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Enhancing Generative AI Usage for Employees: Key Drivers and Barriers

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Abstract

This study examines the use of AI tools within work environments, particularly Generative AI (Gen-AI). Its objective is to comprehend the factors affecting employees' adoption and utilization of such tools. The research applies the Technology, Organization, and Environment (TOE) framework to pinpoint potential factors and formulate hypotheses regarding their influence on employees' Gen-AI usage frequency. A quantitative research approach was conducted among a sample of 316 American employees. Results suggest that employees' perceived Gen-AI intelligence and warmth positively impact their usage through the mediation of performance expectancy. Effort expectancy only mediates the relationship between perceived Gen-AI intelligence and Gen-AI employee usage. Findings also show that the perceived severity of Gen-AI has a negative influence on employees' usage and that an organization's absorptive capacity of Gen-AI does not influence employees' usage. Critical drivers for Gen-AI utilization encompass technological proficiency, peer influence, and regulatory backing. These outcomes underscore the significance of nurturing a corporate culture that encourages innovation and adherence to regulations to successfully integrate Gen-AI in workplaces.

Keywords: Generative Artificial Intelligence (Gen-AI), AI use, Technology acceptance, Organiza-tional adoption, TOE Framework.

Introduction

The adoption and integration of artificial intelligence (AI) tools in the workplace have gained significant attention in recent years. According to IBM Global AI Adoption Index (2023), over the past four years, the adoption of artificial intelligence (AI) by enterprises has remained relatively consistent, with 42% of information technology (IT) professionals indicating that they have deployed AI, and an additional 40% reporting that they are actively exploring its potential. McKinsey's annual Global Survey has identified 2023 as Gen-AI's breakout year. Gen-AI, a subset of AI, encompasses machine learning solutions trained on large datasets to generate new data such as images, sound, and text based on user prompts. North America, held the largest AI market share in 2023 with 36.90%, highlighting significant engagement with AI technologies (Precedence Research, 2023).

As organizations become more data-centric, integrating Gen-AI into work processes is increasingly significant (Akter et al., 2023). Despite its recent public availability, experimentation with Gen-AI tools is already common, with many respondents expecting these new capabilities to transform their industries. McKinsey's Global Survey (2023) shows a rapid increase in Gen-AI tool usage in businesses. The deployment of Gen-AI increased significantly, with 65% of respondents indicating that their organizations use it on a regular basis, representing nearly double the percentage observed in the previous year. This surge in AI usage has elevated it from a niche technology to a top executive priority, with about a quarter of suite leaders personally using Gen-AI tools for work and over a quarter of AI-using companies making Gen-AI a board-level priority. Furthermore, 40% of respondents anticipate increased AI investment due to advances in Gen-AI.

The potential business disruption due to Gen-AI is substantial, with respondents expecting significant changes to their workforces. The widespread interest in ChatGPT, since November 2022 has the potential to reshape workplaces (Bloom et al., 2023). Reuter reports that over 100 million people used these tools within two months of their release, making it the fastest-growing consumer software application in history.

By August 2023, worldwide unique visitors reached 180.5 million. While existing literature extensively explores technology adoption, it falls short regarding AI tools, particularly Gen-AI tools. In today's dynamic business landscape, organizations must adapt to technological and environmental challenges, necessitating thorough integration of Gen-AI to harness its benefits. Employee engagement with AI tools is crucial for organizational adoption. Despite rapid research growth due to Gen-AI's impact, the dynamics and drivers of AI adoption and use by employees remain relatively unexplored. This study aims to investigate factors influencing employees' acceptance and use of Gen-AI tools. Using the Technology, Organization, and Environment (TOE) framework, several elements emerge as major factors explaining Gen-AI usage intention.

This paper is organized as follows: The Literature Review section discusses the theoretical underpinnings guiding our research. The Methodology section describes the quantitative research design, data collection from 316 American employees, and statistical methods for hypothesis testing. The Results section summarizes our empirical findings. In the Discussion section, we interpret these findings and connect them to the broader literature on technology adoption and organizational behavior. The paper concludes with limitations and directions for future research.

Literature Review

Numerous theories explain innovation acceptance and adoption. The Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1975) suggests that behavioral intentions depend on attitude and subjective norms. The Theory of Planned Behavior (TPB) (Ajzen, 1991), an extension of TRA, adds the individual's perceived control over their behavior to explain behavioral intentions. Based on TRA, the Technology Acceptance Model (TAM) (Davis, 1989) asserts that behavioral intentions to use a system are determined by perceived ease of use, usefulness, and subjective norms. Building on these, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which contends that behavioral intentions toward technology are influenced by four moderators (age, gender, experience, and voluntariness of use) and four variables: performance expectancy, effort expectancy, facilitating conditions, and social influence. Efforts have extended models like TAM from an individual to an organizational context. However, most research in organizational technology adoption draws from the Innovation Diffusion Theory (IDT) by Rogers (1983) and the Technology-Organization-Environment (TOE) framework by Tornatzky and Fleischer (1990). Rogers (1962) developed IDT, describing how innovations spread within a social system, emphasizing characteristics like relative advantage, complexity, compatibility, trialability, and observability. Critiques argue that IDT lacks precision for specific information technology innovations (Chau & Tam, 1997).

Research on artificial intelligence acceptance and usage is still emerging. Researchers call for integrating various predictors to understand AI specifics. Recent studies examine the TOE model's appropriateness in assessing technological, organizational, and environmental factors impacting AI integration in corporate settings (Kinkel et al., 2022; Agrawal et al., 2022; Ameye et al., 2023). The TOE framework explores how technology, organization, and environment influence the adoption and implementation of technological innovations.

Based on the TOE framework and a literature review of potential dynamics and drivers of Gen-AI adoption and use by employees, we propose studying the impact of perceived competence, perceived severity, technological resource proficiency, absorptive capacity, peer influence, and regulatory support.

Technology characteristics

According to the TOE model, the technological dimensions refer to the technologies relevant to business operations (Jo & Bang, 2023). The integration of these technological dimensions in various research studies has mainly depended on the context in which the TOE model is used. Some studies have linked this technological aspect to the ease of use of the technology (Jo & Bang, 2023), its usefulness and perceived benefits (Olivera & Martins, 2011), its availability (Zhu et al., 2006), or its ability to provide help and solutions to its users (Hu et al., 2019) without forgetting the risks of the technology associated with technical issues (Teo et al., 2008) or with the perceived negative consequences of its use (Cao et al., 2021). Based on the various works on AI derived from the TOE model, we consider three sub-dimensions of the technological dimension: the employees' perceived competence and warmth of the technology (gen-AI in our context) (Belanche et al., 2021; Ha et al., 2022) conceptualizing the positive technological aspects of Gen-AI and the perceived severity linked to the negative technological aspect of Gen-AI (Cao et al, 2021).

Usage Intensity as the dependent variable

According to Ellison et al. (2007), the assessment of technology use refers to the intensity with which individuals use AI technology, which depends on three dimensions: (1) the active involvement of individuals in its use (2) the emotional connection they can establish with this technology and (3) the extent to which the technology is integrated into their daily activities. The latter, the third dimension of intensity of usage, can refer to the notion of continuity of use by individuals and the notion of re-use, associated with loyalty (Sirohi et al., 1998).

