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Unlocking the potential of generative artificial intelligence: adoption drivers and organisational performance

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Abstract: Generative artificial intelligence (GenAI) is rapidly transforming business practice, yet systematic evidence on organisational adoption remains scarce. This study applies a streamlined technology-organisation-environment (TOE) framework to investigate how firms adopt GenAI, focusing on perceived benefits, technological complexity, and organisational readiness. Survey data from 778 decision-makers across multiple industries indicate that perceived benefits and readiness are the strongest enablers, while complexity represents a persistent barrier. Leadership support and strategic alignment emerge as critical for translating technical opportunities into business value. In contrast, external pressures, including regulation, exert only limited influence, and adoption patterns are broadly consistent across firm sizes. These findings contribute to innovation management research by clarifying the organisational capabilities that drive GenAI adoption beyond technological potential, and they offer actionable guidance for managers seeking to align GenAI initiatives with strategic goals.

Keywords: generative artificial intelligence; GenAI; organisational readiness; technology-organisation-environment framework; adoption drivers; innovation management; digital transformation; Europe.

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1 Introduction

Generative artificial intelligence (GenAI), a subcategory of artificial intelligence (AI), has emerged as a transformative technology with significant implications for organisations and innovation management. Its potential to drive productivity gains and reshape business strategies has positioned it as a central subject in applied research and practice (Kanbach et al., 2024). GenAI technologies can increase productivity by 2.6 to 4.4 trillion US dollars annually, roughly equivalent to the UK's annual gross domestic product and emphasising the disruptive potential (McKinsey, 2023; Statista, 2023).

The first practical applications of GenAI in an enterprise context emerged between 2017 and 2019 with the introduction of neural networks and transformer models at Google, as well as the OpenAI GPT 2, the first generative language model (cf. Kanbach et al., 2024). Technological advances over the last seven years have allowed companies to increase operational efficiency and create new value-creation capabilities. GenAI technologies are changing business strategies, reshaping competition, and revolutionising organisational structures (Agrawal et al., 2024). Firms that fail to adopt GenAI technologies risk losing their competitive edge (cf. Gupta et al., 2024). Therefore, the fundamental question is not whether GenAI will be adopted in companies but how, when, and to what extent (Singh et al., 2024). The strategies and challenges of introducing GenAI differ depending on the company's size. While large companies often have dedicated data science/GenAI teams, compliance structures, and extensive resources, small and medium-sized enterprises can benefit from more flexible innovation processes but struggle with resource constraints (Cucari et al., 2023; Chatterjee et al., 2021). Understanding these differences is crucial for management recommendations, especially in the diverse European innovation landscape. As part of Europe, the DACH region provides a strategically relevant context for studying GenAI adoption, particularly since Europe lags behind GenAI frontrunners such as the US and China (Kanbach et al., 2024).

To address these dynamics, this study employs the technology-organisation-environment (TOE) framework, a well-established theoretical model, to identify and analyse the key factors driving GenAI adoption (Bryan and Zuva, 2021). By examining the relationships among technological factors, such as technological relative advantage (TRA) and technological complexity (TC), organisational factors like organisational alignment (OA) and organisational readiness (OR), as well as environmental dimensions (E), this research enhances the understanding of how organisations can successfully adopt and integrate GenAI into their operations to drive innovation and improve business performance (Mariani and Dwivedi, 2024). Focusing on the DACH region, Germany, Austria, and Switzerland, this study contributes unique insights into the specific cultural, regulatory, and organisational factors shaping GenAI adoption. By analysing survey responses from 778 participants, this research offers a novel perspective on the factors influencing GenAI adoption in enterprises by reflecting the perceptions of managers and decision-makers (Kanbach et al., 2024; Sedkaoui and Benaichouba, 2024). Reflecting current discussions on the intersection of human, entrepreneurial, and AI-driven innovation, this study examines how organisational factors influence the adoption of GenAI in practice and addresses the following central research questions (Cucari et al., 2023; Schiavone et al., 2022):

Research question 1 What are the crucial factors driving the adoption of GenAI in enterprises regarding technology, organisation, and environmental dimensions?

Research question 2 How do the effects of these crucial factors on GenAI adoption differ between small to mid-cap and large enterprises?

Despite the disruptive potential of GenAI for organisational innovation, there is a lack of empirical research exploring how businesses, particularly in Europe, strategically incorporate these technologies into their innovation practices. Agostini et al. (2020) emphasise that the European environment has unique institutional, cultural, and regulatory characteristics that shape digital transformation trajectories but are still underrepresented in current innovation research (Agostini et al., 2020). Ancillai et al. (2023) highlight that, despite the rising integration of digital technologies in business model innovation, empirical evidence surrounding their adoption within organisations remains inconsistent.

This paper reflects Cucari, Schiavone, and Palese's call for more differentiated research on adopting GenAI in organisations of different sizes and governance models. Their work demonstrates how organisational structure, leadership commitment, and regulatory constraints shape adoption strategies. This study empirically examines an intersection using the TOE framework in the DACH region (cf. Ancillai et al., 2023; Cucari et al., 2023; Schiavone et al., 2022).

2 Theoretical background

2.1 Brief overview of GenAI

GenAI is a transformation in AI and differs from traditional AI in its ability to generate new content rather than analyse and respond to existing data (Feuerriegel et al., 2024; Mariani and Dwivedi, 2024). GenAI models are trained on extensive datasets to identify patterns and relationships, enabling them to produce new content similar, not identical, to the training data (Gupta et al., 2024). Unlike traditional AI systems, which primarily focus on classifying or predicting outcomes based on structured data, GenAI generates novel and context-sensitive content, which requires more interpretative, human-in-the-loop interaction and opens new forms of value creation (Saetra, 2023). Applications of GenAI span over various domains like natural language processing, i.e., the coding of language and derivation of a task based on a previously transcribed model [e.g., LLaMA (Meta, 2024) and GPT-4.0 (OpenAI, 2024; Gao et al., 2023)], video and image creation and processing (e.g., Adobe, 2024; Midjourney, 2024), coding (e.g., GitHub, 2024) and audio (e.g., Google, 2024). In addition, GenAI enables multimodal applications, such as recognising objects in photographs and generating contextual responses based on visual inputs.

