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Beyond the hype: Organisational adoption of Generative AI through the lens of the TOE framework–A mixed methods perspective

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ABSTRACT

It is widely accepted that the impact of Generative Artificial Intelligence (GenAI) has been nothing short of transformational, with tangible impacts on industry, education, healthcare and government. But beyond the headlines, how are organisations actually using GenAI, what are the key challenges experienced by decision makers and has the reality on the ground matched the hype? This study adopts a mixed-methods approach, utilising the Technology-Organisation-Environment (TOE) framework to reveal greater insights to how organisations are adopting GenAI, the drivers that affect decision making and the key challenges associated with greater use of the technology. This research adopts a mixed method approach incorporating an explorative qualitative step with industry participants followed by a survey of 304 (three hundred and four) decision makers from a cross section of industry sectors from around the world including: North America, Europe, Africa, Australia and Asia, to gain further insight to the underlying factors that drive GenAI adoption. The research model was validated using Structural Equation Modelling (SEM) and reveals the intricate and inherent complexities related to greater levels of GenAI adoption. The analysis highlights the critical role of change capacity of the organisation in moderating complexity and staff skills. This research provides valuable and timely insights for senior management and policy makers that are attempting to better understand the interdependencies and perspectives on the key challenges facing organisations looking to deliver greater impact on organisational performance through GenAI.

1. Introduction

Generative Artificial Intelligence (GenAI) has emerged as a transformative technology, capable of autonomously creating content, text, images, audio, video, code, simulations, and synthetic data through Natural Language Processing (NLP)-based input (Budhwar et al., 2023; Dwivedi et al., 2023a). Powered by large language models (LLMs) such as OpenAI's GPT-4, Anthropic's Claude, Google's Gemini, and others, GenAI utilises deep learning to generate outputs that replicate human-like creativity and communication, disrupting numerous industries (Malhotra & Manzoor, 2025; Patil et al., 2024; Rana et al., 2024).

Driven by expanding use cases, organisational investment in GenAI is rising sharply. By 2027, 35 % of projected $297.9 billion AI software spending will target GenAI, up from 8 % in 2023 (Gartner, 2023). Major initiatives like the $500 billion Stargate Project (OpenAI, 2025), backed by Arm, Microsoft, NVIDIA, Oracle, and the U.S. government, further reflect the scale of investment in GenAI infrastructure. Applications span content generation in media and design (Vayadande et al., 2023), advances in healthcare such as drug discovery and personalised medicine (Chen et al., 2024), fraud detection in finance (Remolina, 2024), and predictive maintenance in manufacturing (Andreoni et al., 2024). GenAI has automated routine tasks, enabling employees to focus on strategic work, reducing costs, and accelerating time-to-market (Héjja et al.,

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2024; Ooi et al., 2023).

Yet, GenAI's rapid adoption raises questions about the evolving role of human input and the organisational readiness to adapt. While the literature reflects growing interest in GenAI's transformative potential (Mohammed & Skibniewski, 2023), empirical studies analysing adoption through a structured lens remain limited. Although AI and automation have been widely studied, the rise of GenAI introduces novel capabilities and challenges that remain poorly understood in current literature. By focusing directly on GenAI, this study provides timely insights into a technology that is quickly reshaping professional and industrial landscapes. Researchers have explored key drivers such as operational efficiency, innovation, and decision-making (Agrawal et al., 2024), yet more nuanced, empirically grounded studies are needed to understand adoption dynamics within varied organisational contexts (Kanbach et al., 2024; Saha, 2024). Trust, risk perception, and alignment with strategic objectives significantly influence GenAI adoption (Boston Consulting Group, 2024). Environmental concerns, such as GPT-4's water usage in Iowa, underscore the sustainability challenges associated with GenAI's scale (Nature, 2024; Gopal et al., 2024).

There is growing academic interest in GenAI adoption within higher education (Luo, 2024; Malik et al., 2023), yet a gap persists in cross-sector empirical studies. Adoption disparities reflect varying levels of GenAI maturity, ROI expectations, and organisational capabilities. Trust, change readiness, and managerial support are central to overcoming barriers (McKinsey, 2024a; Klein et al., 2024). Although some recent work (e.g., Rana et al., 2024) has empirically examined GenAI's performance impact, mixed-methods studies remain scarce. We argue that combining qualitative exploration with quantitative analysis will yield deeper insights into the organisational factors shaping GenAI adoption.

The Technology–Organisation–Environment (TOE) framework (Tornatzky et al., 1990) offers a robust lens to study these dynamics. Widely applied in AI research (Chatterjee et al., 2021; Salah & Ayyash, 2024), TOE is particularly suited to exploring the interplay of internal and external factors influencing GenAI integration and adoption. While the TOE framework has been extensively applied to traditional IS and AI adoption studies, its application to GenAI remains limited. This study extends prior TOE-based research by operationalising the framework within the rapidly evolving and high-impact context of GenAI, where the interplay of complexity, organisational readiness, and environmental uncertainty presents distinct challenges and novel adoption dynamics. We assert that this approach will offer a deeper understanding of the key constructs and inherent challenges in adopting emerging technology and ability of organisations to adapt to change.

With this in mind we pose the following research questions:

RQ1. : What is the key underlying technology, organisational and environment focused factors that influence the use of GenAI within organisations?

RQ2. : What are the key moderating factors that influence the use of GenAI and how do they impact decision making within organisations?

Through this mixed methods, theoretically grounded research, we seek to answer these research questions and develop additional insight to the underlying complexities and drivers for the continued adoption of GenAI within organisations. The remainder of this study is as follows: Section 2 analyses the extant literature that supports the approach and necessity of this research; Section 3 outlines the research design including the theoretical framework. Section 4 details the Phase 1 (qualitative) approach and findings and Section 5 outlines the Phase 2 (quantitative) approach and findings. The Discussion section is detailed in Section 6 where we outline the key aspects of the research findings within the context of the literature and discuss the implications for theory and practice. The research is concluded in the final section.

2. Literature review

The launch of OpenAI's GPT transformer in late 2022 marked the advent of GenAI, sparking profound transformations across a wide range of industries and societal domains (Chen et al., 2023; Dwivedi et al., 2023a). However, as adoption of GenAI has exponentially increased within organisations, significant challenges have emerged that directly impact the realisation of benefits from the technology. The literature highlights several key challenges that organisations face as they strive to enhance their use of GenAI, navigate the complexities of increased adoption, and adapt their existing processes accordingly (Fosso Wamba et al., 2024; Sedkaoui & Benaichouba, 2024). However, much of this literature remains descriptive or sector-specific, and few studies have adopted a robust theoretical lens to systematically explore the organisational and contextual enablers of GenAI adoption. For example, affordance theory (Andrieux et al., 2024), institutional theory and ethical frameworks (Rana et al., 2024) all have explanatory power and are examples of theoretical lenses that have been adopted in existing GenAI literature, yet whilst these theories explain the mechanisms by which management adopts new technology, "examining the interaction of internal and external factors in one model will enhance the ability to explain new technology adoption more effectively than other models and theories" (Wael AL-Khatib 2023, p. 2). Therefore, applying the TOE framework to this emergent and fast-evolving context helps to reveal the multidimensional pressures shaping adoption decisions, providing an optimal lens and extending its utility into next-generation digital technologies.

A number of studies have discussed ethical and trust related challenges associated with GenAI including topics such as: privacy and data protection, biases and misinformation, transparency and accountability, misuse and trust (Belanche et al., 2020; Bhattacharya et al., 2024; Chen et al., 2023; Khan, 2023). The study by Sison et al. (2024) forecasts an overreliance on GenAI resulting in the deskilling of industry and significant impact of misinformation and hallucinations. Researchers have referred to privacy concerns, risks to the organisation from data security and insufficient regulation to protect data (Al-Kfairy et al., 2024; Dwivedi et al., 2023a; Benbya et al., 2024). Academics and practitioners consistently identify concerns over GenAI technologies and the potential for biases within LLM training (Al-kfairy et al., 2024; Manduchi et al., 2024; Sieja & Wach, 2023), advocating for diverse and representative training data. The research by Sison et al. (2024) acknowledged that mitigation strategies for bias are complex and permeate the entire GenAI development process (Bhattacharya et al., 2024). These challenges have a direct impact on how decision makers trust the accuracy and reliability of GenAI technologies in the context of the business advantages through AI use (Brewer et al., 2024; Chakraborty & Biswal, 2024; Khan, 2023).

The complexities surrounding the integration of GenAI into existing systems and processes is also identified as a key challenge in the literature. Dwivedi et al. (2023a) refer to the benefits and complexities of integrating ChatGPT into existing systems and Davenport & Tiwari (2024) found that whilst senior management are excited about GenAI, they also recognise that significant work is needed with regard to data preparedness and integration strategies. Organisation size is also cited as a factor in the context of advantages in the ability to deliver benefits from GenAI (Fosso Wamba et al., 2024). The ability to fully integrate GenAI can be exacerbated by limited budgets for smaller organisations and the inherent complexities in adapting existing legacy systems at scale, which could be problematic for many organisations (Fosso Wamba et al., 2024; Rajaram & Tinguely, 2024). Although some researchers have stated that GenAI is user-friendly and requires minimal familiarisation (Wolf & Maier, 2024), the training on effective GenAI use amongst stakeholders, has posed significant challenges (Fui-Hoon Nah et al., 2023; Maier 2024). Real benefits can only be realised where organisations understand the importance of training and upskilling employees but also recognising the change implications and potential staff resistance to GenAI technology (Fosso Wamba et al., 2024). Various studies refer to staff skills and adequate training as a challenge (Fui-Hoon Nah et al., 2023), suggesting that training on prompt engineering will be important for those who are more frequently engaging in interaction with GenAI. More accessible GenAI as well as GenAI literacy training will help to bridge the skill gap and provide equal opportunities.

Issues relating to the regulation and governance of GenAI has received prominence in the literature. Studies have highlighted the lack of legislative and regulatory controls to adequately deal with the emerging issues from GenAI (Bashir et al. 2024). Bhattacharya et al. (2024) refer to a gap in governance where GenAI currently lacks contextual understanding and real-time information processing, resulting in a void in governance from output validation. Chen et al. (2023) and Wach et al. (2023) claim a lack of meaningful, strategic and internationally focused governance or legislation, making it difficult to attribute responsibility for errors or violations caused by the technology. A number of studies call for further research and renewed frameworks that are sufficient for the task of regulating GenAI (Amankwah-Amoah et al., 2024; Chen et al., 2023). Paterson (2024) suggest that effective AI regulation will inevitably be multifaceted due to its use in many contexts and Bhattacharya et al. (2024) call for an established multi-pronged framework of governance and oversight, establishing strong governance structures and vigilant oversight mechanisms to ensure responsible adoption, transparency and accountability. The lack of regulation and governance of GenAI is a major concern, as is the capacity of regulators to take enforcement action to ensure fairness, competitive balance and safety (Paterson, 2024; Sieja & Wach, 2023).

The training of large datasets for GenAI has led to increased computing power and energy consumption (Baxter & Schlesinger, 2023), contributing to environmental degradation, accelerated depletion of natural resources (Bashir et al., 2024), pollution and waste generation (Stahl & Eke, 2024). As Bashir et al. (2024) note, "unfettered growth in GenAI has notably outpaced global regulatory efforts, leading to varied and insufficient oversight of its socioeconomic and environmental impact" (p. 5). This underscores the urgent need for the responsible development of GenAI, prioritising not only efficiency improvements but also the alignment of its growth with social and environmental sustainability goals alongside economic opportunities. The rapidly evolving legal and ethical landscape, coupled with cross-jurisdictional inconsistencies and the lack of comprehensive governance frameworks amid the accelerated adoption of generative AI, renders regulatory navigation significantly more complex and risk-laden than in the case of traditional information technology innovations.