Relationship inputs: perceived competence & perceived warmth

Within the framework of social cognitive dimensions (Fiske et al. 2007), the notions of perceived competence and perceived warmth are the central perceptions in individual evaluation formation (Cuddy et al., 2008; Judd et al., 2005; Güntürkün et al., 2020).

According to (Fiske et al., 2007), perceived competence refers to the ability of individuals to perceive, assess, and judge others' competence through their ability to perform a task, their skills, intelligence, creativity, and efficiency. Perceived warmth is also a perception, evaluation, and judgment of the intentions of others to be benevolent, to foster and maintain good social relationships, and to look after social well-being. The scope of these concepts has been extended to the context of AI (Gilad et al., 2021 Güntürkün et al., 2020) and underpins the Humanness-Value-Loyalty (HVL) model developed by Belanche et al. (2021) in the context of AI, in particular in Gen-AI by considering robot technology. Drawing on the authors' approach, to perceive and assess a Gen-AI, an individual needs to (i) perceive how human the Gen-AI in question is (the human dimension), (ii) perceive value (the value dimension) and (iii) develop a kind of loyalty (the loyalty dimension) towards this Gen-AI. The main difference between the conception (the two universal perceptions) of Fiske et al. (2007) and that of Belanche et al. (2021) lies in the humanness dimension. Belanche et al. (2021) argue that beyond the perceived competence and warmth of AI, individuals need to perceive the resemblance and closeness of Gen-AI to humanness, which is called human likeness. This aligns with the concept of AI anthropomorphism, which consists of attributing human reactions to AI (Ha et al., 2022). Perceived competence and warmth in the HVL model are two of the three sub-dimensions (perceived competence, perceived warmth, and perceived human-likeness) of the humanness dimension, considered as the inputs of the model which posits that a positive perception of the humanity of the Gen-AI infers a greater perceived value of the Gen-AI, which determines a favorable intention to use (Liu et al., 2022) and reuse it and therefore loyalty towards it (Belanche et al., 2021).

Performance & effort expectancies as underlying mechanisms

Based on the TAM model, performance expectancy and effort expectancy are two determinants of intention to use a specific technology according to the UTAUT model of Venkatesh et al (2003). According to the authors, performance expectancy relates to the cognitive dimension of the attitude that individuals develop towards the use of technology and is defined as "the degree to which an individual believes that using the system will help him or her to achieve gains in job performance", whereas effort expectancy is defined as "the degree of ease associated with the use of the system", inspired by the concept of ease of use of technology. Sari et al. (2024) proposed a categorization based on the concept of perceived value: performance expectancy corresponds to perceived benefits (Sari et al., 2024) and effort expectancy to perceived cost since the latter refers to the perceived effort of user anticipated for the use of technology. Studies using the UTAUT model have shown that performance expectancy and effort expectancy play a significant role in behavioral intention, whether in the use of technology (Idayani et al., 2024; Li et al., 2023; Sari et al., 2024; Venkatesh et al., 2003) or in other practices (Gonzalez-Tamayo et al., 2024; Kim & Hall, 2020).

In the application and use of the UTAUT model, some works have directly applied the original model with all its variables (Idayani et al., 2024), while others have been inspired by the original model to test other relationships (Ben Arfi et al., 2021a; 2021b). However, few works have incorporated antecedents to performance expectancy and effort expectancy and explored their role as underlying mechanisms in a model where the dependent variable is intentions to use technology. Only Turan et al. (2015), in the context of AI and not in the Gen-AI context, have proposed an untested conceptual model that incorporates antecedents to performance expectancy and effort expectancy: personal innovativeness and user involvement.

To summarize, we highlighted that the direct effect of perceived competence, as well as perceived warmth and intention to use Gen-AI, has been demonstrated in the literature (Belanche et al., 2021; Liu et al., 2022; Moussawi et al., 2021). To our knowledge, we also noted that the determinants of behavioral intention, especially performance and effort expectancy, have never been tested as mediating variables in models developed for Gen-AI. It would, therefore, be relevant to explore these different mediating relationships while considering the intensity of use, our dependent variable. Along these lines, we put forward our initial hypotheses:

H1: The employee's performance expectancy from GEN-AI mediates the influences of the GEN-AI perceived competence on its Usage Intensity.

H2: The employee's performance expectancy from GEN-AI mediates the influences of the GEN-AI perceived warmth on its Usage Intensity.

H3: The employee's effort expectancy from GEN-AI mediates the influences of the GEN-AI perceived competence on its Usage Intensity.

H4: The employee's effort expectancy from GEN-AI mediates the influences of the GEN-AI perceived competence on its Usage Intensity.

Perceived severity

Several theories have been used in the literature to conceptualize individuals' perceived severity. To this end and in different contexts such as mental health (Lahlouh et al.,2023), professional sanctions (Hoolinger & Clark, 1983), or technology (Cao et al., 2021), research works have drawn on several theories to argue and discuss this concept (Liang & Xue, 2009; Omar et al., 2021; Salancik & Pfeffer, 1978; Schwesig et al., 2023; Zhao et al., 2023).

The Social Information Theory, SI, developed by Salancik and Pfeffer (1978) and mainly considered in this part, explains how individuals develop attitudes and make decisions in their workplace - considered as their social environment - based on the information they receive from this environment. The use of new technologies such as Gen-AI within companies is one of the 'new information' tools to which workers of different companies are exposed (Sharma et al., 2020). They then proceed to interpret it, inferring a positive or negative perception of it and thus forming a favorable or unfavorable attitude towards using AI (Dwivedi et al., 2017). Perceived severity is defined as an individual's belief regarding the degree of the negative consequences of using AI to make bad decisions (Cao et al., 2021). One of the considerations of this research is the relationship between negative perception and intention to use new Gen-technologies. In this context, negative perceptions of the use of AI have been associated with perceived risks and threats (Cao et al., 2021; Chen & Zahedi, 2016; Liang & Xue, 2010, 2009), generally concerning perceived severity in the use of AI (Cao et al., 2021; Liang & Xue, 2009). On the one hand, perceived severity has been shown to negatively influence individuals' behavioral intentions (Omar et al., 2021) in general and the intention to use technologies within companies, especially in the context of AI (Schwesig et al., 2023).

To our knowledge, this relationship has not yet been studied for Gen-AI, and the behavioral intentions linked to the intensity of use, as defined by Ellison et al. (2007), have not yet been studied either. On the other hand, Cao et al (2021) have shown that the intention to use AI does not depend significantly on the perceived threat resulting from the perceived severity of using AI. It is nevertheless important to specify that the direct or indirect relationship (the underlying effect of perceived threat) between perceived severity and the intention to use AI did not arouse these authors' interest: these two effects were not tested in the context of their work. Based on the two observations above, it, therefore, makes sense to explore the relationship between the perceived severity and the behavioral intentions, particularly in terms of intensity of usage in the context of Gen-AI, hence our second hypothesis assumes that:

H5: The perceived severity of GEN-AI has a negative influence on employees' usage intensity.