When strategically implemented within organisations, GenAI can significantly improve operational efficiency, streamline processes, and enhance automation, increasing profitability and growth (cf. Kanbach et al., 2024). OpenAI's ChatGPT exemplifies the rapid adoption of GenAI technologies, becoming the fastest technology to reach 100 million users between 2022 and 2023 (McKinsey, 2023). The evolution of models released is dynamic, as demonstrated by OpenAI's GPT-3.5 and GPT-4. ChatGPT-3.5, launched in March 2023, utilised 175 billion parameters, while GPT-4, released in March 2024, expanded to 1 trillion parameters, providing improved contextual understanding and generating more accurate responses (OpenAI Community, 2022). Despite its rapid adoption, GenAI presents challenges, particularly regarding regulation. The EU AI Act, effective in June 2024, marks a significant step in establishing a legal framework for AI governance in Europe. This paper also considers at a high level the specifics of the EU AI Act and its implications for GenAI adoption, emphasising the importance of incorporating regulatory considerations into future research and practice (European Parliament, 2023).

Given GenAI's transformative potential and associated challenges, it is crucial to understand the factors that influence its adoption within organisations. These productivity gains result from enhanced efficiency and the creation of new demand through personalised customer interactions and innovative solutions (Strategy&, 2024).

2.2 Conceptual foundations of the TOE framework

Developed by Tornatzky and Fleischer (1990), the TOE framework provides a comprehensive explanation for adopting and implementing technology innovations at an enterprise level. It categorises the determinants into three dimensions: technological, organisational, and environmental (Tornatzky and Fleischer, 1990). TOE incorporates similar ideas and approaches to the diffusion of innovation (DOI) model but extends it to include external influencing factors such as regulatory or governmental action and sets it in the context of innovation (Agrawal et al., 2024). Therefore, the TOE model provides more accurate insights and comprehensive predictions. Unlike other models, such as the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT), which focus on individual decision-making processes, TOE examines broader organisational and environmental factors. The application of GenAI, especially in Europe, is still fragmented and requires differentiated contextualisation (Agostini et al., 2020). GenAI differs from traditional IT innovations by enabling creative and knowledge-intensive tasks (Saetra, 2023), often involving high levels of user interaction, data dependency, and ethical uncertainty (Tsamados et al., 2021). These characteristics alter the interpretation and relevance of classic TOE factors such as TC or OR.

Technological factors include complexity, relative advantage, and compatibility (Bryan and Zuva, 2021). In the context of GenAI, perceived complexity includes not only technological aspects such as system integration or training effort but also cognitive and procedural elements such as prompt engineering to validate and concerns about hallucinations or accuracy in the utilisation of various inputs and outputs (Saetra, 2023; Budhwar et al., 2023). Furthermore, the relative advantages of GenAI go further than traditional efficiency gains and include the strategic potential for creativity, innovation acceleration, and new business models (Gupta et al., 2024).

Organisational factors encompass readiness, resources, and structural attributes such as top management support and strategic alignment. These factors include the availability of high-quality data, data governance mechanisms, and employees with the skills to interact effectively with GenAI systems (Budhwar et al., 2023). Environmental factors include external pressures and influences, such as customer demands, regulatory frameworks, and competitive pressures (Rahmani et al., 2024).

In the case of GenAI, the regulatory environment is still evolving. The EUAI Act proposed by the European Union has not yet been fully implemented. It has only been in force since June 2024, leaving companies with significant uncertainties regarding compliance, liability, and ethical obligations (European Parliament, 2023; Tsamados et al., 2021). On the one hand, it can discourage risk-averse companies in regulated industries; on the other hand, it can enable early experimentation for companies with a higher orientation towards innovation or in less regulated sectors (Kanbach et al., 2024).

The TOE Framework has been widely applied across various adaptive innovations in different fields and industries. It has proven to be effective in past research, including information systems (Depietro et al., 1990), e-commerce (Rowe et al., 2012), cloud computing (Lian et al., 2014), impact and adoption of social media use in organisations (Parveen Tajudeen et al., 2017; Salah and Ayyash, 2024), mobile applications (Chiu et al., 2017), adoption of big data analytics (El-Haddadeh et al., 2020; Iranmanesh et al., 2023), online retail utilisation (Nguyen et al., 2022), determinant of blockchain adaption (Hashimy et al., 2023), sustainability integration (Mishra and Pathak, 2024; Rahmani et al., 2024), and machine learning operations (Das and Bala, 2024). Recently, studies have also applied the TOE Model to the AI adoption in different countries and industries (Badghish and Soomro, 2024; Agrawal et al., 2024; Salah and Ayyash, 2024; Al-Khatib, 2023). This study adds to this for the DACH region and provides empirical insights into GenAI adoption by investigating how technological, organisational, and environmental factors influence adoption decisions based on data from 778 corporate respondents.

3 Hypotheses development

3.1 TOE-based hypotheses

This section outlines the hypotheses based on the TOE framework, focusing on the key enablers and constraints that influence the adoption of GenAI. Unlike traditional AI systems, which typically focus on prediction or classification, GenAI technologies generate new content and rely heavily on human interaction, creativity, and contextual interpretation, while also raising new challenges in data governance and regulatory compliance (Saetra, 2023; Tsamados et al., 2021). The aim is to provide a structured understanding of the factors that influence the organisational integration of GenAI technologies.

Technological factors significantly influence an organisation's decision to adopt innovations. This study analyses the factors of relative advantage (TRA) and TC.

Relative advantage (TRA), defined as the degree to which a technology is perceived as better than its predecessors, has consistently impacted adoption decisions positively (Parveen Tajudeen et al., 2017; Gupta et al., 2024). In the context of GenAI, relative advantage manifests itself through improved operational efficiency, enhanced decision-making, and advanced innovation capabilities. Organisations are increasingly attracted to GenAI because it can automate knowledge work, support creativity, and personalise interactions (Gupta et al., 2024).