The ability of the organisation to adapt to change can be a core factor in the success of AI initiatives (Bhatia et al., 2024). Developments in automation brought on by GenAI have the potential to threaten an increasing number of existing roles, effectively reshaping current labour markets (Dwivedi et al., 2023b; Fui-Hoon Nah et al., 2023; Sieja & Wach, 2023). Aspects of the literature posit a more evolutionary perspective, highlighting a shift in human labour and redefinition of roles, citing a necessity for humans to adapt to the shifting landscape of GenAI induced change (Budhwar et al., 2023). Studies have also posited a link between change capacity and organisational culture, highlighting that the disruption and impact from GenAI is related to how decision makers adapt the organisational culture to GenAI use (Harvard Business Review, 2023; An et al., 2024). To fully realise the benefits of GenAI adoption, organisations must understand the employee led complexities of change and invest in reskilling and retraining initiatives to empower workers to effectively leverage the technology (Fui-Hoon Nah et al., 2023; Sedkaoui & Benaichouba, 2024). These efforts will ensure that employees can integrate GenAI into their workflows, optimise its use, and align its capabilities with ethically focused organisational goals, thereby maximising productivity and innovation while minimising resistance to change (Sedkaoui & Benaichouba, 2024; Sison et al., 2024). Table 1 presents a summary of the key gaps in the GenAI related literature.

While prior studies have explained facets of AI adoption through affordance theory, algorithm aversion, sociotechnical systems, and institutional theory (Andrieux et al., 2024; Smit et al., 2024; Song et al., 2025) we posit a TOE+ integrative host lens that can incorporate these perspectives to extend classical TOE for emerging AI technologies.

Table 1
Research Gaps in the GenAI literature - identified via the literature review.

Topic or theme	Recommended Future Research	Sources
Empirical mixed-methods studies	There is a lack of empirical and peer reviewed research on GenAI. This limits theoretical and practical understanding of GenAI. Few studies have analysed the underlying elements related to GenAI from a mixed methods perspective.	AlJaloudi et al. (2024), Al-Kfairy et al. (2024), Dwivedi et al. (2023), Rana et al. (2024), Richey et al. (2023), Sison et al. (2024), Stahl & Eke (2024), Susarla et al. (2023)
Context	There are calls for further research to be conducted across different countries, sectors, industries, functions and fields of study.	Chakraborty & Biswal (2024), Chen et al. (2023), Dwivedi et al. (2023b), Kshetri et al. (2024), Sedkaoui & Benaichouba (2024), Wamba et al. (2024)
Stakeholder perspectives	Future research should engage with a broad range of stakeholders.	Al-Kfairy et al. (2024), Dwivedi et al. (2023a), Kshetri et al. (2024), Stahl & Eke (2024), Wolf & Maier (2024)
Underlying factors that affect adoption and implementation	A greater understanding of the underlying factors associated with the use of GenAI across organisations is needed. For example, the environmental, inter-organisational and ethical influences.	Wolf & Maier (2024), Rana et al. (2024), Stahl & Eke (2024), Wamba et al. (2024)
Benefits and challenges of GenAI adoption	Additional research is required to understand the benefits and challenges of GenAI adoption in the long term.	Alavi (2024), Sison et al., (2024), Wach et al. (2023), Wamba (2023), Rana et al. (2024), Stahl & Eke (2024), Fosso Wamba et al. (2024)

3. Research design

The adoption of GenAI is a complex and multidimensional process that necessitates a comprehensive understanding of both human perceptions and measurable behavioural patterns. Given the intricate challenges surrounding GenAI adoption within organisations, this study aims to develop a more in-depth, holistic understanding of the underlying complexities while providing empirical insights through a mixed methods approach. In alignment with prior research advocating developmentally oriented methodological designs (Venkatesh et al., 2013), we employ a sequential exploratory mixed methods approach, beginning with a qualitative phase followed by a quantitative stage. The qualitative phase enables the identification and development of key constructs, which are then systematically tested through quantitative analysis to validate a set of hypotheses. This two-stage approach enhances the validity and reliability of findings (Dwivedi et al., 2023b; Doyle et al., 2009). Given the exploratory nature of GenAI adoption, where individual motivations, concerns, and experiences shape adoption behaviours, this methodological framework is particularly well-suited. By first exploring the phenomenon through qualitative inquiry and subsequently validating findings through a broader, generalisable quantitative study, this approach ensures a rigorous and well-rounded understanding of GenAI adoption dynamics (Creswell and Clark 2017). The recent study from Kumar et al. (2025) although focusing on GenAI adoption within a B2B context, illustrates a similar mixed method approach where the researchers used the initial phase 1 study to help formulate a testable set of hypotheses for the phase 2 quantitative element.

To fully explore the complexities of GenAI adoption within organisations, this study employs the TOE framework as its primary theoretical lens. The TOE framework has been widely recognised for its effectiveness in analysing technological adoption in complex organisational contexts (Chatterjee et al., 2021; Min & Kim, 2024; Salah & Ayyash, 2024). With a broad and well-developed theoretical underpinning, the TOE framework offers a reliable lens for analysing technology adoption (Na et al. 2022; Ravishankar & Logasakthi, 2023; Sivathanu et al., 2025; Singh et al., 2025). TOE provides a structured approach to understanding the technological, organisational, and environmental factors that influence adoption decisions, making it particularly suitable for examining the multidimensional challenges of GenAI adoption. The TOE framework is justified in this study due to its ability to capture both internal and external factors affecting GenAI adoption. Within organisations, factors such as technological readiness, perceptions of risk, trust in AI, and adaptability to change are critical determinants of adoption. Externally, competitive pressures, regulatory concerns, and industry trends further shape organisational strategies (Na et al., 2022; DiMaggio & Powell, 1983; Jianxun et al., 2021). The application of this structured theoretical approach aligns with existing research that utilises technology adoption frameworks to better understand this type of phenomena (Mujalli & Almgrashi, 2020; Rana et al., 2024; Raut et al., 2017; Sastararuji et al., 2021).

However, existing research related to AI and GenAI adoption does reveal limitations in the TOE framework. For example, authors have confirmed stress points in different contexts (Awa et al., 2017; Cruz-Jesus et al. 2019; Hanna & Gohar, 2020; Kandil et al. 2018; Li et al. 2015; Malik et al, 2021; Min & Kim, 2024; Stenberg & Nilsson, 2020; wael AL-khatib, 2023; Yang et al., 2022) or made adaptations (Ahmad Khan et al., 2024; Bouteraa, 2024; Chatterjee et al., 2021; Kalmus & Nikiforova 2024; Marei, 2024; Na et al., 2022; Raut et al., 2017; Ravishankar & Logasakthi, 2023; Religia et al., 2023; Sastararuji et al., 2021). In the technology dimension, issues like trust, complexity, and regulatory uncertainty often matter more than TOE assumes (Hanna & Gohar, 2020). For organisation factors - leadership, support and skills are important but studies have identified that these are sometimes less influential than predicted (Min & Kim, 2024; Wael Al-Khatib, 2023). The environmental dimension extends further than TOE's traditional emphasis on competition, as regulatory requirements, customer trust, and institutional pressures have been shown in previous studies to influence adoption (Stenberg & Nilsson, 2020; Malik et al., 2021; Yang et al., 2022; Yuan et al., 2025). Taking account of these factors, we posit the need for a recalibration and adaptation of the TOE framework in the context of GenAI.

The model presented in Fig. 1 sets out the adopted research design and process in alignment with the developmental approach as set out in Venkatesh et al. (2013), depicting the initial qualitative then quantitative phases of the research. This study has taken a sequential exploratory design that enhances its theoretical and practical relevance by grounding the quantitative phase in insights derived from real-world stakeholder experiences. The qualitative findings shaped the development of the conceptual model, ensuring that the constructs and relationships tested in Phase 2 were contextually valid and empirically grounded. This approach strengthens the overall validity of the TOE application by aligning theoretical constructs with lived organisational realities in the GenAI domain. The phases of mixed methods approach are outlined below:

4. Phase 1 qualitative phase approach and findings

4.1. Overview - rationale and approach

This phase of the research adopts a qualitative and exploratory approach to uncover in-depth insight from organisational stakeholders that are using GenAI technology within their organisations. This approach is indispensable for emerging and immature areas of research (Malhotra & Grover, 1998; Wamba et al., 2024), such as the use of GenAI, where the phenomenon is still evolving, lacks well-established theoretical frameworks, and requires deeper exploration to uncover key adoption drivers, barriers, and contextual influences (Stubbs et al., 2023). Interviewing was deemed an appropriate qualitative inquiry method for collecting rich, in-depth data and a semi-structured format chosen to ensure flexibility while allowing participants' voices to be fully captured (Rubin & Rubin, 1992). Conducting an early-stage scoping of the topic is particularly valuable in gaining a broad understanding of the subject, helping to establish conceptual boundaries and define key units of analysis (Miles & Huberman, 1994). This foundational exploration serves to inform and refine the subsequent data collection phase, ensuring alignment with the study's objectives.

4.2. Method

The selected participants were mid-level employees of organisations that had adopted GenAI and representative of a diverse range of sectors in the United Kingdom and Australia. They were recruited using the purposive methods of convenience and snowball sampling (Bryman &

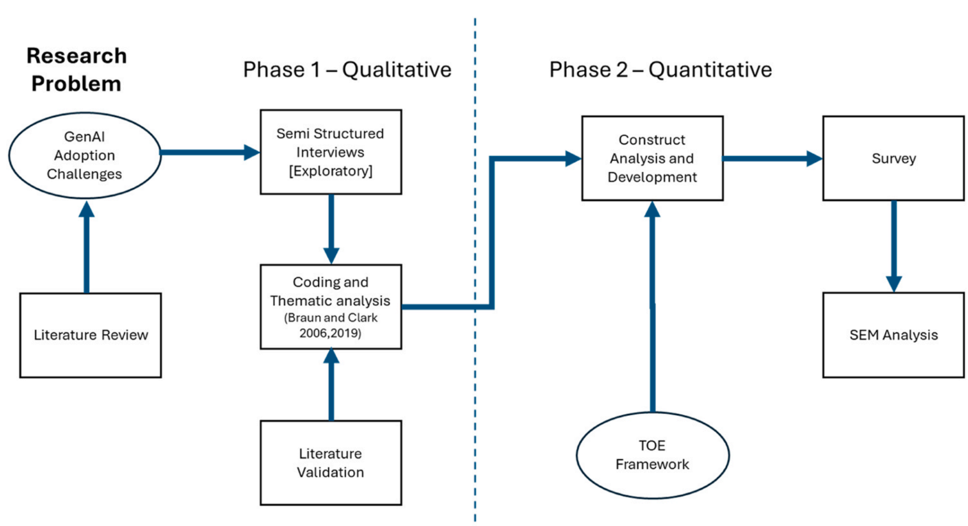

Fig. 1. Research Design and Approach.

Bell, 2011) and informed consent was sought before data collection commenced. Interview questions were formulated in alignment with the TOE framework to uncover challenges related to technological, organisational and environmental aspects of GenAI (see Appendix) and the research protocol delivered by members of the research team. Questions were semi-structured in nature.

Fourteen semi-structured interviews were conducted in total and recorded transcriptions were coded and analysed using thematic analysis as outlined in Braun and Clarke (2006), to interpret various aspects of the research topic. Key phases of analysis included: 1) familiarisation with the data, 2) generation of initial codes, 3) search for themes, 4) review of themes, 5) defining and naming themes and 6) producing the analysis. Multiple iterations of initial, axial and selective coding (Miles & Huberman, 1994) were adopted, and themes established inductively to derive meaning from the data and gain insight into the challenges related to GenAI adoption in organisations. Finally, the thematic analysis outputs were validated against the literature.

Ethical approval was secured prior to data collection, and informed consent was obtained from all participants before the commencement of the interviews.

4.3. Results

Using the TOE framework, interview transcripts were thematically analysed to identify key underlying constructs emerging from participants' discussions on the use and adoption of GenAI within their organisation. The interview transcripts thus identified constructs that aligned with either **technological readiness**, **organisational readiness** or **environmental readiness** in the context of GenAI adoption challenges. To ensure theoretical coherence between the qualitative insights generated in Phase 1 and the quantitative constructs developed in Phase 2, the emergent themes were mapped onto the TOE framework. Our operationalisation process was guided by validated TOE-based instruments used in prior GenAI and digital innovation studies. This process was not a mere classification exercise, but rather a deliberate analytical translation grounded in the conceptual underpinnings of each TOE dimension. Specifically, each theme was examined for its alignment with established constructs within the TOE literature such as *complexity, and relative advantage* (Technology), *staff skills and change capacity* (Organisation), and *regulatory factors* (Environment). This alignment process was guided by prior empirical and theoretical studies (Bouteraa, 2024; Rahman et al., 2024; Dehghani et al., 2022) which provided definitional clarity and supported the conceptual positioning of the themes within TOE categories.