Organizational factors

The widespread adoption of AI in companies is currently prevalent in research and practice, indicating the potential of AI. However, only a few studies have dealt with the organizational aspects of AI adoption (Pumplun, 2019).Different organizational factors can explain why some businesses are better able to adopt technology than others. Many AI studies have focused on the advances made in its various technologies, such as machine learning, deep learning, natural language processing, etc. However, little research has focused on the impact of these technologies on organizational performance (Albelaihi & Khan, 2020), and even less on analyzing the organization's readiness to integrate and support AI projects (Pumplun et al., 2019).

Technological resource proficiency

Technological resource proficiency, often referred to as technological readiness, plays a crucial role in the adoption of Gen-AI in organizations. This concept encompasses various elements such as IT infrastructure, IT capabilities (Agrawal, 2024), and the overall ability of an organization to embrace and utilize new technologies. Technological readiness at the company level implies that the company possesses the ability to embrace and use new technological assets (Parasuraman, 2000). From an IS perspective, readiness (e-readiness or technological readiness) refers to the organizational (or individual) ability/capability to adopt and benefit from technological innovation (Richey et al., 2007; Parasuraman, 2000), thereby gaining a competitive advantage in the market (Issa et al., 2022).

The adoption of Gen-AI requires a solid IT infrastructure. This includes hardware and software capable of handling the computational demands of AI technologies like machine learning, deep learning, and natural language processing. Organizations with advanced IT infrastructure are better positioned to implement Gen-AI tools effectively. Proficiency in using advanced technologies, such as AI and its subsets, is crucial. Organizations with a workforce skilled in these areas are more likely to adopt and integrate Gen-AI tools into their operations successfully. This includes having employees who are knowledgeable in data science, AI programming, and developing algorithms. Technological readiness also implies an organization's adaptability and openness to new technologies. Technological resource proficiency significantly influences the adoption of Gen-AI within organizations. The existing literature, based on the TOE framework and empirical studies, supports the idea that an organization's ability to adopt and benefit from Gen-AI is heavily influenced by the readiness and sophistication of its IT infrastructure. Thus, we propose the following hypothesis:

H6: The organization's proficiency in technological resources positively influences employees' GEN-AI usage intensity.

Absorptive capacity

First defined as "the ability to value, assimilate and apply new external information to commercial ends," Cohen and Levinthal (1990, p. 128); this capability is critical for innovation and competitive advantage, allowing organizations to effectively leverage external knowledge. The concept of absorptive capacity has been the subject of numerous studies and developments in various contexts and industries (Ramezanian, 2011). The work of Zahra & George (2002) has made it possible to operationalize absorptive capacity in four dimensions (acquisition, assimilation, transformation, and exploitation). Acquisition pertains to the ability of a business to locate and obtain outside knowledge essential to its operations. Assimilation describes the procedures and methods used by the company to receive, process, assess, and comprehend information from outside sources.

Transformation means the organization’s ability to innovate and improve processes, enabling previously acquired and internalized knowledge to be integrated with newly acquired knowledge. Exploitation is possible by incorporating newly acquired and transformed knowledge into its operations. Organizations can refine, extend, and leverage their current competencies or develop new ones. A company's capacity to be innovative fundamentally depends on its ability to value, absorb, and use new external information for corporate objectives (Cohen & Levinthal, 1990). An organization's absorptive capacity is critical in determining how effectively it can integrate and use generative AI technologies. This includes recognizing generative AI's potential, assimilating technical knowledge, transforming existing workflows to incorporate AI capabilities, and leveraging these capabilities to improve organizational performance. Therefore, we propose the following hypothesis:

H7: The organization's absorptive capacity of GEN-AI positively influences employees’ usage intensity.

Environmental factors

The environmental context refers to the distinct business setting within which an organization and its employees function. This includes competitors, industry dynamics, interactions with governmental entities, and all regulations governing the activity (Tornatzky & Fleischer, 1990). Along the same lines, the institutional theory asserts that the institutional environment instigates social expectations, norms, and regulations that dictate appropriate organizational structures and behaviors, encompassing operations and practices (DiMaggio & Powell, 1983). In addition, Social Information Theory (Salancik & Pfeffer, 1978) posits that individuals form attitudes and decisions within their workplace, regarded as their social environment, relying on information and mimetic pressure. Considering all these elements, and given the specificities of Gen-AI, we have chosen to focus on the impact of social influence and regulatory support on employee Gen-AI usage.

Peer influences

Social influence encompasses a range of social processes and mechanisms that lead individuals to shape their perceptions of various aspects of information technology (Venkatesh & Bala, 2008). The UTAUT Model was among the first to explain user intentions and usage behavior in the voluntary adoption of information technology or information systems. The model proposes that performance expectancy, effort expectancy, and social influence directly impact behavioral intention, subsequently exerting an indirect influence on actual behavioral use (Venkatesh et al., 2003). Venkatesh et al. (2016) posit that social influence predicts intention to use information technologies in organizational settings, a proposition supported by numerous empirical studies (Qeiroz & Fosso Wamba, 2019). Likewise, social influence can explain behavioral intentions regarding the use of artificial intelligence. For instance, it is proposed that using AI necessitates enhancing employees' technological skills (Ransbotham et al., 2018). Additionally, social influence, including peer pressure, plays a significant role, as discussed by van Esch and Black (2019), who highlighted "the negative consequences of being left behind." Moreover, even though not within an organizational setting, Sohn and Kwon (2020) have demonstrated the impact of social influence and subjective norms in accepting AI healthcare services and artificial intelligence-based intelligent products. In fact, across diverse industries, social influence has been found to positively predict intentions to adopt artificial intelligence (Gursoy et al., 2019; Lin et al., 2021).

More recently, Venkatesh (2022) and Cao et al. (2022) claimed significant social influence exists on employee adoption and use of AI tools. It therefore makes sense to explore this relationship in the context of Gen-AI; hence the hypothesis below:

H8: Peer influences positively influence employees' GEN-AI usage intensity.

Regulatory concerns

Due to the rapid adoption of Gen-AI and the limited understanding of its long-term effects on various businesses and industries, coupled with the current absence of regulations and policies, apprehensions arise regarding its risks (Buiten, 2019). Consequently, as Gen-AI develops and is implemented, a network of experts and organizations is evolving to address the technical assessment and public perception of the risks associated with AI (White & Lidskog, 2022). Governments are actively prioritizing the implementation of regulations, employing diverse regulatory approaches, to guarantee the development of 'Trustworthy AI.' This is recognized as a primary tool for influencing the behavior of AI stakeholders (Smuha, 2021). For example, since 2016, The White House report on AI proposes that enhancing transparency can effectively tackle numerous ethical concerns associated with artificial intelligence5. Similarly, the European Union aims to establish regulations for artificial intelligence (AI) to guarantee improved circumstances for advancing and applying this cutting-edge technology.

