean difference | 2.5% | 97.5% | Permutation p value |
|---|---|---|---|---|---|
| ACT | -0.314 | -0.046 | -0.782 | 0.734 | 0.491 |
| BI | 0.031 | -0.048 | -0.761 | 0.634 | 0.939 |
| CONT | 0.151 | -0.041 | -0.699 | 0.609 | 0.679 |
| GAIC | 0.344 | -0.025 | -0.620 | 0.535 | 0.271 |
| PE | 0.596 | -0.040 | -0.607 | 0.611 | 0.057 |
| TTF | -0.093 | -0.024 | -0.560 | 0.549 | 0.745 |

## *Appendix N: MGA for Gender (Female vs. Male) Bootstrapping*

| Path | Original (Female) | p value (Female) | Original (Male) | p value (Male) | Invarient |
|---|---|---|---|---|---|
| BI -> ACT | 0.672 | 0.000 | 0.665 | 0.000 | Yes |
| CONT -> TTF | 0.119 | 0.285 | 0.187 | 0.024 | No |
| GAIC -> TTF | 0.692 | 0.000 | 0.562 | 0.000 | Yes |
| PE -> BI | 0.762 | 0.000 | 0.552 | 0.000 | Yes |
| TTF -> BI | 0.111 | 0.490 | 0.222 | 0.056 | Yes |
| TTF -> PE | 0.662 | 0.000 | 0.613 | 0.000 | Yes |