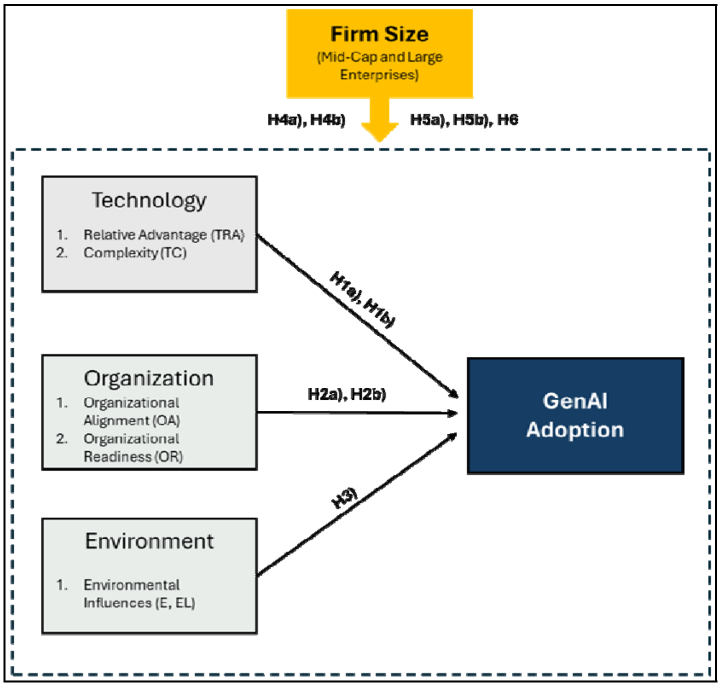
As Parveen Tajudeen et al. (2017) highlighted, organisations are more inclined to adopt technologies that offer clear performance improvements and competitive advantages. The following hypothesis is proposed:

H1a TRA positively affects GenAI adoption.

TC refers to the perceived difficulty of understanding and implementing a technology. High complexity has been identified as a significant barrier to adoption, particularly for organisations with limited technological expertise (Iranmanesh et al., 2023). Challenges such as steep learning curves, infrastructural requirements, and high implementation costs can hinder the adoption of GenAI (Rjab et al., 2023). GenAI-specific complexities such as prompt engineering, managing non-deterministic outputs, and ensuring the explainability and quality of generated content further increase perceived complexity (Budhwar et al., 2023).

H1b TC negatively affects GenAI adoption.

Figure 1 Proposed research model (see online version for colours)



Organisational factors encompass companies' internal capabilities, resources, and structural preparedness. These elements influence the firm's capacity to adopt and effectively integrate emerging technologies such as GenAI (Iranmanesh et al., 2023; Parveen Tajudeen et al., 2017; Rjab et al., 2023).

OA for innovation is a collective category encompassing key organisational dimensions relevant to adopting GenAI, especially the ability of leadership to foster responsible experimentation and to embed human-in-the-loop processes that ensure oversight and ethical handling of generative outputs. These include recognising GenAI as an opportunity for enhancing business models, integrating ethical considerations such as human oversight, and ensuring active leadership involvement to drive adoption efforts (Agrawal et al., 2024; Zennouche et al., 2014). This categorisation covers the strategic, ethical, and leadership-related aspects, as support from top management is crucial for the company's willingness to innovate and is commonly discussed in the literature (Chatzoglou and Chatzoudes, 2016; Parveen Tajudeen et al., 2017; Sharma et al., 2024). It is advisable to consider the different factors on an individual level. Creating this collective category is important to maintain the model's validity and reliability statistically.

Table 1 Content structure and survey items

Category	*Variables*	*Sources*	*Items*	*Question*
Endogenous	AI adoption	Chatterjee et al. (2021), Iranmanesh et al. (2023)	G1	How widespread is the use of generative AI in your department?
			G2	How often do you personally use applications like ChatGPT in your daily work?
			G3	Has your company already implemented or developed applications based on generative AI?
Technology	Technological relative advantage	Gupta et al., (2024), Parveen Tajudeen et al. (2017)	TRA1	How much time savings do you estimate can be achieved in your area of work by using generative AI?
			TRA2	How much has your daily work routine changed due to the use of generative AI applications?
	Technological complexity	Kapoor et al. (2014), Budhwar et al. (2023), Iranmanesh et al. (2023)	TRA3	Have your initial expectations of ChatGPT been met?
			TC1	How satisfied are you with the user-friendliness of ChatGPT?
			TC2	How satisfied are you with the results of ChatGPT?
Organisational	Organisational alignment	Prasad Agrawal (2024), Chatzoglou and Chatzoudes (2016)	OA1	Do you see generative AI applications as an opportunity for your business model?
			OA2	Does your company consider ethical aspects (e.g., human oversight) when planning for generative AI?
			OA3	Does the company's leadership/management actively drive the topic of generative AI forward?
	Organisational readiness	Sharma et al. (2022), Badghish and Soomro (2024); Iranmanesh et al. (2023)	OR1	How widespread is the use of generative AI in your company?
			OR2	Have employees in your company been trained in the use of generative AI applications?
			OR3	How well is your company prepared for generative AI?
Environmental	Environmental influence	Al-Khatib (2023), Kanbach et al. (2024), Hilb (2020)	E1	How well is your industry prepared for generative AI?
			EL1	Do you believe the EU Artificial Intelligence Act will strengthen or weaken Europe as a location for AI?
			EL2	Are you familiar with the contents of the EU Artificial Intelligence Act?

H2a OA for innovation positively affects GenAI adoption.

In contrast, OR refers to an organisation's internal capacity to adopt and integrate technological innovations. This encompasses tangible and intangible resources, such as structures, processes, and human capital, that enable the organisation to implement new technologies effectively (Badghish and Soomro, 2024; Parveen Tajudeen et al., 2017; Sharma et al., 2024). Unlike OA, which emphasises strategic alignment and leadership, OR focuses on the operational preparedness of an organisation. Key dimensions include the quality of human resources, the availability of technical infrastructure, and the organisation's adaptability to change of innovation (Badghish and Soomro, 2024; Parveen Tajudeen et al., 2017; Sharma et al., 2024). Research consistently demonstrates that high readiness levels enhance the adoption and integration of new technologies, making it a foundational enabler for GenAI adoption (Sharma et al., 2024).