The European Commission put forth the inaugural regulatory framework for artificial intelligence in the European Union in April 20216. In an organizational setting, regulatory support plays a crucial role in safely fostering the proliferation of innovation (Han et al., 2022). Hence, policymakers should examine ways in which Gen-AI can function as a collaborator with employees rather than a competitor. Additionally, policymakers can advocate algorithmic accountability to underscore transparency in the integration of Gen-AI within organizational workplaces (John-Mathews et al., 2022; Kim et al., 2020). By establishing a governance framework, entities can proficiently handle and minimize the risks linked to Gen-AI implementation. This structure will guarantee the inclusion of ethical considerations, safeguard data privacy, and uphold compliance with applicable regulations (Kelley, 2022). Therefore, the hypothesis below is proposed:

H9: Regulatory concerns positively influence employees' GEN-AI usage intensity.

The resulting framework model, emerging from this comprehensive analysis, is presented as follows:

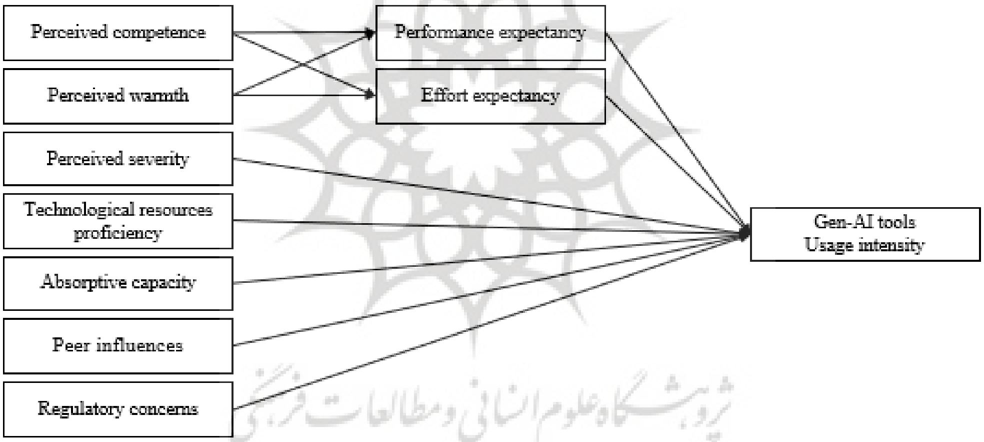

Figure 1. Framework Model

Methodology

Quantitative research was conducted among American employees to test the causal model. The choice of the American market as the focus of this research is justified by the fact that it represents the most mature environment for artificial intelligence. According to data from the European Patent Office (2021), the United States has the largest number of artificial intelligence patents, with 46,533 patents filed in 2021, followed by Germany (25,969), Japan (21,681), and China (16,665). In addition, as shown by data from Precedence Research (2023), the American AI market is estimated at $123.7 billion, with a projected estimate of $594 billion by 2032.

Data collection and measurement instruments

Initially, participants reported prior GEN-AI use in professional tasks. Only experienced users answered model-related questions using established measurement scales. Data collection used Prolific, an online research marketplace known for efficient engagement with reliable participants, chosen for its high data quality track record (Peer et al., 2022). A total of 280 employees responded to the questionnaire, of which 250 answers were considered valid.

The measurement scales used for the concepts in this study were inspired by existing literature. The scale for peer influences, performance expectancy, and effort expectancy measurements were adapted from Venkatesh et al. (2012), while technological resource proficiency and regulatory concerns were adapted from the scale developed by Agrawal (2024). Absorptive capacity was conceptualized and operationalized in very different ways (Chauvet, 2015); the scale used in our study was taken from Agrawal (2024). The scale of perceived warmth was inspired by the scale developed by Judd et al. (2005), also used by Hu et al. (2021), and the scale of competence was adapted from Dwivedi et al. (2023). The perceived severity scale was adapted from Judd et al. (2005), and Chen and Zahedi (2016). Finally, the scale for intensity of use was adapted from the scale created by Ellison et al. (2007). As defined above, we emphasize that the intensity of usage differs from the intention of use in that it is based on two main dimensions: the continuity of usage and the involvement in usage.

Results

Sample characteristics

The survey's sample size included 316 respondents. Regarding gender, 36.08% of the respondents were women, 63.92% were men. Concerning their managerial positions within their respective organizations, 34.81% of the respondents were employees, 25.32% were supervisors/team leaders, 26.58% were middle management, 6.33% were senior management, and 6.96% were executives/C-suite.

The respondents worked in various business sectors. The most represented sectors were Entertainment (22.15%), Information Services (14.24%), Education (13.29%) and Hotel Services (11.08%). Other sectors included Finance (8.86%), Agriculture (8.54%), Health Care (7.59%), Food Services (6.96%), Publishing (2.53%), Utilities (1.27%), Data Processing (1.27%), Legal Services (1.27%) and Military (0.95%).

Accuracies of measurement scales

The analysis conducted on the psychometric properties of the measurement scales indicates that all meet the reliability and validity standards established in the current literature, as stated by Hair et al. (2021, 2022). The measured items have loadings greater than 0.7. The eigenvalues are higher than 1 (Table 1), and the extracted variances meet the minimum thresholds established by Hair et al. (2022). The scores of both Cronbach's alpha and Dillon-

Goldstein's Rho, which exceed 0.8, indicate that all measures have satisfactory composite reliability (Table 1).

We used the Fornell-Larcker criterion (1981) to assess construct validity. The results of the analyses (Table 4, Appendix 1) show that the explained variance of each construct (AVE) was greater than the square of the inter-construct correlation. This indicates that the variables share more variance with their indicators than other considered variables. This confirms that the measures used have both convergent and discriminant validity. The results of the HTMT matrix (Table 5, Appendix) support this statement. They show that all values between the constructs are below the critical threshold of 0.85 (Henseler et al., 2015), indicating good discriminant validity. This means that each construct is sufficiently distinct from the others, reinforcing the reliability and relevance of your analysis model.

Next, we proceed to rule out any significant influence of common method variance using two tests. First, Harman's one-factor test is run (Korsgaard & Roberson, 1995), where all the items are loaded onto one factor (Table 6, Appendix 1). The results show seven factors accounting for 71% of the variance in the data. Thus, no single factor emerged; the first factor did not capture most of the variance (35% only, less than the threshold of 50%). Second, the Unmeasured Latent Marker Construct approach proposed by Chin, Thatcher, and Wright (2012) is used. The analysis of the correlations between the error terms of the indicators shows that all the indicators' errors have a low correlation with each other, less than 0.2 (Table 7, Appendix 1). Thus, these results suggest that common method variance is not an issue in this study.