The following sections provide a detailed discussion of these three TOE factors, incorporating participant transcript quotes for each construct while drawing connections to relevant literature. These constructs illuminate the key challenges interviewees perceive in the adoption and use of GenAI within their organisation.

Table 2 presents the relevant TOE constructs, supported by the relevant literature grounded in the TOE framework aligned with key quotes from the Phase 1 analysis. The cited studies correspond directly to each construct, reinforcing their relevance and theoretical grounding within the context of GenAI adoption.

4.3.1. Technology context

This theme focuses on the technological aspect of GenAI adoption within the organisation. In the context of technology challenges, two constructs were identified from the interview transcript data, namely complexity and relative advantage.

Complexity: was a recurring theme when integrating GenAI into existing infrastructure. Interviewees described significant barriers to organisation wide adoption and integration of this technology. One participant stated that "*GenAI is too complex for most departments to integrate, requiring extensive training and knowledge transfer.*" This particular finding reflects the widespread concern that the practicality of

Table 2
TOE Constructs and Quotes.

TOE Analysis Level	Construct	TOE Literature Alignment	Interview Transcript Source
Technology Context	Complexity	Ahmadi et al. (2015);Ahmadi et al. (2017); Borgman et al. (2013); Alatawi et al. (2013); Low et al. (2011); Nam et al., (2015); Rath et al. (2023); Rosli et al. (2024); Sun et al. (2018); Siew et al. (2020); Thong (1999); Wang et al. (2016)	*"GenAI is too complex for most departments to fully integrate, requiring extensive training and knowledge transfer." "The challenge is that GenAI systems have to be integrated into existing systems, and that's where a lot of the problems arise." "The biggest challenge I can actually see would be standardizing its use throughout the company." "We've also seen some concerns from clients about how we're using AI in our services, especially around transparency." "We have to ensure everything is reviewed thoroughly by a person before it goes to the client... we can't rely solely on AI." "Explainability is a big challenge...."*
	Relative Advantage	Ahmadi et al. (2015); Ahmadi et al. (2017); Alsheibani et al. (2020); Borgman et al. (2013); Chatterjee et al., (2021); Dwivedi et al. (2009); Kulkarni and Patil, (2020); Low et al. (2011); Rath et al. (2023); Sun et al. (2018); Siew et al. (2020); Thong (1999); Wang et al. (2016)	"GenAI *offers a significant advantage in streamlining processes, but the road to get there is difficult." "Marketing and developing content is a key area where AI is used...." "I think it has a lot of benefits in society and also business...." "I think everyone can see the benefits of it... if it eliminates mundane tasks, then that's great. But... you see the scary side... you can't believe anything you see... technology on video now is terrible." "Overall it is definitely a huge positive for society... it is a really amazing opportunity because we can make sense of unstructured text..."*
Organisational Context	Staff Skills	Hsuet al. (2014); Kuan and Chau (2001); Kulkarni and Patil, 2020; Nam et al., 2015; Srivastava and Teo (2010); Thong (1999); Wang et al. (2016)	*"Management is excited about GenAI because it can potentially cut costs, but they are overlooking the training needs of employees." "I think one of my concerns is junior lawyers becoming over-reliant on it... missing out on basic legal training." "There's risk of displacement and job loss due to AI, but there's also potential for retraining and*

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Table 2 (*continued*)

TOE Analysis Level	Construct	TOE Literature Alignment	Interview Transcript Source
			repurposing employees." "We don't have in-house expertise issues with AI. We are on top of it, but we rely on Azure for infrastructure." "Training the workforce on responsible AI use is the most important thing we can do right now."
	Change Capacity	Ahmadi et al. (2015); Ahmi et al. (2014); Alsheibani et al. (2020); Borgman et al. (2013); Chatterjee et al., (2021); Chukwudi et al., (2018); Liu et al. (2021), Low et al. (2011); Pudjianto and Zo (2009), Pudjianto et al. (2011), Rath et al. (2023); Rosli et al. (2012b), Rosli et al. (2012a), Wang et al. (2016)	*"The challenge is that AI systems have to be integrated into existing systems, and that's where a lot of the problems arise." The management is a bit slow to adapt because of the industry we're in, which requires a lot of safety considerations and trust." "Management is excited about AI because it can potentially cut costs, but they are overlooking the training needs of employees." "There's a cultural change required in management to trust AI, especially in industries with high safety standards."*
Environmental Context	Regulatory Environment	Alsheibani et al. (2020); Borgman et al. (2013); Pudjianto and Zo (2009), Pudjianto et al. (2011); Sun et al. (2018); Zhu et al. (2006)	*"I'm probably quite optimistic about it. I think it's got huge potential if it's governed right… there are a lot of benefits… but where it's scary is where there's not the governance." "In our industry, there are strict regulatory frameworks that we have to adhere to, and GenAI systems need to meet those standards." "We work in a highly regulated environment that requires high accuracy of information, and these tools aren't that accurate." "Privacy and data protection are big concerns… we would never run confidential contracts through open AI platforms." "Some competitors may choose to play fast and loose with GenAI and… security around patient information could be compromised."*

successful integration of GenAI requires a high level of technical expertise which may not be readily available within organisations (Klein et al. 2024; Roux et al., 2023). Implementing GenAI effectively can be a significant learning curve, posing a major challenge, especially for departments with limited experience in advanced AI technologies (McKinsey, 2024b). Additionally, the need for a robust technical architecture and adequate IT infrastructure can present a significant technical and operational hurdle (Denni-Fiberesima, 2024).

Relative Advantage: was widely acknowledged by interviewees, particularly regarding GenAI's potential to streamline business processes and minimise the time spent on repetitive tasks. Participants also recognised its ability to extract valuable insights from unstructured data, enhancing decision-making and operational efficiency. While many participants highlighted the opportunities and benefits GenAI could bring to both businesses and society, they also emphasised that realising these advantages is not without challenges—notably, implementation hurdles and technological barriers that must be addressed for successful adoption. Without adequate support and simplification of these processes, technological adoption is likely to face resistance or delays (Klein et al. 2024; Sarri & Sjölund, 2024). These findings emphasise the importance of user-friendly interfaces, robust support systems, and clear implementation pathways to address the complexity concerns associated with GenAI. A driving force for the technology's adoption stems from the perceived *relative advantages* of GenAI's transformative potential (Brewer et al. 2024; Chakraborty & Biswal, 2024; Khan, 2023). This is summed up with a participant quote - "*I think everyone can see the benefits of it… if it eliminates mundane tasks, then that's great…*" Thus, if human resources can be freed up from such tasks then staff can be redeployed onto more strategic and creative endeavours.

4.3.2. *Organisational context*

This theme encompasses the internal factors that influence an organisation's ability to adopt and integrate GenAI effectively. Two constructs were identified from the interview transcript data and thematic analysis, namely staff skills and change capacity.

Staff Skills: and lack of adequate training was felt to be a reason why GenAI was not being adopted within organisations more readily. Thus, whilst management may be enthusiastic about GenAI's potential to improve efficiency and cut costs, they often overlook the significant training and upskilling required for employees to effectively use the technology (Fui-Hoon Nah et al., 2023). This leaves employees unprepared to integrate it into their workflows. Addressing the skills gap is essential for ensuring that employees can confidently and competently engage with GenAI tools (Wolf & Maier, 2024).

Change Capacity: is important within an organisation if they are to adapt to the changes needed to integrate GenAI into their daily practices. This could mean restructuring workflows or systems which needs practical readiness within an organisation along with system compatibility. Study participants voiced issues around resistance to cultural change at the managerial level along with challenges within their organisation in aligning AI systems with existing infrastructure. The capacity for organisational change plays a pivotal role in shaping how decision-makers support and implement GenAI technologies (Bhatia et al., 2024). Organisations with high levels of change capacity are better positioned to manage the inherent challenges of integration, such as technical complexity and workforce adaptation (Fosso Wamba et al. 2024).

The insights regarding the role of change capacity in enabling GenAI adoption can be further enriched by viewing this factor through the lens of organisational learning theory. Organisations with high change capacity often possess robust learning systems that enable them to absorb, disseminate, and institutionalise knowledge across teams and departments (Fosso Wamba et al. 2024). This reduces reliance on individual staff competencies by transforming tacit knowledge into shared routines and practices. In this view, change capacity is not merely a structural substitute for skills, but a dynamic capability that orchestrates internal resources under uncertainty. It facilitates collective learning, experimentation, innovation and adaptation (Kurup and Gupta, 2022), all key processes that support GenAI integration in complex environments. By framing change capacity as a learning enabler, this study contributes a more nuanced understanding of how organisations mobilise and reconfigure resources to navigate emerging technologies.

4.3.3. Environmental context

This theme includes external influences such as regulatory requirements that affect adoption decisions of GenAI. Here the identified construct from the interview transcript data was Regulatory Environment.

Regulatory Environment: encapsulates both the standards and legal requirements organisations need to adhere to. Thus, when adopting and integrating GenAI, organisations must ensure that GenAI systems comply with these regulations and standards. Hence, participants expressed optimism around the potential of GenAI whilst emphasising that the technology's benefits can only be fully realised if the technology is effectively governed. Interviewees highlighted the importance of robust regulatory frameworks in fostering trust and ensuring safe adoption of GenAI. The regulatory environment was identified as a critical factor influencing the adoption of GenAI. Interviewees expressed optimism about the transformative potential of GenAI but stressed the importance of robust governance structures to mitigate risks and ensure ethical and effective use. Hence for industries with stringent regulatory frameworks, compliance with standards is both a challenge and a requirement for GenAI adoption. The regulatory environment not only acts as a safeguard but also has the potential to shape the pace and scope of GenAI adoption (Gopal et al. 2024; Moreno-Ibarra et al. 2024).

5. Phase 2: quantitative phase approach and findings

5.1. Overview - rationale and approach

This study employs the confirmatory research design approach to test the key associations identified in the phase 1 qualitative study and to exploratorily inform the design of the global survey instrument (Venkatesh et al. 2013; Kumar et al., 2025). Whilst the qualitative study provides in-depth insights, establishes the conceptual model in alignment with key aspects of the literature, it also grounds the quantitative phase in the lived experiences from two culturally comparable but distinct national contexts (Tahir, 2025; Venkatesh et al. 2016). We posit the importance of conducting a subsequent confirmatory study to empirically validate these relationships to offer a richer, more substantive perspective on complex phenomena.

The interviews identified critical individual factors affecting GenAI adoption including perceived complexity, relative advantage, staff skills, and regulatory challenges and change capacity. The Phase 1 analysis revealed the potential for change capacity to act as a moderating factor.

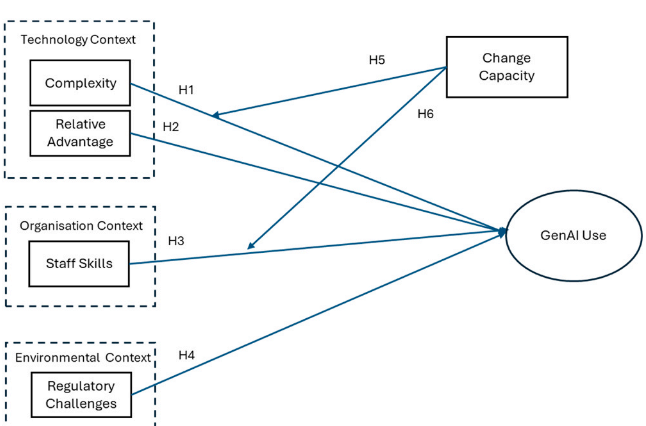

Fig. 2. Proposed Phase 2 Conceptual Model.

5.2. Theoretical background and proposed phase 2 research model

The Phase 2 model presented in Fig. 2 was developed as a direct outcome of the thematic analysis conducted during Phase 1 of the study. This analysis, based on qualitative data obtained from the semi-structured interviews, identified key patterns, categories, and relationships related to the challenges of GenAI adoption within organisations. These emergent themes were validated against the literature and led to the development of the conceptual model. This iterative process reflects the core principles of a mixed methods approach, where qualitative insights inform model construction and are strengthened through theoretical triangulation. By integrating empirical findings with established scholarly work, the Phase 2 model provides a more robust and generalisable representation of the phenomena under investigation, thereby laying the foundation for further quantitative testing and refinement in this second stage.