H2b OR positively affects GenAI adoption.

Environmental factors (E/EL) refer to external pressures, such as market demands, regulatory frameworks, and customer expectations, influencing technology adoption (Bag et al., 2023; Al-Khatib, 2023). E items refer to general environmental influences, while EL items refer to environmental legal influences. In the context of GenAI, customer pressure drives innovation, while regulations like the EU AI Act shape adoption strategies by reducing uncertainty and fostering competitiveness in Europe (Kanbach et al., 2024). This study highlights the external influences on GenAI adoption by assessing industry preparedness and regulatory awareness. This paper addresses the EU AI Act as an influencing factor, as it defines a clear foundation for using GenAI in Europe and classifies different applications of AI in a risk matrix (European Parliament, 2023).

H3 Environmental influences positively affect GenAI adoption.

The selected variables, TRA, TC, OA, OR, and environmental factors are regarded as core determinants of analysing the GenAI adoption based on prior research (Iranmanesh et al., 2023; Agrawal et al., 2024; Al-Khatib, 2023).

3.2 Firm size as a moderator

Firm size is a critical organisational characteristic that influences innovation adoption and presents companies with different challenges. While large companies may have the technological, legal, and human resources to formalise the introduction of GenAI, smaller companies can benefit from flatter hierarchies and greater agility, allowing them to experiment more freely despite limited resources (Chatzoglou and Chatzoudes, 2016; Gupta et al., 2024). Prior research shows mixed findings on the role of firm size, with its impact varying based on technology type and organisational context (Badghish and Soomro, 2024). This study analyses firm size as a moderator, comparing firms with fewer than 2,000 employees (small and mid-cap enterprises) to those with 2,000 or more (large enterprises). This classification aligns with organisational behaviour research, which indicates that organisations exceeding 2,000 employees tend to exhibit more mechanistic structures characterised by increased formalisation and complexity (Ivancevich et al., 1990). The focus is on whether firm size affects the strength of key factors, such as TRA, TC, OA, OR, and Environmental Influences on GenAI adoption. As a result, the following moderation hypotheses were developed:

H4a The association between TRA and GenAI adoption will be stronger and more significant in large enterprises than in small and mid-cap enterprises.

H4b The association between TC and GenAI adoption will be stronger and more significant in large enterprises than in small and mid-cap enterprises.

H5a The strength of the association between OA and GenAI adoption will be more substantial and more significant in large enterprises compared to small and mid-cap enterprises.

H5b The association between OR and GenAI adoption will be stronger and more significant in large enterprises compared to small and mid-cap enterprises.

H6 The association between environmental factors (E) and GenAI adoption will be stronger and more significant in large enterprises than in small and mid-cap enterprises.

This hypothesis H6 builds on the idea that GenAI adoption is influenced not only by internal capacities but also by external conditions, such as regulatory uncertainty and ethical concerns, which may be perceived and handled differently depending on firm size (Singh et al., 2024; Al-Khatib, 2023).

4 Methodology

A quantitative approach using a structured questionnaire was employed to validate the conceptual model and analyse the relationships. Previous constructs based on the TOE framework guided the selection of questionnaire items, thereby forming the empirical foundation for the quantitative analysis.

The quantitative analysis used partial least squares structural equation modelling (PLS-SEM). This approach is particularly suitable for predictive modelling and analysing complex models such as the one applied in this study. PLS-SEM prioritises the maximisation of explained variance (R^2) and evaluates the relationships between latent variables. The statistical analysis was carried out using IBM SPSS AMOS software, which facilitated a comprehensive evaluation of both the measurement and structural models and the examination of the hypothesised relationships (IBM, 2024). PLS-SEM is widely recognised for its robustness in handling reflective constructs and smaller sample sizes. It provides reliable insights even in cases where covariance-based SEM (CB-SEM) might encounter limitations (Hair et al., 2019).

The analysis followed two stages. In the first stage, the quality, validity, and reliability of the measurement model were evaluated through internal consistency using Cronbach's alpha and CR, convergent validity was assessed via average variance extracted (AVE), and discriminant validity employed by the Fornell-Larcker criterion (Hair et al., 2019). In the second stage, the structural model was analysed to test the specified hypotheses by examining path coefficients (β), their significance levels (P-values), and the explained variance (R^2) of the dependent variables (Stoffels et al., 2023).

This two-stage approach facilitates a comprehensive model evaluation, enhancing its predictive capabilities and yielding valuable insights into the factors driving GenAI adoption.

4.1 Data collection and measures

We collected a diverse sample of 778 respondents from DACH region corporate organisations, including managers and employees. For a PLS-SEM, at least 200–300 data points are required, which is more than achieved (Hair et al., 2019). The data collection was conducted between January 2022 and April 2023. One-third of the data originates from a company survey conducted by an IT consulting company based in the DACH region to investigate executives' perceptions of GenAI. To improve the robustness and generalisability of the results, the remaining two-thirds consist of stratified panel data obtained from a professional market research company, the German institute HEUTE UND MORGEN GmbH. The questionnaire has thirteen industry clusters, which are divided into three sections: The first section comprises personal and firm-related information and introductory questions.

In contrast, the second section comprises questions about opinion and attitude to GenAI. The third section encloses questions about company-related questions in the context of GenAI. As the questionnaire was initially designed for a company study, not all questions are relevant and valuable for this paper and therefore not all 35 questions included in the analysis. For this study, 25 questions plus demographical and structural questions out of the questionnaire were identified as relevant for this paper and considered in the data analysis, whereby 16 are based on a Likert scale ranging from 'strongly disagree' (1) to 'strongly agree' (5), six questions are yes, or no questions and three questions are overarching categorial questions. A five-point Likert scale was chosen to maintain consistency with the original corporate survey format. While seven-point scales are often preferred in academic settings, five-point formats are widely accepted in applied management research and offer sufficient variance for robust statistical analysis in PLS-SEM (Hair et al., 2019). Due to the duplication of content and high multi-collinearity of the structural equation model, the initial 25 questions included in the model were reduced to 17 questions plus demographics and statistics. Survey participation was voluntary and initiated via email invitation, with informed consent obtained beforehand. Depending on the question, the sample size varies between 154 and 778 fully answered data sets. Mean imputation was used to enable the analysis and to supplement missing values. Missing values were replaced by the arithmetic mean of the respective variable (Little and Rubin, 1983).