Table 1. Accuracies of the Measurement Scales

Latent Variable	Dimensions	Cross-loadings	Cronbach's alpha	D.G. rho (PCA)	Eigen-values	Communalities (AVE)
Perceived Competence	I perceive Gen-AI to be intelligent	0,826	0.930	0.947	3.916	0.783
	I perceive Gen-AI to be efficient	0,874				
	I perceive Gen-AI to be skillful	0,907				
	I perceive Gen-AI to be capable	0,922				
	I perceive Gen-AI to be effective	0,893				
Perceived Warmth	I perceive that the Gen-AI cares about me while interacting	0,836	0.939	0.954	4.023	0.805
	I perceive that the Gen-AI is kind to me	0,920				
	I perceive that the Gen-AI is friendly to me during the interaction	0,900				
	I perceive that the interaction with the Gen-AI is warm	0,925				
	I feel that Gen-AI is sociable	0,901				
Performance Expectancy	I have the resources necessary to use Gen-AI	0,904	0.927	0.947	3.916	0.820
	I know necessary to understand Gen-AI	0,900				
	Gen-AI is compatible with other technologies I use	0,935				
	I can get help from others when I have difficulties using Gen-AI	0,883				
Effort	Learning how to use Gen-AI is easy for me	0,924	0.941	0.957	3.396	0.849

Expectancy	My interaction with Gen-AI is clear and understandable	0,928				
	I find Gen-AI easy to use	0,911				
	It is easy for me to become skillful at using Gen-AI	0,922				
Perceived Severity	Gen-AI may perpetuate cultural stereotypes in available data	0,858	0.944	0.955	5.275	0.742
	Gen-AI may amplify discrimination in available data	0,851				
	Gen-AI may be prone to reproducing institutional biases in available data	0,881				
	Gen-AI may have a propensity for intensifying systemic bias in available data	0,904				
	Gen-AI may have the wrong objective due to the difficulty of specifying the objective explicitly	0,884				
	Gen-AI may use inadequate structures such as problematic models	0,878				
	Gen-AI may perform poorly due to insufficient training	0,766				
Technological Resources Proficiency	The IT setup of my organization can support applications related to Gen-AI.	0,910	0.931	0.956	2.637	0.878
	My organization is committed to ensuring staff are well-versed and knowledgeable about Gen-AI technologies.	0,952				
	My organization possesses a strong understanding of Gen-AI technologies.	0,949				
	Peers who influence my behavior would think I should use Gen-AI	0,903				
	My superiors who influence my behavior would think I should use Gen-AI	0,938				
	My superiors to whom I report would think I should use Gen-AI	0,914				
	My business partners would think I should use Gen-AI	0,875				
	My organization is committed to ensuring staff are well-versed and knowledgeable about Gen-AI technologies.	0,952				
	My organization possesses a strong understanding of Gen-AI technologies.	0,949				
Absorptive Capacity	There is a high probability that my organization will allocate financial resources towards Gen-AI technologies.	0,932	0.937	0.956	3.376	0.844
	My organization possesses existing knowledge and experience in the field of related technologies.	0,836				
	My organization is probably interested in assimilating Gen-AI technologies to have a competitive edge.	0,952				
	The strategic importance of assimilating Gen-AI technologies is likely to be considered by my organization.	0,950				
	I perceive that the Gen-AI is kind to me	0,920				
	I perceive that the Gen-AI is friendly to me during the interaction	0,900				
	I perceive that the interaction with the Gen-AI	0,925				

	is warm					
	I feel the Gen-AI is sociable	0,901				
	Gen-AI may amplify discrimination in available data	0,851				
	Gen-AI may be prone to reproducing institutional biases in available data	0,881				
	Gen-AI may have a propensity for intensifying systemic bias in available data	0,904				
	Gen-AI may have the wrong objective due to the difficulty of specifying the objective explicitly	0,884				
	Gen-AI may use inadequate structures such as problematic models	0,878				
	Gen-AI may perform poorly due to insufficient training	0,766				
Peer Influences	Peers who are important to me would think I should use Gen-AI	0,895	0.945	0.958	4.097	0.819
	Peers who influence my behavior would think I should use Gen-AI	0,903				
	My superiors who influence my behavior would think I should use Gen-AI	0,938				
	My superiors to whom I report would think I should use Gen-AI	0,914				
	My business partners would think I should use Gen-AI	0,875				
	My organization is committed to ensuring staff are well-versed and knowledgeable about Gen-AI technologies.	0,952				
	My organization possesses a strong understanding of Gen-AI technologies.	0,949				
Regulatory Concerns	The adoption of Gen-AI is motivated by initiatives considered by the government	0,906	0.857	0.933	1.751	0.871
	The adoption of Gen-AI technologies is facilitated by the existence of standards and laws	0,960				
GEN-AI Intensity of Usage	Gen-AI is part of my everyday activity	0.841	0.883	0.913	3.838	0.639
	I am proud to tell people I'm on Gen-AI	0.823				
	I feel out of touch when I haven't logged onto Gen-AI for a while	0.718				
	I feel I am part of the Gen-AI community	0.884				

Data analysis and hypothesis testing

The study adopted the partial least squares structural equation modeling method to investigate the causal model. Xlstat 2020 software is used. Ringle et al. (2020) and Hair et al. (2022) recommend the PLS-SEM method, which is particularly suitable for research focused on theory development and variance explanation (predicting constructs). PLS-SEM is effective in handling single-item constructs without identification issues and provides greater statistical power than covariance-based SEM, enabling the identification of specific relationships in the population (Hair et al., 2021).

Performance and Effort expectancies as mediators of GEN-AI competence influence on GEN-AI Usage Intensity

The empirical findings reveal that the perceived competence of GEN-AI has a significant positive impact on performance expectancy (β=0.595; t=12.957) (Table 2). This implies that when employees consider GEN-AI highly skilled, they have greater expectations regarding its ability to assist them with tasks. Moreover, performance expectancy positively affects GEN-AI usage intensity (β=0.269; t=5.323), suggesting that employees foresee enhanced performance from GEN-AI and are more inclined to utilize it extensively. The mediation analysis, conducted using the test indirect effects as suggested by Hair et al. (2022), demonstrates that GEN-AI competence has a significant indirect influence on GEN-AI usage intensity (β=0.244; Bootstrap LCI=0.121; UCI=0.382) (Table 3). This substantiates that performance expectancy partially mediates (LCI=0.032; UCI=0.460) the association between GEN-AI perceived competence and its usage intensity, supporting Hypothesis 1.

Furthermore, the empirical evidence indicates that GEN-AI's perceived warmth significantly influences performance expectancy (β=0.200; t=4.349) (Table 2). This suggests that when employees perceive GEN-AI as friendly and approachable, they have higher expectations regarding its performance in assisting them with tasks. Additionally, performance expectancy positively affects GEN-AI's usage intensity (β=0.269; t=5.323), implying that employees anticipate better performance from GEN-AI and are more likely to use it intensively. The mediation analysis reveals that GEN-AI's warmth significantly impacts GEN-AI's usage intensity (β=0.070; LCI=-0.018; UCI=0.240) (Table 3). This confirms that performance expectancy partially mediates (LCI=0.032; UCI=0.460) the relationship between GEN-AI's perceived warmth and its usage intensity, supporting hypothesis 2.

Moreover, the results demonstrate that GEN-AI's perceived competence significantly influences effort expectancy (β=0.425; t=7.289) (Table 2). This suggests that when employees perceive GEN-AI as highly skilled, they anticipate it to be more user-friendly and require less effort. In addition, effort expectancy positively affects GEN-AI's usage intensity (β=0.198; t=3.920), indicating that employees expect less effort required when using GEN-AI and are more likely to use it extensively. The mediation analysis reveals that GEN-AI's competence has a significant indirect impact on GEN-AI's usage intensity (β=0.244; LCI=0.121; UCI=0.382) (Table 3). This confirms that effort expectancy partially mediates (LCI=0.038; UCI=0.390) the relationship between GEN-AI's perceived competence and its usage intensity, supporting hypothesis 3.