Consequently, we propose the following phase 2 conceptual model as defined in Fig. 2.

Perceived complexity refers to the extent to which an innovation is perceived as relatively challenging to understand or use (Rogers et al., 1995). In the context of AI adoption in organisations, the complexity is considered as internal organisational issue and is assessed by determining AI application usage, task completion time, decision making effectiveness, system sufficiency, and interface design (Chatterjee et al., 2021). Therefore, in the context of GenAI, complexity can be defined as the degree to which its integration requires substantial transformations to existing systems, workflows, processes, and practices. Higher the complexity, higher will be the uncertainty leading to high resource demands and operational disruptions (Bag et al., 2022; Horani et al., 2023). Organisations often face compatibility issues such as modifications or upgrades to current systems when integrating GenAI with existing systems (Wael AL-Khatib 2023). Furthermore, older systems, may lack the necessary infrastructure and flexibility to interface and interact effectively (Andreoni et al., 2024). Previous studies in different contexts have claimed that perceived complexity negatively affect GenAI adoption (Horani et al., 2023; Wael AL-Khatib 2023). Consequently, we posit that:

H1. : Perceived complexity negatively impacts GenAI adoption.

Relative advantage (RA) refers to "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers & Williams, 1983, p.14). In the context of GenAI, RA can demonstrate improved productivity, efficiency in operational performance, improved decision-making capabilities, cost savings, and automation in complex tasks (Ahmad Khan et al., 2024). When organisations can clearly recognise these tangible benefits, they are more likely to consider GenAI as an investment than risk (Walkowiak & Potts, 2024). This stimulates the confidence amongst the decision makers and stakeholders increasing the likelihood of adopting GenAI within the organisation (Horani et al., 2023). In manufacturing industry, GenAI enables smarter resource allocation, automate workflows, and innovative product development (Doron et al., 2024; Kanbach et al., 2024). While reducing inefficiencies, GenAI help creating new opportunities for innovation and business model transformation to meet changing customer expectations and industry trends (Kanbach et al., 2024). Previous studies in different contexts have confirmed that RA positively affect technology adoption (Horani et al., 2023; Wael AL-Khatib 2023; Wei et al., 2015). Therefore, we posit that:

H2. : The perceived relative advantage positively impacts GenAI adoption.

Staff skills refer to "the technical understanding and subject knowledge that enable employees to carry out their role to the best of their ability" (Wanjiru & Yusuf, 2020, p.4). In the context of AI, staff skills can be defined as the knowledge, competency, and proficiency required to implement, manage and use of GenAI. When an organisation adopting a new technology, the staff may have to work with new workflows, manage large databases, and understanding technology generated outputs (Wamba-Taguimdje et al., 2020). If organisation is equipped with skilled staff, they are more capable of dealing with complexities, which will lead to higher productivity and efficiency (Shimaponda-Nawa & Nwaila, 2024).Training programmes; either on-the-job or off-the-job plays a significant role in skills development, proving that staff are capable enough to adapt growing technical demands bridging the knowledge gaps and to maintain higher performance (Jackson & Allen, 2023). This was further confirmed by the study of Willcocks (2024) claiming that ongoing reskilling and upskilling helps organisations to accept collective challenges of adopting new technologies. The studies in different context have claimed that staff skills positively influence the adoption of new technologies (Armstrong et al., 2024; Balasooriya et al., 2022; Jankovic & Curovic, 2023). In addition, the adoption of innovative technologies requires skilled employees within the organisation to use AI effectively. For instance, when complexity of AI systems and algorithms grow, individuals often perceive them as “black boxes”, requiring specialised knowledge and expertise to understand the AI decision making or performance implications (Shin, 2021). Therefore, organisations may resist adopting GenAI due to a perceived or actual lack of key skills (wael AL-khatib, 2023). Therefore, we posits that:

H3. : Staff skills and competency will positively impact GenAI adoption

Regulatory environment refers to the rules, regulations, and standards imposed by the governments (Yang et al., 2024). Government regulations can either insist or eliminate barriers to adopting new technologies (Horani et al., 2023). In the context of AI, government challenges can be defined as the rules and regulations proposed to ensure ethical implementation and use of AI. Though GenAI provides several benefits, rigorous regulations around data privacy, ethical use, and compliance can lead to challenges in adopting GenAI within organisational settings (Horani et al., 2023). For instance, the data protection laws such as General Data Protection Laws (GDPR) demands strict regulations in implementation GenAI when dealing with personal sensitive data (Chandrasekaran, 2024). Furthermore, organisations cannot input individual data into Large Language Models (LLMs) without obtaining consent from individuals, if their data has been used to train those models (Wirtz et al., 2019). In addition, some organisations are subjected to industry-specific regulations (Solaiman, 2024). For example, although GenAI improve the patient outcomes in healthcare, strict patient data privacy laws prevent use of data for treatment planning (Yu & Zhai, 2024). Furthermore, regulatory pressure can increase the costs of GenAI implementation as organisations have to invest in additional measures such as ethical protocols and government frameworks (Rana et al., 2024). The failure to adhere to these regulations will result in unnecessary consequences such as legal penalties, reputational damage and this will lead to non-adoption of GenAI (Carnat, 2024). Previous studies in different contexts have claimed that regulatory pressure negatively influence the adoption of technology (Ali & Osmanaj, 2020; Darko et al., 2018; Shen et al., 2024). Consequently, we posit that:

H4. : Regulatory pressure negatively impacts GenAI adoption

Change capacity refers to “the latent ability to manage change which is called to be developed” (Montreuil, 2022, p.1189). As an innovative technology, AI has influenced the way the work is done at both employee and process level (Leyer & Schneider, 2021). Also, AI implementation transforms workflows from manual to fully automation or augmenting humans (Kurup & Gupta, 2022). Therefore, change capacity plays a significant role in AI adoption as a core dynamic capability. The study by Kurup and Gupta (2022) claims that the organisation, which has executed similar change will be aware of the barriers and challenges that will bring. Therefore, organisations that have successful experience in change management are more likely to deploy AI. Higher perceived complexity prevent organisation from adopting innovative technologies as it involves in overcoming technological barriers, reskilling, or upskilling employees, and proper resource allocation (Sharma et al., 2024). However, if an organisation is open to change and have utilised proper change management strategies, it will mitigate the complexities of new technology adoption (Bhatia et al., 2024). The change capacity significantly depends on the organisation’s capability in resource allocation, leadership support, employee adaptability, and positive working culture (Cao & Le, 2022). In addition, organisations with lower change capacity significantly depends on the skills and competency of staff (David et al., 2024). Skilled staff offset the barriers in organisations readiness in adopting new technologies (Kelly et al., 2017). However, if the organisation has enough structures, resources, and strategies in place to support change, it will not rely heavily depend on staff skills (Peirson et al., 2012). Therefore, we hypothesise that:

H5. : Change capacity positively moderates the relationship between perceived complexity and GenAI adoption.

H6. : Change capacity negatively moderates the relationship between staff skills and GenAI adoption.

5.3. *Survey method*

To validate the phase 2 conceptual model and test the hypotheses, a comprehensive survey was conducted. The questionnaire included items on constructs that emerged from the phase 1 thematic analysis. Participants were recruited through the online platform - Prolific. Ethical approval was secured prior to data collection, and informed consent was obtained from all participants before they began the survey.

5.3.1. *Participants and procedure*

To ensure high-quality and targeted responses, a pre-screening filter was applied on Prolific to include participants holding managerial roles, such as manager, senior manager, or C-suite executive positions. This ensured that participants fulfilled the criteria of decision-makers within their organisations and could offer informed perspectives on the contributing factors underlying GenAI adoption. Only individuals meeting these pre-screening criteria were able to access the study through an external link hosted on the Qualtrics survey platform. The final sample included decision-makers from organisations spanning multiple continents, industries, and sizes. This diversity not only enhances the external validity of the findings but also enables a more nuanced understanding of how GenAI adoption is shaped by varied organisational and environmental contexts. By capturing perspectives from a broad cross-section of global decision-makers including those in both resource-rich and resource-constrained environments, and across sectors with differing levels of digital maturity the study identifies patterns and divergences in adoption drivers that might otherwise remain obscured in more homogenous samples. It also strengthens the relevance of the findings for policymakers, practitioners, and researchers seeking to understand how organisational readiness, strategic priorities, and contextual pressures interact to influence GenAI uptake across different settings.

The survey contained two main sections: (1) demographic profile of the respondents and (2) the main questionnaire. The first section asked the respondents information corresponding to their gender, age, years of work experience, organisational size, and geographical location. The second section focused on their GenAI use behaviour, as well as their experiences and perceptions related to it. Attention-check questions were incorporated into the survey to identify and exclude inattentive responses (Kung et al., 2018). A total of three hundred and four (304) participants who completed the survey and passed the attention checks were included in the final analysis. Participant demographics, including gender, age, years of work experience, organisational size, and geographical location, are detailed in Table 3. As can be seen from the demographic data in Table 2, the participants were sourced from a range

Table 3
Participants profile.

Characteristics	Number of Participants	Percentage
Gender		
Male	165	54.3 %
Female	137	45.1 %
Prefer not to say	2	0.6 %
Age		
18–30	109	36 %
31–40	104	34 %
41–50	57	19 %
51–60	25	8 %
61 and above	9	3 %
Working Experience		
Less than 1 year	5	2 %
1–3 years	70	23 %
4–6 years	72	24 %
7–10 years	65	21 %
11–15 years	35	12 %
More than 15 years	57	19 %
Firm Size		
Fewer than 50	85	28 %
50–99	55	18 %
100–499	66	22 %
500–999	25	8 %
1000–4999	40	13 %
5000 or more	33	11 %
Location		
Africa	71	23 %
Asia	15	5 %
Europe	62	20 %
North America	105	35 %
South America	13	4 %
Oceania	29	10 %
Others	9	3 %
Total	304	100 %

of locations including: North America, Europe, Africa, Australia and Asia who worked for a range of organisations of varying sizes. Survey data collection was conducted in December 2024.

5.3.2. *Measures*

To ensure high levels of reliability and validity, the questionnaire employed in this study was constructed using items adapted from previously validated instruments in the extant literature. Adapting existing measurement scales is a well-established practice in empirical research, as it enhances construct validity and allows for comparability across studies (DeVellis, 2016; Hinkin, 1995). By drawing on prior empirical work, this study sought to ensure that each construct was measured using indicators that had demonstrated both conceptual clarity and statistical robustness in earlier contexts. Each item was carefully reviewed and, where necessary, linguistically or contextually modified to align with the specific research objectives and the unique organisational and technological setting under investigation. Such modifications were carried out in line with best practices for scale adaptation, ensuring that item meanings were preserved while contextual relevance was enhanced (Behr, 2017; Matsunaga, 2010). All responses were recorded using seven-point Likert-type scales, which are commonly used in organisational and behavioural research to capture the intensity of respondents' attitudes or perceptions (Finstad, 2010). The seven-point format was chosen to increase response variance and measurement sensitivity, while maintaining reliability and interpretability (Dawes, 2008). This format also supports more nuanced statistical analysis, particularly in structural equation modelling and factor analysis. The complete list of measurement items is provided in Appendix.

Complexity was measured with two items adapted from Wang et al. (2016). Example item is "*The implementation of GenAI to existing systems are complex to achieve*". Perceived relative advantage was measured with four items adapted from Siew et al. (2020) and Iranmanesh et al. (2023). Example item is "*GenAI improves the efficiency of your organisation's operations*". Staff skills and competency was measured with four items adapted from Gangwar et al. (2015) and Siew et al. (2020). One example item is "*Your organisation recruit personnel with the necessary skills to use GenAI effectively*". Perceived change capacity was measured by two items adapted from Singh et al. (2024) and Mikalef and Patelli (2017). Example item is "*My organisation has the capacity to easily adapt to changes driven by Generative AI adoption*". Regulatory pressure was measured by two items adapted from Pan et al. (2023), example item is, "*The use of GenAI impacted by government procedure*". In this study, GenAI use was assessed by examining how frequently participants currently employ it in their work (Ivanov et al., 2024). Considering factors that could influence individuals' GenAI use, we include age and working experience as control variables.