The sample demographics highlight a diverse respondent pool. Participants came from various industries, with banking/financial services (12%) and manufacturing/industry (11%) being the most common. Most participants were in management roles (80%), with IT (29%) as the dominant business segment. The companies varied, with the largest share (31%) having 501 to 2,000 employees. Geographically, most organisations were headquartered in Germany (69%), followed by Switzerland (17%) and Austria (13%).

Table 2 Overview of participant demographics and organisational attributes

Category	*Classification*	*Frequency*	*Percentage (%)*
Gender	Female	276	36
	Male	498	63
	Diverse	4	1
	All	778	100
Age	Up to 29 years	100	13
	30 to 39 years	219	28
	40 to 49 years	241	31
	50 years and older	218	28
Industry	Banking/financial services	93	12
	Manufacturing/industry	84	11
	Healthcare/health insurance	78	10
	Retail	71	9
	Transport/logistics	50	6
	Telecommunication	50	6
	Public administration	49	6
	Construction and housing	34	4
	Energy industry	34	4
	Insurance	33	4
	Automotive	28	4
	Media and entertainment	17	2
	Food and beverage industry	15	2
	Life sciences	10	1
	Sports	7	1
	Transport companies	6	1
	Trade fair companies	3	0
	Lottery companies	3	0
	Publishing	3	0
	Other	111	14
Function	Executive/management	39	5
	Department head or manager	622	80
	Other employee	117	15
Company size	Up to 250 employees	92	12
	251 to 500 employees	156	20
	501 to 2,000 employees	239	31
	Over 2,001 employees	291	37
Headquarter	Germany	540	69
	Austria	104	13
	Switzerland	122	17

4.2 Data reliability

To ensure the quality and reliability of the measurement model, an extensive analysis of the reliability and validity of the collected data was conducted. Table 3 presents the summarised results of the reliability analysis. The internal consistency of the constructs was assessed using Cronbach's alpha and composite reliability (CR). Both metrics were slightly above the recommended thresholds of 0.7 for Cronbach's alpha and 0.8 for CR, indicating a high level of internal consistency among the items within the constructs. The results show Cronbach's alpha values ranging from 0.72 to 0.83 and CR values between 0.78 and 0.87. Additionally, the standardised loadings of individual items ranged from 0.70 to 0.85, confirming a strong relationship between the indicators and their underlying constructs (Hair et al., 2019).

Table 3 Construct reliability and validity

Variables	*Items*	*Standard loadings*	*Cronbach´s alpha*	*AVE*	*Composite reliability*
AI adoption	G1	0.85	0.81	0.64	0.87
	G2	0.82			
	G3	0.78			
Technological relative advantage	TRA1	0.75	0.79	0.58	0.82
	TRA2	0.78			
	TRA3	0.72			
Technological complexity	TC1	0.72	0.72	0.55	0.78
	TC2	0.70			
Organisational alignment	OA1	0.75	0.76	0.63	0.80
	OA2	0.72			
	OA3	0.70			
Organisational readiness	OR1	0.80	0.83	0.59	0.86
	OR2	0.85			
	OR3	0.77			
Environmental influence	E1	0.72	0.78	0.60	0.81
	EL1	0.78			
	EL2	0.75			

Convergent validity was assessed using the AVE. All constructs had AVE values just above the recommended threshold of 0.5. The AVE values ranged from 0.55 to 0.64, as shown in Table 3. As suggested by Hair et al. (2019), the model is continued despite the minimum acceptable AVE thresholds being missed, as the CR and Cronbach's alpha values are well above the recommended thresholds (Hair et al., 2019). Furthermore, the model fit indices confirm the overall quality of the model. Therefore, a comprehensive evaluation of the model justifies the examination of the structural relationships among the latent variables (Stoffels et al., 2023).

The Fornell-Larcker criterion was applied to assess discriminant validity. This criterion requires that the square root of a construct's AVE be greater than the correlations of that construct with other constructs (Fornell and Larcker, 1981). The results meet this requirement for all constructs, as illustrated in Table 4. For example, the construct of GenAI adoption has an AVE of 0.64, which exceeds its correlations with technological advantage (0.25) and TC (0.30). This confirms the distinctiveness of the constructs and indicates the absence of multi-collinearity (Fornell and Larcker, 1981). The Fornell-Larcker criterion was applied to assess discriminant validity. This criterion requires that the square root of a construct's AVE be greater than the correlations of that construct with other constructs (Fornell and Larcker, 1981). The results meet this requirement for all constructs, as illustrated in Table 4. For example, the construct of GenAI Adoption has an AVE of 0.64, which exceeds its correlations with technological advantage (0.25) and TC (0.30). This confirms the distinctiveness of the constructs and indicates the absence of multi-collinearity (Fornell and Larcker, 1981).

Table 4 Correlation matrix of constructs

	AI adoption	*Technological advantage*	*Technological complexity*	*Organisational readiness*	*Organisational alignment*	*Environment*
AI Adoption	0.64					
Technological advantage	0.25	0.58				
Technological complexity	0.30	0.18	0.55			
Organisational alignment	0.35	0.22	0.19	0.63		
Organisational readiness	0.28	0.26	0.15	0.29	0.59	
Environmental influence	0.22	0.20	0.13	0.24	0.21	0.60

The reliability and validity analyses demonstrate that the constructs employed are robust and that the measured items adequately reflect the underlying latent variables. However, the thresholds for assessing model consistency and convergent validity are marginally exceeded. The results of the discriminant validity analysis indicate that the constructs can be differentiated from other constructs within the model, supporting their use in PLS-SEM empirical distinctiveness. This establishes a solid foundation for the subsequent SEM to test the hypotheses formulated within the research model.