Concerning hypothesis 4, the findings show that GEN-AI's perceived warmth has no significant effect on effort expectancy (β=0.082; t=1.403; f^2=0.006) (Table 2). This implies that employees' perception of GEN-AI's warmth and friendliness does not significantly influence their expectations regarding the effort required to use it. Moreover, the mediation analysis reveals that GEN-AI's warmth has no significant indirect impact on GEN-AI's usage intensity (β=0.070; LCI=-0.018; UCI=0.240) (Table 3). Therefore, the mediation analysis does not support the hypothesis that effort expectancy mediates the relationship between GEN-AI's perceived warmth and usage intensity, thus rejecting hypothesis 4.

Furthermore, the empirical results demonstrate that employees' perceived severity of GEN-AI significantly negatively influences their GEN-AI usage intensity (β=-0.118; t=-3.208) (Table 3). This suggests that when employees perceive GEN-AI as a severe threat to their job security or the organization's well-being, they are less likely to use it intensively. The negative beta coefficient and the significant t-value support the notion that perceived severity acts as a deterrent to GEN-AI usage. Moreover, the effect size (f^2=0.033) indicates that perceived severity has a slight but notable impact on usage intensity. These findings provide support for hypothesis H5.

Table 2. Results of the Causal Model Relationships

Dependent Variables			Explanatory Variables	Standard Value	Standard error	t	Pr > |t|	f^2
Performance expectancy	R^2 F Pr > F	0,518 168,041 0,000	Perceived competence	0,595	0,046	12,957	0,000	0,536
			Perceived warmth	0,200	0,046	4,349	0,000	0,060
Effort expectancy	R^2 F Pr > F	0,223 45,015 0,000	Perceived competence	0,425	0,058	7,289	0,000	0,170
			Perceived warmth	0,082	0,058	1,403	0,161	0,006
AI Usage intensity	R^2 F Pr > F	0,632 75,416 0,000	Performance expectancy	0,269	0,051	5,323	0,000	0,092
			Effort expectancy	0,198	0,042	4,692	0,000	0,071
			Perceived severity	-0,118	0,037	-3,208	0,001	0,033
			Techological resources proficiency	0,164	0,059	2,789	0,006	0,025
			Absorptive capacity	0,110	0,061	1,807	0,072	0,011
			Peer influences	0,238	0,045	5,312	0,000	0,092
			Regulatory concerns	0,076	0,038	2,015	0,045	0,013

Table 3. Tests of the mediating effect of Performance expectancy and Effort expectancy

From	To	Effects	Effects (Bootstrap)	Standard error (Bootstrap)	Lower bound (95%)	Upper bound (95%)
Perceived competence	Performance expectancy	0,595	0,593	0,096	0,393	0,739
Perceived warmth	Performance expectancy	0,200	0,194	0,109	0,000	0,476
Perceived competence	Effort expectancy	0,425	0,420	0,141	0,114	0,711
Perceived warmth	Effort expectancy	0,082	0,096	0,101	-0,094	0,331
Perceived competence	GEN AI usage intensity	0,244	0,231	0,066	0,121	0,382
Perceived warmth	GEN AI usage intensity	0,070	0,070	0,056	-0,018	0,240
Performance expectancy	GEN AI usage intensity	0,269	0,262	0,116	0,032	0,460
Effort expectancy	GEN AI usage intensity	0,198	0,195	0,075	0,038	0,390

Contributions of Organizational Factors and External Cues to the Intensity of GEN-AI Use

The organization's technological resource proficiency, which refers to its ability to use and manage its technological resources effectively, has a significant positive influence on employees' GEN-AI usage intensity (β=0.164; t=2.789; f^2=0.025) (Table 2). This suggests that when an organization is proficient in managing its technological resources, employees are more likely to use GEN-AI intensively. The positive beta coefficient and the significant t-value support the idea that technological resource proficiency facilitates and encourages GEN-AI usage among employees. Furthermore, the effect size (f^2=0.025) indicates that technological resource proficiency has a small to medium impact on usage intensity. These findings provide support for hypothesis H6.

Regarding the organization's absorptive capacity, the results show a positive but not significant influence on employees' GEN-AI usage intensity (β=0.110; t=1.807; f^2=0.011) (Table 2). This implies that an organization's ability to recognize, assimilate, and apply new external knowledge related to GEN-AI does not significantly affect employees' intensity of using the technology. The positive beta coefficient suggests a potentially positive relationship. Still, the non-significant t-value (t=1.807) and the small effect size (f^2=0.011) indicate that the impact of absorptive capacity on usage intensity is not substantial enough to be considered statistically significant. Consequently, hypothesis H7 is not supported by the empirical evidence.

In addition to the organizational factors, the results also highlight the importance of peer influences on employees' GEN-AI usage intensity. Peer influences have a significant positive impact on usage intensity (β=0.238; t=5.312; f^2=0.092) (Table 2), suggesting that when employees perceive their peers as supportive and encouraging of GEN-AI usage, they are more likely to use the technology intensively. The positive beta coefficient, significant t-value, and medium effect size (f^2=0.092) emphasize the crucial role of peer influences in shaping employees' GEN-AI usage behavior.

Lastly, the results indicate that regulatory concerns have a significant positive influence on employees' GEN-AI usage intensity (β=0.076; t=2.015; f^2=0.013). This implies that when employees perceive the regulatory environment as supportive and conducive to GEN-AI usage, they are more likely to use the technology intensively. The positive beta coefficient and significant t-value support the idea that a favorable regulatory environment encourages GEN-AI usage. However, the small effect size (f^2=0.013) suggests that the impact of regulatory concerns on usage intensity is relatively minor compared to other factors.

Conclusion

The research provides empirical validation for the efficacy of the TOE framework as a suitable tool for comprehending the adoption of Gen-AI within organizations. Concerning the technological factors, we considered three sub-dimensions: perceived competence, perceived warmth, and perceived severity of Gen-AI. The findings demonstrated a positive effect of perceived competence on employee performance expectancy and effort expectancy from Gen-AI. This means that the more employees perceive Gen-AI as able to perform tasks the more their performance and effort expectancies from Gen-AI are improved. Although these hypotheses have not yet been explicitly tested; the results are in line with those of Belanche et al. (2021) who empirically verified that the perceived competence of frontline robots positively relates to the expected value of a service; with a meaningful effect on the expected utility derived from the quality and performance of a service. Our results corroborate the findings of previous works: the perceived competence of AI is an explanatory factor of the intention to use AI (Belanche et al., 2021; Liu et al., 2022; Moussawi et al., 2021). Our study, therefore, confirms that the perceived competence of Gen-AI technology is a determining variable in employees' intention to adopt the technology within their workplace.