5.4. *Results*

5.4.1. *Evaluation of measurement model*

We conducted a confirmatory factor analysis (CFA) using R Studio (2024.09.1 +394) to assess the measurement model. CFA is a widely adopted technique in SEM that allows researchers to test whether the data fit a hypothesised measurement model based on theory or prior empirical findings (Brown, 2015; Kline, 2023). Factor loadings, reliability, convergent validity, and discriminant validity were calculated as part of the analysis.

The results showed strong internal consistency and reliability, as evidenced by Cronbach's alpha and composite reliability values for all constructs, which were above 0.80 (Table 4) and well above the threshold of 0.70 (Hair et al., 2019). Convergent validity was tested by calculating the average variance extracted (AVE), with all AVE values exceeding 0.68, surpassing the recommended cut-off of 0.50 (Fornell & Larcker, 1981). As presented in the correlation matrix (Table 4), the square roots of all constructs' AVE values were higher than the corresponding correlation values between themselves and other constructs, demonstrating satisfactory discriminant validity (Fornell & Larcker, 1981).

Finally, in terms of the model fit indices, the overall measurement model exhibited excellent model fit indices: $\chi 2$ / df = 2.13, $p < 0.001$, Tucker-Lewis Index (TLI) = 0.965, Comparative Fit Index (CFI) = 0.975 and Standardised Root Mean Square Residual (SRMR)= 0.043. These results are presented in Table 5 and provide strong evidence for construct validity (Hair et al., 2019). Collectively, these findings indicate a well-fitting measurement model, providing a sound basis for proceeding with the structural model and hypothesis testing.

We examined the potential impact of common method bias on our data using multiple approaches. First, we reviewed the correlation matrix (Table 4) and confirmed that no correlation exceeded the 0.90 threshold, as recommended by Bagozzi et al. (1991). Additionally, we employed the CFA-based Harman's single-factor test. The fit indices for the common factor model (χ^2/df = 13.7, CFI = 0.673, TLI = 0.608, SRMR = 0.12) were found to be unacceptable and significantly worse than the actual measurement model. These findings further suggest that common method bias is not a concern in this study (Kamboj et al., 2018).

Table 6 presents a comprehensive assessment of the measurement model's reliability and convergent validity, offering evidence of the internal consistency and construct validity of the scales used in the study. The table reports key indicators factor loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) which are widely recognised in SEM as essential for evaluating the quality and robustness of latent construct measurement. The CFA results indicated that the factor structure was adequate, with all factor loadings exceeding 0.70, meeting the recommended threshold (Hair et al., 2019). This suggests that the indicators exhibit strong convergent validity and are sufficiently representative of their respective constructs. While SEM generally recommends three or more items (Cheah et al., 2018), two-items constructs are not unusual in applied research (Eisinga et al., 2013), especially in recent studies in the context of AI adoption

Table 4
Correlations matrix.

	1.	2.	3.	4.	5.	6.	7.	8.
1. Complexity	(0.83)	−.19**	−0.09	0.09	−0.18**	−0.23**	−0.02	−0.07
2. Relative advantage	−0.19**	(0.84)	.68**	0.41**	0.59**	0.56**	−0.19**	−0.13*
3. Staff skills	−0.09	0.61**	(0.85)	0.62**	0.71**	0.54**	−0.27**	−0.11
4. Regulatory challenges	0.09	0.41**	0.59**	(0.82)	0.33**	0.28**	−0.26**	−0.11*
5. Change capacity	−.18**	0.59**	0.72**	0.31**	(0.85)	0.47**	−0.18**	−0.07
6. GenAI use	−.23**	0.56**	0.54**	0.28**	0.47**		−0.17**	−0.04
7. Age	−0.02	−0.19**	−0.28**	−0.26**	−0.18**	−0.17**		0.63**
8. Working experience	−0.07	−0.13*	−0.14*	−0.11*	−0.07	−0.04	0.63**	

Note: N = 304. **Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed). Square root of AVE for each construct appears on the main diagonal in parentheses.

Table 5
Model fit indices for the measurement and structural models.

Measure	Measurement model	Structural model	Threshold (Hair et al., 2019)
(χ2/df)	2.13	2.32	1–3
P-value (Chi-square)	p < 0.001	p < 0.001	
Tucker-Lewis Index (TLI)	0.965	0.943	≥ 0.9
Comparative Fit Index (CFI)	0.975	0.957	≥ 0.9
RMSEA	0.061	0.066	≤ 0.08
SRMR	0.043	0.078	≤ 0.08

(Hu et al., 2025; Shaikh et al., 2023; Mohr & Kühl, 2021). In this study, complexity, regulatory pressure, and change capacity were each measured using two items. Despite the limited number of indicators, all constructs met thresholds for factor loadings (>0.7), composite reliability (> 0.8), and average variance extracted (> 0.6), supporting their reliability and convergent validity.

5.4.2. Testing hypotheses

Following the confirmation of reliability and validity through CFA, the study proceeded to test the hypothesised relationships by evaluating the structural model using SEM. The structural model analysis was conducted to assess the strength and significance of the proposed path coefficients, providing insight into the direct effects between constructs in the theoretical framework. After progressing to the hypothesis-testing phase, we evaluated the structural model's fit. The fit indices remained excellent, exceeding all recommended thresholds, as presented in Table 6. Collectively, these indices suggest that the hypothesised model provides a satisfactory representation of the observed data.

To evaluate potential multicollinearity in the structural model, variance inflation factor (VIF) values for the latent constructs were examined (Hair et al., 2019). All calculated VIF values are between 1.04 and 3.95, below the conservative threshold of 5, suggesting that multicollinearity was not a concern in this analysis (Hair et al., 2019). Table 7 presents the detailed VIF values. Furthermore, the coefficient of determination (R^2) for the GenAI use construct was 0.412, indicating that approximately 41.2 % of the variance in GenAI use can be explained by the predictors included in the model, indicating moderate predictive power (Chin, 1998; Hubert et al., 2025). In addition, we calculated 95 % confidence intervals for each hypothesis to confirm that the average mean true score fell within the interval with a bootstrapping procedure with 5000 subsamples (Jiang et al., 2012). The results of the standardised coefficient (β), standard error (SE), 95 % confidence interval (CI), and p-value for each hypothesis tested are shown in Table 7.

The analysis revealed several statistically significant relationships between the predictor variables and GenAI use. Specifically, relative advantage demonstrated a strong positive influence on GenAI use ($\beta = 0.340$, $p < 0.001$), indicating that the more beneficial GenAI is perceived to be compared to existing practices, the more likely it is to be adopted within organisations. This finding aligns with previous innovation adoption research, where perceived benefits have consistently emerged as a critical driver (Rogers, 2003; Venkatesh et al., 2003). Similarly, Staff Skills exhibited a significant positive effect ($\beta = 0.390$, $p < 0.001$), suggesting that employees' digital competencies and readiness are essential enablers of GenAI use. This reinforces the importance of workforce capabilities in the successful adoption of emerging technologies (Trenerry et al. 2021). In contrast, Complexity had a significant negative effect on GenAI use ($\beta = -0.135$, $p < 0.05$), indicating that perceptions of GenAI being difficult to understand or implement may inhibit its organisational uptake. This is consistent with prior findings that technological complexity can be a barrier to adoption, particularly in settings where change management resources are limited (Thong, 1999). Therefore, hypotheses 1, 2, and 3 are supported.

Hypothesis 4 posited that regulatory challenges would negatively influence GenAI use. However, the structural path coefficient was not

Table 6
Reliability and convergent validity of the model.

	Mean (Std. Deviation)	Cronbach's α	Composite Reliability (CR)	Average variance extracted (AVE)	Factor loadings in the measurement model	Factor loadings in the structural model
Complexity	3.38 (1.28)	0.81	0.82	0.69	(Complex 1) 0.924*** (Complex 2) 0.740***	(Complex 1) 0. 973*** (Complex 2) 0.703***
Relative advantage	4.85 (1.22)	0.90	0.91	0.71	(Advantage 1) 0.886*** (Advantage 2) 0.915*** (Advantage 3) 0.811*** (Advantage 4) 0.753***	(Advantage 1) 0.889*** (Advantage 2) 0.912*** (Advantage 3) 0.810*** (Advantage 4) 0.757***
Staff skills	3.82 (1.39)	0.83	0.88	0.72	(Skills 1) 0.856*** (Skills 2) 0.893*** (Skills 3) 0.791***	(Skills 1) 0.861*** (Skills 2) 0.896*** (Skills 3) 0.778***
Regulatory challenges	2.86 (1.65)	0.80	0.81	0.68	(Regulatory 1) 0.879*** (Regulatory 2) 0.765***	(Regulatory 1) 0.877*** (Regulatory 2) 0.767***
Change capacity	4.33 (1.41)	0.83	0.84	0.72	(Change 1) 0.900*** (Change 2) 0.795***	(Change 1) 0.898*** (Change 2) 0.797***

Note: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05.

Table 7
Hypothesis testing.

Hypothesis	Path	VIF	Std. est(β)	Std.Err (SE)	t Statistics	CI.Lower	CI.Upper	p-value	Supported?
H1	Complexity → GenAI Use	1.15	−0.135	0.079	- 2.267	- 0.326	- 0.025	0.023	Yes
H2	RelativeAdvantg → GenAI Use	2.14	0.340	0.101	4.864	0.306	0.704	0.000	Yes
H3	StaffSkills → GenAI Use	3.95	0.390	0.115	3.521	0.185	0.634	0.000	Yes
H4	RegltryChllngs → GenAI Use	2.79	−0.123	0.100	- 1.183	- 0.339	0.055	0.237	No
H5	(Complexity× change) → GenAI Use	1.04	0.12	0.042	2.388	0.018	0.183	0.017	Yes
H6	(Staffskills × change) → GenAI Use	2.00	−0.147	0.051	−2.029	−0.201	−0.003	0.043	Yes

- R^2= 0.419
- Δ R^2 (Complexity× change)= 0.025
- Δ R^2(Staffskills × change)= 0.018

Note: VIFs for main predictors are based on the structural model. VIFs for interaction terms (StaffSkills × Change, Complexity × Change) are based on the moderation models.

statistically significant (β = −0.123 p = n.s.), as shown in Table 6. The corresponding t-value of −1.183 and p value 0.237 falls out of the critical threshold, indicating insufficient evidence to support the hypothesised negative relationship. Consequently, Hypothesis H4 was not supported. This finding suggests that, within the scope of this study, regulatory concerns are not perceived as a primary deterrent to the adoption of Generative AI. One possible interpretation is that organisations may view regulatory uncertainty as manageable or secondary compared to internal factors such as technological readiness or human capability. Alternatively, it may reflect a lag in awareness or response to emerging AI governance frameworks, particularly if formal regulatory pressures have not yet materialised or been enforced at scale (Floridi et al., 2018). For the control variables, age (β = −0.087; p = n.s.) and working experience (β = 0.083; p = n.s.) did not have a significant influence on GenAI use.

Hypothesis 5 proposed that an organisation's change capacity would moderate the relationship between perceived complexity and GenAI use, such that increased change capacity would mitigate the negative impact of complexity. Mean-centering was applied to the independent variables and moderator prior to generating the interaction terms to reduce multicollinearity (Aiken and West, 1991). As reported in Table 6, the interaction term (complexity × change capacity) was positively and significantly associated with GenAI use (β = 0.12, $p < 0.05$). This finding indicates that change capacity plays a positive moderating role, attenuating the negative effect of perceived complexity. In other words, organisations with a higher capacity for change are better able to overcome the perceived difficulties of GenAI implementation, thus facilitating greater adoption despite complexity concerns. Adding the interaction term (Complexity × Change) increased the explained variance in GenAI Use by 2.5 % ($\Delta R^2 = 0.025$). Given that interaction effects in social science research typically account for 1–3 % of variance in the dependent variable, the 2.5 % explained by the interaction term in this study reflects a meaningful moderation effect (Fairchild & McQuillin, 2010; Champoux & Peters, 1987).