5 Results

The findings from the structural equation modelling (PLS-SEM) analysis provide valuable insights into the relationships among the constructs and the validity of the proposed hypotheses.

5.1 Structural model assessment

Table 5 outlines the structural relationships and hypothesis testing results. TRA ($\beta = 0.28$, $p < 0.001$), OA ($\beta = 0.22$, $p < 0.001$), and OR ($\beta = 0.33$, $p < 0.001$) were found to have significant positive effects on GenAI adoption. Conversely, TC ($\beta = -0.15$, $p = 0.012$)

exhibited a significant negative relationship, indicating that higher complexity might negatively impact the GenAI adoption process. However, environmental factors ($\beta = 0.12$, $p = 0.088$) did not significantly influence the model. The detailed path coefficients, standard deviations, t-values, and p-values support the hypothesised relationships.

Figure 2 Empirical model results (see online version for colours)

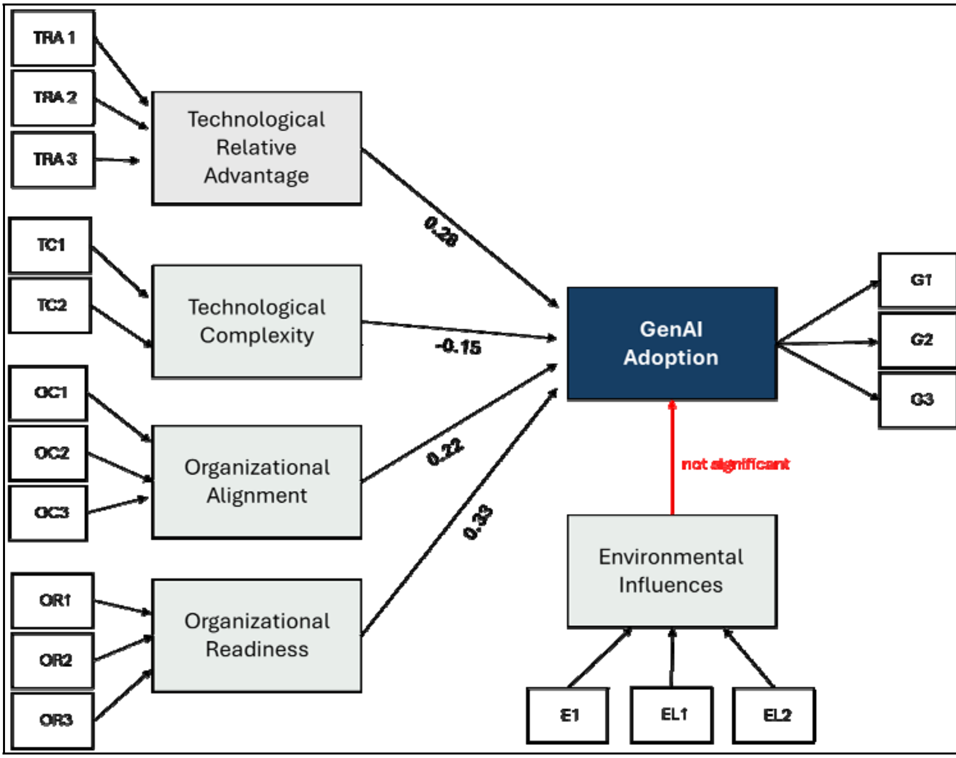


Table 5 Hypothetical relationships and structural model

H. no.	*Relationship*	*Beta (β)*	*STD*	*T-value*	*P-value*	*Findings*
H1a	TRA -> AI adoption	0.28	0.05	5.6	<0.001	Supported
H1b	TC -> AI adoption	–0.15	0.06	–2.5	0.012	Supported
H2a	OA -> AI adoption	0.22	0.05	4.4	<0.001	Supported
H2b	OR -> AI adoption	0.33	0.04	8.25	<0.001	Supported
H3	E-> AI adoption	0.12	0.07	1.71	0.088	Not supported
H4a	TRA -> AI adoption	0.129	-	-	0.615	Not supported
H4b	TC -> AI adoption	0.031	-	-	1.512	Not supported
H5a	OA -> AI adoption	0.025	-	-	1.491	Not supported
H5b	OR -> AI adoption	0.042	-	-	1.495	Not supported
H6	E-> AI adoption	0.024	-	-	1.487	Not supported

To conclude, Hypotheses H1a, H1b, H2a, and H2b are supported, while hypothesis H3) is not supported by the analysis.

5.2 Evaluation of model fit

The calculated fit indices for the PLS-SEM model indicate a strong model fit, with an R^2 of 0.62, indicating that the independent constructs explain 62% of the variance in GenAI adoption. Additionally, a predictive relevance (Q^2) of 0.58 and an SRMR of 0.072 confirm the model's robustness and reliability (Hair et al., 2019).

5.3 Multi-group comparison by company size

A multi-group analysis evaluated whether firm size moderates the relationship between factors such as relative advantage, TC, OR, environmental influences, and GenAI adoption. Therefore, the dataset was divided into two groups based on firm size, distinguishing between companies with fewer than 2,000 employees and firms with 2,000 or more employees. A bootstrapping-based multi-group analysis was employed to assess potential disparities. This technique involves re-sampling the data multiple times to generate empirical distributions of the path coefficient differences between the two groups (Efron and Tibshirani, 1985). Bootstrapping is a robust, nonparametric method widely used for hypothesis testing in multi-group comparisons. The beta difference reflects the variation in the strength of factor influences on GenAI adoption between the two groups. Differences are significant if the bootstrap p-value is below 0.05 (Davison et al., 2003). This method provides a robust framework for assessing group-specific effects without relying on distributional assumptions (Efron and Tibshirani, 1985).

The results of the multi-group analysis, presented in Table 5 as well, indicate no statistically significant differences in the impact of the analysed factors on GenAI adoption between small and medium-sized enterprises. The beta differences across all paths were minimal, ranging from 0.024 to 0.129, and the bootstrap p-values for all hypotheses exceeded the significance threshold of 0.05. The minor beta differences and non-significant p-values indicate that firm size does not substantially influence the analysed relationships.