Perceived warmth has only a significant positive influence on employee performance expectancy. This result is not, however, in line with those of Belanche et al. (2021) who find that perceived warmth has the greatest effect on emotional value rather than utilitarian value like performance. These divergent results can be explained by the fact that Gen-AI remains different from frontline robots with whom the customer can establish real relationships which facilitates service delivery (Tussyadiah & Park, 2018).

We also highlighted the mediating effect of performance and effort expectancy of the relationship between perceived competence and warmth and Gen-IA usage intensity. The mediating hypothesis revealed that performance expectancy partially mediates the effect of perceived competence and perceived warmth on Gen-IA usage intensity. While the hypotheses of the mediating role of performance expectancy between perceived competence and employee usage have not undergone explicit testing, the findings align with those of Li et al. (2021), who empirically confirmed that perceived usefulness mediates the impact of perceived competence and warmth on engagement and intentions to continue use. In technology information literature perceived usefulness is strongly connected to performance since that usefulness is defined as the extent to which a system will enhance performance and productivity (Davis, 1989).

The mediating effect of performance expectancy between perceived warmth and employee usage is corroborated by the findings of Lv et al (2021) who empirically demonstrated that performance expectancy mediates the relationship between AI assistant cuteness and customer tolerance of service failure. Lv et al. (2021) define cuteness as a warm feeling of affection toward an AI assistant. In addition, the tolerance to a service failure means that users will continue to use AI assistants even if they fail thanks to their warmth and cuteness and their subsequent effect on performance expectancy.

The mediating effect of effort expectancy has been only verified for the relationship between perceived competence and Gen-IA usage intensity. No mediating effect of effort expectancy has been noticed for the impact of perceived warmth on Gen-IA usage intensity. Furthermore, perceived warmth has no direct significant effect on effort expectancy. This suggests that employees' views on GEN-AI's warmth and cuteness do not substantially affect their expectations about the effort needed to use it.

As for, perceived severity, the non-significance of the results can be discussed from two complementary perspectives. The first perspective refers to the notion of perceived value. Indeed, the perceived severity of Gen-AI has been linked to perceived risk (Wach et al., 2023) and perceived threat (Cao et al., 2021), which have a negative influence on perceived value, since this severity is seen as a perceptible cost (Kumari & Biswas, 2023) which, when combined with perceived benefits, shapes individuals' perceived value (Hsiao & Chen, 2016). However, in some research, Gen-AI provides more benefits than costs, or even more benefits than costs (Gregory et al., 2021), which could marginalize and take precedence over the risks associated with this technology and, therefore, its perceived severity. Thus, unconsciously, individuals (employees) only consider the perceived benefits when forming their behavioral intentions, which explains the insignificance of the effect of perceived severity on the intensity of use.

The idea that proficiency in technological resources or technological preparedness does not decisively influence the adoption of Generative Artificial Intelligence (Gen-AI) may seem counterintuitive at first. One might assume that resource proficiency or readiness is crucial for adopting advanced technologies. However, a comprehensive examination reveals a complex landscape where simply possessing technological resources does not ensure successful Gen-AI integration. The intricate relationship between organizational behavior and human-centric considerations introduces challenges that surpass mere technological readiness. For instance, inherent resistance to organizational change often overshadows technological preparedness (Sánchez-Prieto et al., 2019; Nov & Ye, 2009). This reluctance, combined with a lack of specialized AI expertise within the workforce, creates substantial obstacles to adoption (Tornatzky & Fleischer, 1990; Cohen & Levinthal, 1990). Additionally, concerns over job security and doubts about the dependability of AI-driven decisions further complicate matters, detracting from the potential for smooth Gen-AI integration (Zahra & George, 2002; Agrawal, 2024). The gap between theoretical readiness for Gen-AI and its actual application underscores the need to tailor AI capabilities to the specific needs and strategic goals of the organization.

Recognizing the critical role of human elements and organizational culture is vital for addressing the challenges associated with Gen-AI adoption. Insights from various researchers advocate for a balanced approach that harmonizes technological capabilities with the intricacies of human and organizational dynamics, which is essential for unlocking the full potential of Gen-AI.

Several factors can explain the finding that an organization's absorptive capacity has a positive but non-significant influence on employees' GEN-AI usage intensity. For starters, because GEN-AI technologies are still in their early stages of adoption, organizations and employees will need more time for absorptive capacity to fully manifest its effects (Cohen & Levinthal, 1990). Second, the complexity and novelty of GEN-AI tools may necessitate more specialized skills and targeted training than general absorptive capacity (Zahra & George, 2002). Organizational culture is also important; resistance to change, fear of job displacement, and a lack of motivation can all undermine the benefits of absorptive capacity (Ramezanian, 2011). Furthermore, the effective use of GEN-AI tools relies heavily on adequate resources, infrastructure, and support, which may be lacking in some organizations (Akter et al., 2023).

The relevance and applicability of GEN-AI tools to specific job requirements and workflows vary, potentially limiting employee usage intensity (Agrawal et al., 2022). Measurement and timing issues may obscure the interaction between absorptive capacity and usage intensity, as the study may not capture all of the nuances or provide enough time for significant effects to emerge (Bloom et al., 2023). Furthermore, prioritizing short-term operational results over long-term strategic integration can limit the use of GEN-AI tools (Venkatesh, 2022). Finally, the level of employee autonomy and the availability of a supportive environment that encourages experimentation and learning are critical, but these aspects may not be fully developed in all organizations (Venkatesh & Bala, 2008). These factors explain why absorptive capacity has a limited impact on employee GEN-AI usage.

While the results show that regulatory support positively impacts the intensity of employees' usage of GEN-AI; we can notice that their influence is still minor. Moreover, Agrawal (2024) unexpectedly found that regulatory support impedes the adoption of Gen-AI. The probable explanation for these results may be that regulating an innovation process lacking comprehensive understanding may hamper its development and diminish the potential benefits society could derive from the resulting technology, even when implemented with the best intentions (Han et al., 2022). Several researchers have warned of over-regulation of artificial intelligence (Han et al., 2022; Kelley, 2022; White & Lidskog, 2021). It is undoubtedly interesting to emphasize the importance of self-regulation when dealing with employees' acceptance of artificial intelligence. Self-regulation is essentially based on good communication, management support, and training (Kelley, 2022).

Managerial recommendations

This study offers valuable insights to guide employees in effectively implementing Gen-AI technologies. Organizations can effectively address skills gaps by augmenting employees' AI skills through targeted training and peer learning. Implementing an AI literacy program with modules focused on fundamental AI concepts and skills can bolster employees' confidence, especially for women who may experience apprehension due to technophobia or barriers related to new technologies. Such programs could be tailored to foster self-competence and self-efficacy, with online and in-person collaborative projects ensuring inclusivity and active participation.

Service providers are advised to introduce Gen-AI with higher levels of competence and warmth regarding their effects on performance and effort expectancies and their subsequent effect on employee use intensity. For instance, incorporating cute features like emojis can enhance perceived warmth. Similarly, adding some attributes like advice for a better search of information can make Gen-AI tools appear more competent.