To demonstrate the moderation effect, simple slopes were estimated and plotted using unstandardised coefficients (see Fig. 3). Predicted values of GenAI use were calculated at one standard deviation above and below the mean of change capacity. As shown in Fig. 3, when change capacity was low (−1 SD), the negative relationship between complexity and GenAI use was stronger (b = −0.366, SE=2.633, p = 0.890). In contrast, under high change capacity (+1 SD), the relationship remained negative but was weaker (b = −0.106, SE=2.922, p = 0.971). This pattern suggests that greater change capacity attenuates the negative impact of complexity on GenAI use. Even though the simple slopes were not statistically significant individually, the significant interaction term in the structural model (in Table 6) indicates that the difference between these slopes is statistically meaningful. This supports the presence of a moderation effect, supporting Hypothesis 5. Substantively, this means that higher change capacity buffers the adverse effect of complexity on GenAI use, aligning with our theorisation that organisations with stronger change capacity adapt and absorb new practices more steadily, even when main effects appear small at isolated moderator values.

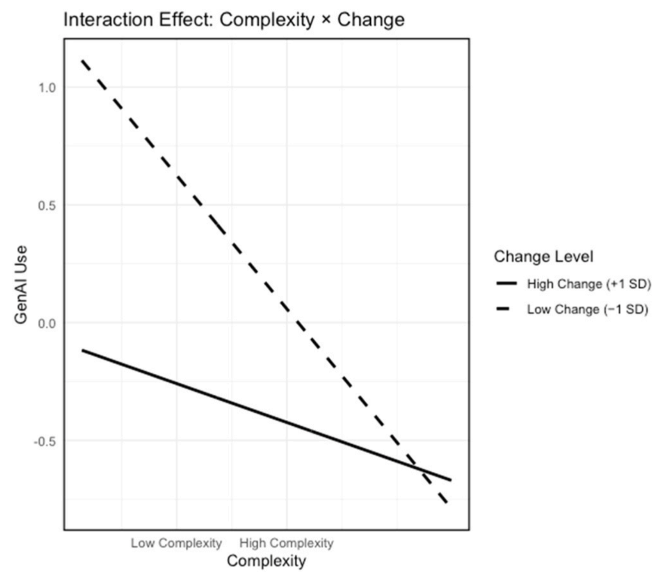

Fig. 3. The interaction effect of change capacity and complexity on GenAI Use.

In parallel, Hypothesis 6 posited that change capacity would moderate the relationship between staff skills and GenAI use, such that higher change capacity would weaken the positive influence of staff skills. As seen in Table 6, the interaction term (staff skills × change capacity) was found to be negatively and significantly related to GenAI use (β = −0.147, $p < 0.05$). This suggests that change capacity negatively moderates the relationship between staff skills and GenAI use. Specifically, as organisational change capacity increases, the marginal benefit of staff skills decreases, potentially due to overlapping or compensatory mechanisms between structural enablers and human capital. In contexts where change infrastructure is strong, reliance on individual competencies may be less critical. Adding the interaction term (Staff skills × change) increased the explained variance in GenAI Use by 1.8 % (ΔR^2 = 0.018), indicating a small but meaningful moderation effect (Fairchild & McQuillin, 2010; Champoux & Peters, 1987). To demonstrate the moderation effect, simple slopes were estimated and plotted using unstandardised coefficients (see Fig. 4). Predicted values of GenAI use were calculated at one standard deviation above and below the mean of change capacity. As shown in Fig. 4, when change capacity was low (−1 SD), the positive relationship between staff skills and GenAI use was stronger (b = 0.87, SE=3.238, p = 0.7883). In contrast, under high change capacity (+1 SD), the relationship remained positive but was weaker (b = 0.611, SE=3.506, p = 0.8618). This pattern suggests that greater change capacity reduces the reliance on staff skills for driving GenAI use. Again, although the

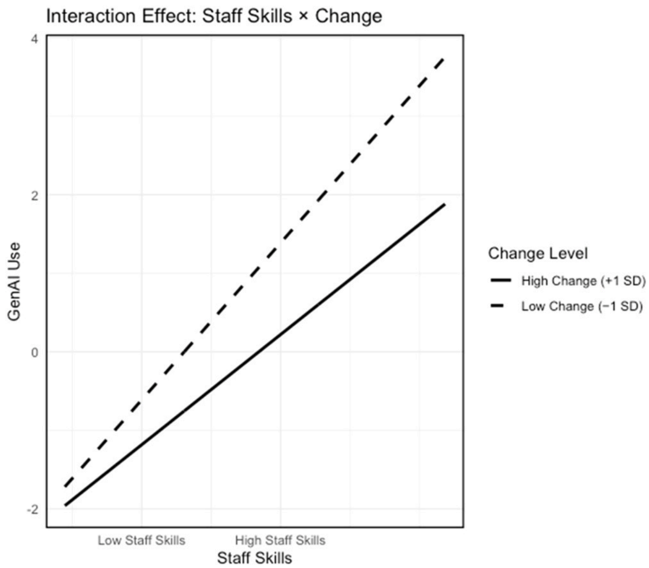

Fig. 4. The interaction effect of change capacity and staff skills on GenAI Use.

simple slopes were not statistically significant individually, the significant interaction term in the structural model indicates that the difference between these slopes is statistically meaningful, supporting the presence of a moderation effect and providing evidence for Hypothesis 6. Substantively, GenAI adoption becomes less sensitive to skill variation when change capacity is high, and more sensitive when change capacity is low, consistent with our hypothesis that organisations enact adoption differently depending on their readiness for change. Practically, organisations that invest in change capacity (e.g., change routines) can offset skill gaps. This aligns with the need to pair workforce development strategies with organisational change-readiness initiatives, especially in new technologies such as GenAI adoption environments (Agrawal et al., 2024; David et al., 2024; Hayes, 2017).

These findings highlight the nuanced role of change capacity as a contingency factor in GenAI adoption. While it can buffer the effects of perceived barriers such as complexity, it may also redistribute the influence of internal resources like staff skills, underscoring the importance of a systems-level view of organisational readiness for emerging technologies.

A visual path diagram summarising all supported relationships is shown in Fig. 5.

6. Discussion

This study investigated the key factors influencing the use of Generative AI (GenAI) in organisations, guided by the TOE framework. The quantitative findings complement the earlier qualitative phase and offer an integrated view of the organisational conditions shaping GenAI adoption.

6.1. The impact of complexity

Although many organisations are currently experimenting with GenAI to explore its potential and assess its impact on existing business models, moving beyond pilot projects toward full-scale integration remains a significant challenge. This transition is often hindered by factors such as technological uncertainty, lack of organisational readiness, insufficient governance frameworks, and the complexity of aligning GenAI capabilities with strategic goals. As a result, while exploratory use is becoming widespread, the path to sustainable and value-driven GenAI adoption is far from straightforward. Consistent with prior literature and interview data, the survey results confirmed that perceived

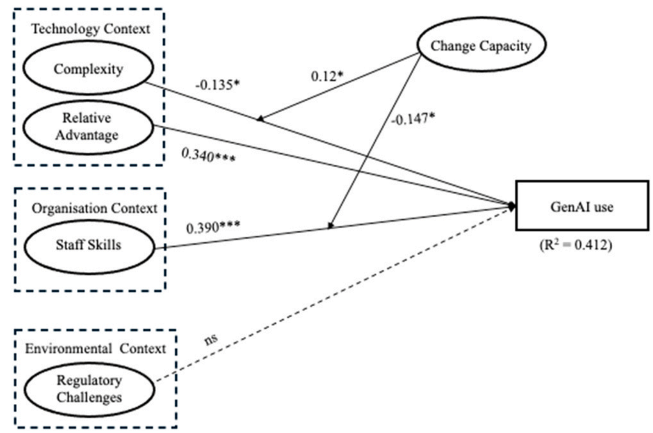

Fig. 5. Results of the structural model testing (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ns = not supported). Note: Continuous line indicates an empirically significant relationship, and a dotted line indicates a statistically non-significant relationship.

technological complexity negatively affects GenAI use. Complexity in this context refers to the extent to which GenAI technologies are perceived as difficult to interpret, configure, and importantly, integrate into existing IT infrastructure. As a technological barrier, complexity aligns with TOE's technological context, which underscores how perceived characteristics of an innovation such as compatibility, trialability, and complexity influence its adoption (Rogers, 2003; Venkatesh & Davis, 2000). The qualitative findings also highlighted concerns about the explainability of generative models, unpredictability of outputs, and technical integration challenges. These concerns align with recent findings in the AI literature, which highlight implementation uncertainty and technical limitations as barriers to adoption (Dwivedi et al., 2023b).

6.1.1. Complexity → Explainability complexity

While it is unsurprising that respondents viewed GenAI as complex, this should not be reduced to a generic barrier. In classical IT studies, complexity typically refers to integration difficulties or steep learning curves (Dwivedi et al., 2009; Wang et al., 2016). With GenAI, however, our findings point toward explainability complexity, the epistemic difficulty of making sense of GenAI outputs that may be simultaneously useful, biased, or unpredictable. This reframing shifts the technological dimension of TOE from purely technical assessments to include cognitive and interpretive challenges. Therefore, it is important to address the specifics of interpretability by organizations considering both the functionality of GenAI systems and their ability to trust and authenticate outputs that are often non-transparent. This reframing shifts the technological dimension of TOE from purely technical evaluations to cognitive and interpretive challenges. Adoption decisions, therefore, are not only about functionality but also about whether firms can trust and legitimise outputs they do not fully understand. Therefore, understanding explainability complexity is important for organisations aiming to handle the suggestions of GenAI adoption effectively.

6.2. Relative advantage as a key driver

Relative advantage, a core construct within the technological context of the TOE framework, emerged as the strongest positive predictor of GenAI use in this study. This construct reflects the degree to which an innovation is perceived as offering greater benefits than the existing systems or processes it replaces. Its strong influence on adoption aligns with Rogers' (2003) diffusion of innovations theory, which emphasises that the more clearly an innovation is seen to provide benefits, the more likely it is to be adopted. The survey data showed that relative advantage had the highest mean score across all constructs, suggesting that organisations clearly recognise the value proposition of GenAI technologies. These perceived advantages often included gains in efficiency, improved decision-making, enhanced customer interaction, and productivity boosts across various departments. From a TOE perspective, this reinforces the idea that positive technological characteristics particularly when they are well understood can directly drive adoption intentions. The interviews corroborated this view, with respondents citing practical benefits such as improved content creation and data analysis capabilities. These results reflect recent literature that positions GenAI as a general-purpose technology capable of reshaping workflows across industries, an insight that maps directly onto the perceived relative advantage dimension (Dwivedi et al., 2023b; Horani et al. 2023). Moreover, because GenAI tools often integrate with existing platforms (e.g., CRM, content management systems, data pipelines), organisations may perceive the adoption process as lower risk, further amplifying the sense of advantage.

6.3. Role of staff skills

Staff skills, situated within the organisational context of the TOE framework, were found to have a significant positive effect on GenAI use. This construct reflects the organisation's human capital capacity specifically, the digital, analytical, and problem-solving competencies of its workforce. Within TOE, the organisational context encompasses internal characteristics such as employee expertise, managerial support, and structural readiness that shape an organisation's ability to adopt and implement new technologies. The strong influence of staff skills in this study supports the notion that internal competence is a foundational enabler of innovation adoption. This reinforces existing research that positions workforce capability as essential for successful technology adoption (Zhu & Kraemer, 2005; Bharadwaj, 2000). Organisations where employees possess high levels of technical literacy, AI familiarity, or prior experience with automation technologies are more likely to engage in experimentation, customisation, and integration of GenAI tools. Recent studies echo the importance of upskilling and technical literacy for AI readiness, particularly in rapidly evolving fields like GenAI (Morandini et al. 2023).

6.3.1. Skills → Capability complementarity

Our results confirm that skills are important for GenAI adoption, but this finding requires reinterpretation beyond a routine TOE driver. Unlike prior IT contexts where skills were primarily internal resources (Zhu & Kraemer, 2005; Bharadwaj, 2000), GenAI foregrounds capability complementarity—the interplay between human expertise and machine generativity. Skills such as prompt engineering or curating training data are not only organisational competencies but also mechanisms for unlocking technological affordances. This complexity stresses that the relationship between human and AI capabilities is not merely additive; rather, it is a synergistic interaction that redefines our understanding of resource integration in technology adoption. This challenges TOE's assumption that skills sit squarely within the organisational pillar, suggesting instead that GenAI adoption is contingent on *socio-technical skills* that cut across categories. In this way, the "skills effect" is less about capacity in isolation and more about the *fit* between human and AI capabilities. Accordingly, we extend TOE's applicability, recognising that successful adoption hinges on the dynamic interplay between human and AI capabilities, rather than on isolated organisational resources.