6 Discussion

6.1 Discussion on theoretical implications

The findings of structural equation modelling (PLS-SEM) provide valuable insights into the factors influencing the adoption of GenAI in organisations across the DACH region. Among the technological factors, TRA exhibited a significant positive effect on GenAI adoption ($\beta = 0.28$, $p < 0.001$). This medium-strong effect indicates that companies perceive GenAI as a technology that offers significant advantages and is, therefore, worth adapting within the organisation. This aligns with previous studies suggesting that organisations prioritise technologies that offer clear performance improvements and competitive advantages (Agrawal et al., 2024; Al-Khatib, 2023).

Conversely, TC negatively affects GenAI adoption ($\beta = -0.15$, $p = 0.012$). Although the effect size is smaller than TRA, it is statistically significant. This finding reflects the challenges associated with implementing complex technologies, including GenAI, such as steep learning curves and infrastructural requirements that discourage organisations with limited technical knowledge from adopting them (Kanbach et al., 2024). When comparing TRA value directly with TC value, it can be inferred that the relative advantages of the technology outweigh the technological complexities.

Additionally, the results are consistent with the literature examining innovation adoption, which states that high complexity is a significant barrier to the adoption of GenAI (Al-Khatib, 2023). The data from this study suggests that the perceived technical complexity of GenAI in the DACH region has a stronger negative impact compared to other studies conducted in other regions (Al-Khatib, 2023; Agrawal et al., 2024).

Within the organisational factors, OR demonstrated the most substantial positive effect on GenAI adoption ($\beta = 0.33$, $p < 0.001$). This result underscores the critical role of internal capacity, including tangible and intangible resources, in facilitating GenAI adoption. Based on the PLS-Sem, however, it can be said, compared to previous studies, that this factor has a more substantial positive influence on adoption in the Dach region than is the case in other regions (Al-Khatib, 2023; Agrawal et al., 2024).

OA for innovation ($\beta = 0.22$, $p < 0.001$), as a collective category, has a significant impact on GenAI adoption. While the effect size is slightly smaller than that of OR, it reflects the importance of strategic alignment, leadership support, and a culture that promotes innovation. This result also underlines the growing need for leadership responsibility in introducing GenAI. As Schiavone et al. (2022) and Hilb (2020) emphasise, top management and executive boards play a crucial role in ensuring responsible and strategic integration of GenAI technologies. Leadership must balance innovation and ethical governance, especially given generative systems' uncertainty and creative autonomy. Both OA and OR have a significant impact on GenAI adoption. The stronger effect of OR suggests that in the early stages of GenAI integration, operational capabilities such as data infrastructure, employee skills, and process flexibility are more critical than strategic leadership alone. This finding emphasises an important theoretical implication. Besides top management support as the primary driver, the adoption of GenAI depends more on the organisation's ability to implement it. Future research could investigate whether this pattern holds for all maturity levels or changes as adoption progresses (Sharma et al., 2024; Budhwar et al., 2023).

Interestingly, environmental Factors (E), including competitive pressure and regulatory influences as a collective category, did not significantly impact GenAI adoption ($\beta = 0.12$, $p = 0.088$). This underlines the need to explore further how legal and regulatory measures impact technological adoption over time. The study of Agrawal et al. (2024) analysed environmental factors based on various individual factors. It confirmed that competitive pressure, for example, is not a relevant influencing factor, which can also be derived from this study (Agrawal et al., 2024). Minguez et al. (2024) conducted a study on a qualitative basis. However, the key finding is that the adoption of GenAI, especially in the European market, is primarily driven by the desire to obtain competitive advantages, which contradicts the results of this study (Minguez et al., 2024). Therefore, it can be stated that a quantitative perception differs from a qualitative perspective. Based on this study, the legal framework conditions also have no significant influence on the overall construct of environmental factors based on this data analysis.

Regarding the *first research question*, *what are the crucial factors driving the adoption of GenAI in enterprises regarding technology, organisation, and environmental dimensions?*, the findings confirm the critical roles of TRA, TC, OR, and OA. Among these, TRA emerges as a significant driver, underscoring the importance of perceived operational efficiency and competitive advantages offered by GenAI solutions. Simultaneously, TC demonstrates a negative effect, highlighting the adoption challenges due to steep learning curves and infrastructural demands. Organisational factors, particularly OR and OA, emerge as pivotal enablers, reflecting the need for robust internal capacities and leadership alignment. These results emphasise the interdependence of technological and organisational preparedness in driving successful GenAI adoption.

Answering the *second research question*, *how do the effects of these crucial factors on GenAI adoption differ between small to mid-cap and large enterprises*, the results of the study are somewhat limited due to the simple comparison between small (<2,000 employees) and mid-cap companies and large companies (>2,000 employees). The results state no significant differences between the two clusters in the GenAI adoption coverage and indicate that firm size may not influence GenAI adoption as strongly as previously assumed. One important resolution is that regardless of the organisation's size, companies face similar challenges and opportunities when implementing GenAI solutions. This indicates that the sufficient prerequisites, such as a good and structured database, technical data architecture expertise in the organisation, support from top management and the willingness to change, i.e., the degree of maturity for GenAI implementations, are presumably more relevant than the size of the company itself. This contrasts with established assumptions in innovation literature but may still be correct in the causal context and emphasises the need for more differentiated studies across different industries and maturity levels (cf. Badghish and Soomro, 2024).

The findings contribute to the growing body of knowledge on adopting emerging technologies and offer practical implications for organisations aiming to leverage GenAI and confirm the applicability of the TOE framework for analysing innovative technologies. While numerous studies have applied TOE to examine the adoption of technologies like big data, blockchain technology, or e-business adoption, this current research is one of the leading in identifying and measuring factors for adopting GenAI (Bag et al., 2022; El-Haddadeh et al., 2020; Chatzoglou and Chatzoudes, 2016). The study highlights that GenAI, unlike other analysed digital innovations, requires not only technological capabilities but also significant OR, particularly in terms of data management and employee competence. Furthermore, the weak impact of environmental pressures challenges established assumptions from previous innovation literature and emphasises the need for differentiated adoption models in regulated European contexts. These findings extend the theoretical relevance of the TOE by demonstrating its application to an emerging, creative and uncertain class of technologies, focusing on the highly regulated and technologically conservative environments such as the DACH region. By focusing on reducing complexity, aligning organisational strategies, and enhancing readiness, firms can better position themselves to harness the transformative potential of GenAI. It underscores the need for tailored approaches to address organisational and technological complexities; comprehensive research in this area is still developing.