Given the positive but non-significant influence of absorptive capacity on GEN-AI usage and the limited impact of technological preparedness alone, managers should adopt a comprehensive integration strategy. This includes targeted training, fostering an innovative culture, aligning AI tools with specific tasks, and providing sufficient resources. Addressing human-centric considerations, such as mitigating resistance to change and ensuring job security, is crucial. Establishing partnerships with universities and startups can support innovation. By harmonizing technological readiness with human and organizational dynamics, managers can effectively drive Gen-AI adoption and enhance organizational performance.

Moreover, organizations can amplify the benefits of peer-to-peer learning and mentorship by matching experienced employees with those beginning their AI journey, which can be a potent mechanism for knowledge transfer and skill enhancement. This can be particularly supportive for women in the workforce, who may benefit from seeing successful peer examples in AI uptake. While technical expertise is certainly important, the strategic application of AI will ultimately drive usage and adoption rather than mere technological know-how. Therefore, it is paramount for organizations to remain informed and compliant with relevant regulations and to use regulatory support as a foundation for developing their AI initiatives.

In addition, it would be appropriate for companies to offer support and skills supervision for employees following training on the new technology or technologies adopted by the company. This support aims to ensure that employees have acquired the skills they need to use the technology and to offer mentoring to any employees who are not up to speed. This will reduce the perceived lack of skills among employees towards the use of technologies.

The insights gleaned from this study will be particularly useful for companies seeking to develop effective strategies to enhance employees' willingness to accept and use Gen-AI, especially at different managerial levels. Communication and initiation strategies that can be extrapolated from these insights will serve as a blueprint for organizations to effectively mobilize the necessary tools for Gen-AI adoption among their workforce, while also addressing any risks and concerns that may hinder its usage.

Limitations and research opportunities

This study explores the factors influencing employees' adoption of Gen-AI, acknowledging several limitations that affect its generalizability and causal conclusions. The research is based on a relatively small sample of American employees surveyed at a single time, which restricts the ability to generalize findings and draw causal inferences. Additionally, the reliance on self-reported survey data introduces potential biases and lacks input from various employee levels.

The study employs a quantitative model with a focus on the organizational adoption of Gen-AI in the US, which overlooks the dynamics of change over time and individual adoption contexts. Despite these limitations, the findings highlight that integrating AI into organizations is a complex and dynamic process requiring a thorough understanding of individual and organizational factors influencing its adoption. While existing research provides valuable insights, much remains to be explored to understand this process's nuances and complexities fully. Adopting a multi-level approach that considers interactions between individual and organizational levels is necessary for a more comprehensive understanding of technology adoption behaviors, as recommended by Burton-Jones and Gallivan (2007).

Future research could investigate the role of organizational culture in adopting Gen-AI. Organizations with a strong culture of innovation are more likely to embrace new technologies, whereas those with traditional cultures may resist change. Examining how cultural factors influence Gen-AI adoption could yield valuable insights into the dynamics of technology adoption in organizations. Given the maturity of the US market in Gen-AI usage and adoption, it would be beneficial to test the model in other countries where this technology is emerging or being established. This cross-cultural analysis would allow for comparisons across different phases of adoption and help identify cultural differences in Gen-AI usage and adoption.

Another promising area for exploration is the impact of Gen-AI on employee attitudes and behaviors. Research has demonstrated that new technologies can significantly affect job satisfaction and performance. Understanding how Gen-AI influences employee motivations, attitudes, and behaviors is crucial for its successful adoption and implementation. Further exploration of variables such as management perception and leadership methods could elucidate the effects of technological, organizational, and environmental factors on the intensity of Gen-AI use. Additionally, research should consider the ethical implications of Gen-AI integration within organizations. Addressing ethical dimensions such as privacy, bias, and transparency becomes essential as Gen-AI becomes more prevalent in the workplace. Understanding these ethical considerations can help organizations make informed decisions and develop responsible policies.

These areas for future research highlight the complexity and multifaceted nature of Gen-AI integration in organizations. A rigorous empirical investigation into these topics could provide valuable insights and inform best practices for successfully adopting and integrating Gen-AI in the workplace.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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Appendix 1

Table 4. The Fornell–Larcker criterion of discriminant validity of the measurements (Squared correlations < AVE)

	Perceived competence	Perceived warmth	Performance expectancy	Effort expectancy	Perceived severity	Technological ressources proficiency	Absorptive capacity	Peer influences	Regulatory concerns	GEN AI usage intensity
Perceived competence	0,783									
Perceived warmth	0,270	0,805								
Performance expectancy	0,489	0,259	0,820							
Effort expectancy	0,218	0,092	0,285	0,849						
Perceived severity	0,051	0,055	0,043	0,001	0,742					
Techological resources proficiency	0,209	0,145	0,201	0,113	0,001	0,878				
Absorptive capacity	0,234	0,118	0,264	0,077	0,002	0,605	0,844			
Peer Influences	0,275	0,184	0,283	0,076	0,002	0,258	0,306	0,819		
Regulatory concerns	0,060	0,142	0,059	0,007	0,037	0,097	0,037	0,059	0,871	
GEN AI usage intensity	0,303	0,229	0,455	0,252	0,042	0,343	0,327	0,365	0,096	0,639

Table 5. HTMT Matrix

Constructs	PI	AC	TRP	C	PS	RC
Peer influences (PI)	-	0,687	0,632	0,641	0	0,261
Absorptive capacity (AC)	0,687	-	0,81	0,498	0,078	0,237
Technological resources proficiency (TRP)	0,632	0,81	-	0,508	0,036	0,386
Compétence (C)	0,641	0,498	0,508	-	0,244	0,317
Perceived Severity (PS)	0	0,078	0,036	0,244	-	0,052
Regulation concerns (RC)	0,261	0,237	0,386	0,317	0,052	-

Table 6. Eigenvalue and explained variance of the Harman's Single-Factor Test

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Eigenvalue	16,432	6,162	3,828	2,208	1,578	1,402	1,134	0,951	0,592	0,425
Variability (%)	35,723	13,395	8,322	4,801	3,431	3,048	2,465	2,067	1,287	0,924
Cumulative %	35,723	49,118	57,440	62,241	65,672	68,720	71,185	73,252	74,539	75,463

Table 7. Standard Error Matrix

Variable	PS	GAIC	GAIW	PE	EE	AC	TRP	PI	RC	GAUI
Perceived Severity (PS)	-									
GEN AI competence (GAIC)	0.150	-								
GEN AI Warmth (GAIW)	0.141	0.068	-							
Performance Expectancy (PE)	0.154	0.074	0.087	-						
Effort Expectancy (EE)	0.146	0.123	0.096	0.091	-					
Absorptive Capacity (AC)	0.114	0.114	0.121	0.100	0.113	-				
Technological Resource proficiency (TRP)	0.119	0.081	0.090	0.093	0.101	0.050	-			
Peer Influences (PI)	0.126	0.101	0.102	0.103	0.133	0.080	0.079	-		
Regulatory concerns (RC)	0.149	0.106	0.096	0.098	0.110	0.121	0.102	0.110	-	
GEN AI usage intensity (GAUI)	0.150	0.076	0.087	0.064	0.079	0.071	0.062	0.073	0.086	-

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