Moreover, staff skills are not just about technical proficiency, but also about adaptability and cognitive flexibility, especially given the emerging nature of GenAI. The ability to engage in prompt engineering, assess AI outputs for accuracy and bias, and apply GenAI in a domain-specific context all require a unique blend of domain knowledge and digital agility. These findings are echoed in the literature, where the concept of "AI readiness" increasingly includes the development of workforce capabilities as a central dimension (Raisch & Krakowski, 2021; Dwivedi et al., 2023b). The qualitative phase further supported this, revealing that organisations with in-house AI expertise experienced fewer barriers to implementation. From a TOE perspective, the findings reinforce that organisational readiness is not limited to infrastructure or budget it must include skills, knowledge-sharing practices, and cultural openness to innovation. For GenAI in particular, where use cases and best practices are still evolving, the ability to experiment, learn, and iterate internally becomes a strategic asset. Organisations that invest in upskilling and internal capability-building are more likely to move beyond pilot projects and achieve meaningful, scalable adoption (Chatterjee et al. 2021).

6.4. Regulatory challenges

Contrary to expectations, regulatory challenges were not significantly associated with GenAI use. This finding may indicate a lack of regulatory clarity or enforcement at the time of data collection. Although respondents recognised the existence of regulatory issues, these challenges did not appear to be strong enough to influence adoption behaviours. This finding may reflect a regulatory ambiguity specific to GenAI where organisations have yet to implement formal, enforceable policies tailored to generative AI technologies. As such, the perceived external pressure from regulatory bodies may have been low, especially when compared to more mature technologies that are subject to established compliance regimes. Respondents appeared to acknowledge the presence of regulatory issues such as data protection, transparency, and ethical use but these concerns did not significantly impact adoption behaviour, likely because they were still seen as emerging or non-urgent.

6.4.1. Regulation → Regulatory flux and institutional voids

The non-significant role of regulatory pressure could be read as evidence that "regulation does not matter," but we argue it reflects a deeper institutional phenomenon: regulatory flux. GenAI adoption unfolds amid rapidly shifting, fragmented, and often ambiguous rules. From an institutional theory perspective, this could point to a regulatory void where governance structures lag behind technological advance, creating weak institutionalisation. In such contexts, organisations cannot anchor adoption logic in external mandates, so the environmental pillar of TOE loses explanatory strength. Instead, internal organisational factors, particularly change capacity, become decisive and a core dynamic capability. This observation underlines the need for deeper theorisation around regulatory flux, specifically how weak institutionalisation in GenAI governance creates a void that organisations must steer. By framing regulatory pressure within this context, we expose that the lack of clear governance can significantly affect the dynamics of adoption. This finding extends TOE by highlighting how institutional immaturity alters the balance of forces shaping adoption.

Furthermore, linking this to broader institutional theory, we propose that the relationship between regulatory voids and organizational change capacity is vital for understanding how organisations accomplish technological integration in the absence of steady regulatory frameworks. From a TOE perspective, this disconnect highlights a temporal gap between environmental change and organisational response. The institutional environment may be evolving more slowly than the pace of technological advancement, particularly in the case of AI. The literature supports this view, noting that many organisations operate in a "regulatory grey area", where AI policies are either under development or inconsistently enforced (Floridi et al., 2018; Stix, 2021). Another interpretation is that internal technological and organisational factors currently outweigh external ones when it comes to GenAI adoption.

In this early stage, decisions may be driven more by the perceived value and feasibility of GenAI, as well as internal skills and change capacity, rather than by compliance concerns. This is in line with TOE-based findings in other studies where environmental factors play a stronger role in later adoption stages or when regulation becomes more explicit and enforced. Despite these explanations the finding is inconsistent with previous literature, which identified regulatory pressure as a significant external barrier to AI Adoption (Ali & Osmanaj, 2020; Darko et al., 2018; Shen et al., 2024). Studies in healthcare, finance and government signify concerns related to data privacy, algorithmic accountability, legal liability prevent organisations from adopting AI technologies (Bak et al., 2022; Jaxon, 2024; Novelli et al., 2024). However, we posit that the contextual variation may be a factor in this study. The participants of this study represent organisations across North America, Africa, Europe, and Oceania. This geographic diversity could weaken the strength of regulatory pressure as a general factor, as many regions are still developing or implementing AI specific regulations. For instance, while EU has introduced EU AI Act (2024), several authorities in Africa and Asia have yet to implement AI policies (Walter, 2024). Accordingly, the perception of regulatory impact may vary widely, making the overall effect statistically non-significant. However, this does not imply that regulatory issues are irrelevant rather, their influence may be lagging. As policy frameworks such as the EU AI Act (EU AI Act, 2024) and other national AI regulations gain traction, organisations may soon face more direct compliance obligations. This calls for longitudinal monitoring, as the influence of the environmental context is likely to increase over time. It also points to a need for proactive governance readiness within organisations, even before formal regulation is enacted.

6.5. Predictor strength and practical implications

Among the significant predictors, relative advantage and staff skills both of which fall under the technological and organisational contexts of the TOE framework, respectively had the strongest influence on GenAI use. These findings underscore the importance of internal drivers in shaping early-stage adoption of emerging technologies like GenAI. Relative advantage, representing the perceived benefits of GenAI over current systems, reflects how organisations evaluate the strategic value and operational improvements a new technology can deliver. Staff skills, meanwhile, reflect the organisation’s readiness and absorptive capacity to leverage these innovations effectively.

These results suggest that organisations are more likely to adopt GenAI when the utility and performance benefits are clearly demonstrated, and when there is sufficient internal expertise to engage with the technology. In practical terms, this means that adoption can be facilitated through targeted initiatives to communicate use cases and demonstrate ROI, as well as by investing in workforce development—especially in areas like prompt engineering, AI ethics, and applied data literacy. They also align with resource-based and dynamic capability theories, which emphasise the importance of internal capabilities and perceived value in innovation uptake (Barney, 1991; Teece, 2007). Moreover, these results are echoed in contemporary literature on AI implementation, which stresses the dual importance of technological fit and organisational readiness (Dwivedi et al., 2023b).

From a theoretical standpoint, these findings align with resource-based views (Barney, 1991) and dynamic capability theory (Teece, 2007), which argue that firms with stronger internal resources be it human, technological, or structural are better positioned to integrate and derive value from complex innovations. The interplay between these TOE domains further supports the idea that GenAI adoption is not merely a matter of technology availability, but one of organisational alignment, learning, and strategic fit. Recent AI implementation studies also highlight the dual importance of technological fit (i.e., the compatibility and perceived usefulness of the innovation) and organisational readiness in successful adoption outcomes (Dwivedi et al., 2023b). In the context of GenAI, where the technological potential is high but use cases and governance norms are still developing, these internal enablers become even more critical.

It should also be noted that the limited influence of regulatory pressure observed in this study may reflect broader dynamics in GenAI governance. From an institutional theory perspective, emerging technologies often evolve within weakly institutionalised environments, where formal rules and enforcement mechanisms are still taking shape (Andrieux et al., 2024). In such regulatory voids, organisations tend to rely on internal governance, industry norms, or informal practices rather than external mandates. This suggests that GenAI adoption is currently driven more by perceived opportunity and internal capability than by institutional coercion. As regulatory frameworks mature, future research should explore how institutional pressures evolve and begin to shape organisational decision-making more decisively.

6.6. Change capacity as a strategic moderator

The study identified a dual moderating role for change capacity, which can be understood as a dynamic organisational capability reflecting the organisation’s ability to adapt, reconfigure, and respond effectively to technological change, in particular the rapid and unpredictable evolution of GenAI (Montreuil, 2023). The inclusion of change capacity within the TOE organisation context complements the organisational context by enriching our understanding of how internal structures and cultures influence the adoption process especially in the face of uncertainty and complexity (Awa et al. 2017). Change capacity was found to positively moderate the relationship between complexity and GenAI use, meaning that in organisations with high change capacity, the negative impact of technological complexity on adoption was significantly reduced. This suggests that adaptive organisations are better positioned to absorb the perceived risks and uncertainties associated with GenAI, such as interpretability issues, data dependency, and system integration challenges. This is particularly relevant given the fluid and experimental nature of GenAI technologies, which often lack clearly defined implementation pathways. When organisations possess strong change capacity manifested in agile structures, continuous learning cultures, and resilient leadership they are more likely to approach complexity as a challenge to be managed, rather than as a barrier to avoid (Stenberg & Nilsson, 2020).

The study found that change capacity negatively moderated the relationship between staff skills and GenAI use. In other words, in organisations with high change capacity, the dependency on individual staff competencies for GenAI adoption decreases. This can be interpreted through a TOE lens as a form of organisational slack or redundancy, where systemic adaptability compensates for variations in human capital. High-change-capacity environments often have established support mechanisms such as change agents, cross-functional collaboration, and decentralised decision-making that reduce reliance on specific roles or individual expertise. In contrast, in low-change-capacity settings, the burden of innovation adoption may fall more heavily on skilled individuals, making their presence a more decisive factor. This interpretation aligns with the earlier qualitative findings, where change capacity was shown to function not only as a structural enabler but also as a learning-oriented capability. Organisations with robust change capacity institutionalise learning across teams, reducing reliance on individual expertise and fostering adaptive routines that support GenAI integration (Agrawal et al. 2024; David et al. 2024; Raisch & Krakowski, 2021). This reinforces the view that change capacity is a dynamic capability one that orchestrates experimentation, knowledge sharing, and strategic alignment in the face of technological uncertainty.

6.6.1. Change capacity → Organisational learning loops

The moderating effect of change capacity also deserves re-theorisation. It is tempting to describe this as a substitution logic firms with more change capacity simply do better. Yet from an organisational learning perspective, change capacity reflects the ability to conduct learning loops: experimenting with GenAI applications, absorbing feedback, and iteratively reconfiguring routines under uncertainty. This framing alters the importance from a static view of capacity to a dynamic process of investigation and adaptation. In this light, our results suggest that GenAI adoption is not a one-off implementation decision but an ongoing process of exploration and adaptation. By integrating change capacity in TOE as a dynamic capability, we demonstrate how firms orchestrate internal sources to navigate generativity and uncertainty. This perspective not only improves the understanding of change capacity but also extends TOE beyond static uptake toward a model of continuous learning and adaptation. Embedding change capacity in TOE as a dynamic capability demonstrates how firms orchestrate internal resources to navigate generativity and uncertainty, extending TOE beyond static uptake toward continuous learning.

While the substitution explanation offers one interpretation, the finding also contributes to the discussion through organisational learning theory. Organisations with high change capacity often have systems in place that support them to explore new technologies, share insights amongst teams, and learn intensely from mistakes and feedback, therefore, reducing over-reliance in individual skills (Argyris & Schön, 1997). Instead of replacing staff skills, these organisations admit and institutionalise those skills into collective practices making GenAI adoption organisation-wide rather than individual-focused. This is aligned with the capability complementarity theory, which considers dynamic capabilities such as change management can strengthen or weaken the effects of other resources (Teece et al., 1997). In this study, the change capacity may alter the impact of skills from individual to organisational level. Contextual variation may also play a significant role. For example, in highly regulated or resource-constrained sectors like healthcare or government, staff expertise may remain central due to strict compliance or limited process flexibility (Van Erp et al., 2020). However, the tech industry usually operates in cross-functional routines, which reduces dependency on specialised roles. This further elaborates that the observed moderation effect is not entirely structural but also sector sensitive.

These findings position change capacity as a form of strategic flexibility that enables organisations to align their internal processes with the demands of emerging technologies like GenAI (David et al. 2024; Raisch & Krakowski, 2021). From a practical perspective, this suggests that building organisational resilience—through investment in adaptive leadership, agile project management, and innovation governance structures—can facilitate not only faster adoption but also more sustainable and scalable use of GenAI. It also implies that change capacity acts as a cross-domain enabler within the TOE framework, influencing how both technological and organisational factors manifest in the adoption process. In the context of GenAI, which is marked by rapid iteration and ongoing regulatory and ethical developments, such strategic agility may be especially valuable. Organisations that can sense, learn, and reconfigure in response to shifts in the technological and environmental landscape are likely to gain a competitive edge—not just in adopting GenAI, but in embedding it meaningfully across their operations (Agrawal et al. 2024; Cao & Le, 2022).