6.2 Managerial implications

The findings provide actionable insights for managers seeking to integrate GenAI into their organisations. The adoption of GenAI, as noted in the introduction, can deliver a competitive advantage by streamlining operations and unlocking new value-creation opportunities, making it a strategic imperative in today's market.

OR emerged as the strongest enabler for GenAI adoption, underscoring the need for investments in technical infrastructure, human resources, and adaptability. Managers should prioritise building internal capacity and fostering an innovation-friendly culture to support successful GenAI implementation. It is crucial to involve employees in technological development through targeted change management. This can be achieved by investing in training programs to upskill employees, adjusting recruitment priorities to attract talent with GenAI expertise, and establishing exchange and learning formats, such as workshops, hackathons, or knowledge-sharing sessions, to encourage collaboration and continuous learning (Budhwar et al., 2023). To support the organisational adoption of GenAI, the hub-and-spoke model, as one example, offers a valuable framework by centralising strategic integration of technology in a central hub while enabling decentralised units (spokes) to implement tailored applications. This approach fosters efficient knowledge sharing and alignment with organisational goals, enhancing scalability and adaptability (Finnie et al., 2024). The focus should also be on the operational and technical readiness for using GenAI solutions and integrating organisations. The essential prerequisites for the use of GenAI applications, such as having a data and AI strategy, making data available in a structured manner, providing a cloud infrastructure for the operation of the AI applications in many cases, and enabling technical units that can maintain GenAI solutions, should be ensured.

Conversely, the negative effect of TC highlights the importance of simplifying the adoption process. Managers should mitigate perceived complexity by ensuring robust support systems, clear implementation roadmaps, and partnerships with technology providers that offer user-friendly solutions. However, the high level of GenAI usage and studies emphasising the simplicity of using GenAI for generating content suggest that its inherent complexity may not be the primary challenge, but rather, the difficulty of applying fitting solutions to complex use cases and structures as well as a not entirely rational perception of the use of GenAI, which is relatively easy for end users to operate through prompting (McKinsey, 2023). These hurdles can be easily overcome with targeted awareness raising, change management, and a willingness to change from top management to the entire organisation.

Furthermore, this study suggests that external regulatory frameworks such as the EU AI Act provide important guidance. However, their practical influence on GenAI adoption decisions may be limited. Although regulatory frameworks such as the EU AI Act aim to provide clear guidelines for GenAI adoption, their influence on organisational decisions regarding GenAI adoption may not yet have been fully realised (Kanbach et al., 2024). This may be due to the relatively low level of maturity of GenAI adoption in the DACH region, with companies currently mainly using a few lighthouse use cases and not yet rolling out the technology across the board.

Beyond adoption, organisations must address ethical challenges such as bias, data privacy, and potential misuse in GenAI models. Establishing transparent AI auditing practices and aligning them with regulatory frameworks like the EU AI Act is critical for mitigating risks. Organisations can reduce risks by implementing policies to prevent bias, safeguard intellectual property, protect user data, build stakeholder trust, and ensure sustainable integration of GenAI technologies.

By addressing these practical considerations, organisations can better position themselves to harness the transformative potential of GenAI, aligning technological advancements with strategic goals and operational needs. These insights are particularly relevant for managers in the DACH region, offering a foundation for informed decision-making in the evolving landscape of GenAI-driven innovation. GenAI represents not just a tool but a critical competitive factor. It should be seen as a part of a forward-looking business strategy, implemented through dimensions such as OR, effective communication, and alignment with external influences. Moreover, organisations that lag in GenAI adoption risk losing top talent to more technologically advanced competitors and losing their competitive edge. Therefore, embracing GenAI is a strategic imperative for operational efficiency and a critical factor in attracting and retaining skilled professionals in today's competitive market.

6.3 Limitations and future research

This study faces several limitations. First, the data exclusively focuses on organisations in the DACH region (Germany, Austria, and Switzerland), limiting the generalisability of the findings to other cultural, regulatory, and market contexts of Europe. Expanding the geographic scope in future studies could offer a more diverse and global perspective on GenAI adoption (Gupta et al., 2024; Mariani and Dwivedi, 2024; Al-Khatib, 2023).

Second, the company size categories used in this study were unevenly distributed, with most data points falling within small to mid-sized enterprises. This limited the ability to draw robust conclusions about differences between small, medium, and large firms. Previous literature has identified a significant difference in factors influencing GenAI adoption between small and medium enterprises. Future research should elaborate on this for GenAI adoption, especially between small, medium, and large enterprises (Badghish and Soomro, 2024).

While the TOE framework provided a solid structure for the analysis, certain influential variables such as top management support, sustainable human capital, and government support were not included due to the limitations of the survey design. Understanding the impact of GenAI adoption on business performance requires deeper exploration and precise measurement. Ethical considerations, including the risks of misuse, bias, and implications for intellectual property, represent another critical area for investigation. Another promising research avenue is understanding the velocity of GenAI adoption and the factors that accelerate or hinder this process. Industry-specific adoption rates and the role of regulatory frameworks, such as the EU AI Act, should be explored further.

The data validity was found to be borderline acceptable, emphasising the need for further validation through alternative models and broader datasets to ensure robustness and reliability.

These limitations create future research opportunities, underscoring the necessity for further investigation. This paper lays a perfect foundation for understanding the adoption of GenAI in the DACH region. It offers initial insights that subsequent studies can leverage to enhance knowledge and broaden the analytical framework within this evolving sector.

Declarations

All authors declare that they have no conflicts of interest.

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