6.7. Model strength

The model accounted for a substantial proportion of the variance in GenAI use ($R^2 = 0.68$), indicating strong explanatory power and supporting the relevance of the TOE framework in understanding emerging technology adoption. The inclusion of constructs spanning the technological (e.g., relative advantage, complexity), organisational (e.g. staff skills, change capacity), and environmental (e.g., regulatory challenges) domains allowed for a multidimensional analysis of the factors shaping GenAI integration within organisations. This finding highlights the value of TOE as a flexible and adaptive host framework, capable of accommodating context-specific variables while retaining theoretical coherence. It also reinforces that internal factors, especially those linked to perceived technological benefits and organisational readiness, are particularly salient in the early stages of GenAI adoption. As a result, organisations can use TOE-aligned models to guide strategic planning and capability development for successful implementation.

6.8. Theoretical contributions and implications

This research makes several key theoretical contributions to the emerging body of literature on GenAI adoption, particularly within organisational contexts where the topic remains under-theorised and empirically limited. By applying the TOE framework to the context of GenAI, this study extends a well-established theoretical model into a new and rapidly evolving technological domain. While TOE has been widely used in studies of traditional IT, cloud computing, and AI more broadly, its application to GenAI has been limited. This study demonstrates the framework's continued relevance and adaptability by showing how classic TOE constructs (e.g. relative advantage, complexity, regulatory pressure) interact with GenAI-specific organisational dynamics and complexities. We posit that this insight indicates that GenAI's generative and rapidly evolving nature surfaces tensions in the TOE framework, necessitating theoretical refinement to capture the emergent and entangled dynamics of its adoption.

This study makes a methodological contribution through its explanatory sequential mixed methods design. By first conducting qualitative interviews and then validating emergent themes through quantitative analysis, the research provides both depth and generalisability, enhancing construct development and theoretical triangulation. The development of the Phase 2 model from the Phase 1 thematic analysis and its validation against both the extant literature and survey data, illustrates how mixed methods approaches can enhance theory building, particularly in novel domains where established constructs may be insufficient. This approach allows for the contextualisation of constructs within organisational realities, capturing both what organisations say they perceive and what they demonstrably prioritise when implementing GenAI technologies. It also strengthens the theoretical contribution by ensuring that new insights such as the moderating role of change capacity are grounded in real-world experience and empirical testing.

Furthermore, this study extends and enriches the TOE framework in the context of GenAI use in the following ways. First, we introduce change capacity as a capability factor - long recognised as a critical dimension for successful AI deployment (Wamba et al., 2024). Embedding this lens into TOE constructs specifies how organisations convert both tangible conditions (e.g., technology characteristics) and intangible ones (e.g., staff skills) into realised GenAI use. While frameworks such as TOE are valuable for understanding factors that impact technology acceptance, they tend not to focus on identifying adoption barriers (Kalmus & Nikiforova, 2024). In addition, the negative interaction between staff skills and change capacity indicates that when an organisation excels at orchestrating change, the reliance on individual skills diminishes. This challenges the typical additive-driver assumption that dominates TOE and emphasises that GenAI adoption within the organisation requires reconsideration of resource configuration factors. In contrast to prior TOE studies, regulatory challenges were non-significant in our context of GenAI use (Hanna & Gohar, 2020). We interpret this as possible evidence of regulatory flux and fragmented governance for GenAI. As organisations are still experimenting with GenAI governance, institutions face uncertainties rather than binding compliance mandates. This is a novel empirical insight that calls for a rethink of the environmental pillar of TOE for transformative technologies. We position TOE as a host framework that can connect specialised theories such as dynamic capabilities and socio-technical perspectives, highlighting GenAI use as a process of mutual shaping between technological models, human capabilities and organisational readiness.

We theorise that GenAI adoption further unsettles traditional TOE categories by blurring the boundaries between technological and organisational factors. Data governance and ownership in GenAI adoption is both a technological and an organisational concern. On the one hand, training data quality, bias, and provenance are technical affordances of the model (Bhattacharya et al., 2024; Al-Kfairy et al., 2024); on the other hand, decisions about who curates, validates, and governs data are deeply organisational practices tied to policies, roles, and accountability structures (Benbya et al., 2024; Sison et al., 2024). This co-production of outputs and entanglement means that what TOE might traditionally classify as a "technological factor" (data quality) cannot be disentangled from "organisational factors" (governance capacity). This is echoed in the findings on change capacity and staff skills as co-constitutive elements (Montreuil, 2022; Fui-Hoon Nah et al., 2023), the interface between skills and complexity, organisational and technological decision making, and also technical design and culture in GenAI adoption. This therefore destabilises TOE's neat separation, requiring a reframing where technology and organisation are understood as co-constitutive in shaping adoption outcomes.

By reframing TOE into a TOE+ perspective, this study moves beyond replication of the framework and accommodates the theoretical advancements indicated above. It demonstrates how adoption dynamics in the GenAI era differ from those of earlier IT innovations. In particular, regulatory flux highlights the fast-shifting, uncertain governance environment; capability complementarity and entanglement of technological and organisational factors that underscore the co-evolution of human and machine skills. The adaptation of TOE to include explainability complexity reflects new cognitive and ethical challenges that traditional IT adoption studies seem to have overlooked. In positioning TOE as an integrative host framework, we provide a pathway for scholars to systematically incorporate complementary theoretical perspectives while retaining TOE's explanatory structure.

We posit the extending of the TOE framework by demonstrating its applicability to the emerging context of GenAI, a domain characterised by rapid technological evolution, uncertain governance, and wide-ranging organisational implications. Importantly, it introduces a novel moderating construct (i.e. change capacity) which deepens our understanding of organisational readiness. By showing how change capacity influences the effects of both technological and organisational factors on adoption, the study offers a more dynamic and nuanced perspective on how internal capabilities shape innovation uptake in high-complexity environments. Finally, the study lays foundational theoretical groundwork for future research in GenAI by identifying key adoption drivers, contextual moderators, and conceptual blind spots. We posit that this research opens pathways for integrating TOE with other frameworks and suggests that adoption theory for GenAI must account for fluid use cases, emerging skills, and organisational experimentation.

6.9. *Implications for practice*

The findings of this study offer several actionable insights for organisations and decision-makers seeking to adopt and implement GenAI in a sustainable and strategic manner. By identifying the most influential factors shaping GenAI adoption namely relative advantage, staff skills, complexity, and change capacity the study provides a clear roadmap for enhancing readiness and effectiveness in deploying GenAI technologies within organisations. The strong influence of relative advantage underscores the importance of clearly articulating and demonstrating the business benefits of GenAI. Organisations should develop use cases that show measurable improvements in productivity, efficiency, or creativity for example, in automating content creation, supporting decision-making, or enhancing customer engagement.

Decision makers can facilitate adoption by showcasing early wins, sharing internal success stories, and aligning GenAI initiatives with broader strategic objectives. Doing so can help build confidence and momentum across the organisation, which is especially important when introducing a technology that may still be perceived as experimental. The positive effect of staff skills indicates that organisations must treat GenAI adoption as not just a technological investment but also a human capital development initiative. Training programs should focus on both technical competencies (e.g. critical evaluation of GenAI outputs) and domain-specific AI literacy that helps staff apply GenAI meaningfully in their roles. Rather than outsourcing GenAI entirely to IT departments or external vendors, decision-makers should empower cross-functional teams to experiment and co-create solutions, fostering AI fluency across business units (Raisch & Krakowski, 2021). This inclusive approach can also mitigate resistance and reduce dependence on isolated pockets of expertise.

Since perceived complexity negatively influences GenAI use, organisations should work to simplify the implementation process wherever possible. This can include launching small-scale pilots, offering user-friendly interfaces, and providing technical support throughout the onboarding phase. Building internal "centres of excellence" or assigning AI champions can also help demystify the technology and provide guidance to teams navigating early experimentation. When complexity is actively managed, organisations are more likely to progress from curiosity to commitment and embrace change. The moderating role of change capacity suggests that adaptive organisations are better equipped to adopt GenAI, even in the face of technological uncertainty or skill gaps. Leaders should prioritise building this capacity by fostering a culture that rewards experimentation. This includes creating mechanisms for continuous learning, iterative feedback, and risk-tolerant innovation processes conditions under which GenAI experimentation can flourish. As change capacity grows, the organisation becomes more resilient and less reliant on specific individuals or teams to drive adoption.

Although regulatory challenges did not significantly affect GenAI use in this study, the low average score suggests that compliance awareness is emerging. Organisations should not wait for formal regulations to be enforced before considering the ethical and legal implications of GenAI use. Developing internal guidelines on AI ethics, transparency, and responsible use can pre-empt reputational or legal risks and position the organisation as a responsible innovator. Leaders should monitor developments like the EU AI Act and align their governance strategies with evolving standards.

For senior leaders and change agents, the findings of this study offer clear strategic guidance for designing and managing GenAI rollout initiatives. The validated model underscores that perceived complexity and insufficient staff skills can significantly hinder adoption unless mitigated by robust change capacity within an organisation. Leadership must therefore adopt a dual focus: investing in upskilling initiatives that foster GenAI literacy across departments within their organisation whilst simultaneously building organisational agility and trust in GenAI systems through transparent governance, pilot testing, and cross-functional alignment. This approach will ultimately support long-term value creation, resilience, and ethical integration.

6.10. *Role-specific practical and policy recommendations*

The findings from this study have an impact on the key roles within the organisation:

6.10.1. *Chief Executive Officers (CEOs) and organisational strategists*

executives should embed GenAI adoption within broader digital transformation goals through a ROI lens. Decision makers should assess the innovation potential and opportunities for augmenting existing employee capabilities. In small firms or low-maturity settings, leaders can focus on one or two high-value use cases to demonstrate early wins and build trust.

6.10.2. *Chief Information Officers (CIOs) and technology leaders*

to reduce perceived complexity, CIOs should prioritise modular, pilot-based deployments of GenAI, allowing iterative learning and system integration. Investing in interoperable architectures and low-code GenAI tools can ease integration burdens across legacy systems. Complexity can be reduced when end-users are engaged early in the life cycle, ensuring working practices and tools align with real workflows.

6.10.3. HR leaders and training managers

building change capacity begins with fostering digital fluency. HR teams should integrate GenAI literacy into existing professional development strategies and incentivise applied GenAI training to relevant to job roles. Change champions and trusted employees who model GenAI use can be deployed to encourage peer adoption and reduce resistance. Special attention is needed in sectors such as healthcare and law, where domain-specific concerns (e.g., trust, accuracy) are high.

6.10.4. Policymakers and regulators

the findings suggest regulatory ambiguity does not yet strongly deter GenAI adoption, but clearer standards are likely to be necessary as the technology matures. Regulatory flux seems to be a defining feature of GenAI adoption: formal rules are emergent, fragmented, and subject to rapid change, leaving firms to navigate institutional voids largely on their own. Policymakers therefore face the dual challenge of providing stability without stifling innovation. Policymakers are encouraged to co-develop GenAI guidance frameworks with industry stakeholders, especially for high-risk sectors. Transparent auditing requirements, environmental sustainability benchmarks, and sector-specific ethical guidelines could help shape responsible GenAI related ecosystems.

While role-specific recommendations offer actionable guidance, it is crucial to differentiate strategies based on organisational context. Small or resource-constrained firms may benefit from low-risk, modular GenAI pilots that align with immediate operational needs, whereas digitally mature enterprises can pursue more integrated deployments tied to long-term transformation agendas. Leaders should view GenAI not as a standalone tool but as a catalyst for broader digital evolution. Strategic rollout requires cross-functional coordination, clear value metrics, and alignment with existing IT and data infrastructures. By embedding GenAI within a phased digital roadmap, organisations can better manage risk, foster internal buy-in, and ensure sustainable value creation.

6.11. Limitations and future research directions

This research is limited in a few areas. The qualitative phase utilised participants from Australia and the UK and although this fulfilled the exploratory aspect of this phase to inform the quantitative phase 2, somewhat limits the generalisation of the findings. The quantitative component relied on cross-sectional self-reported data, which limits the ability to capture changes in adoption behaviour over time and may introduce common method bias and social desirability effects. To mitigate these concerns, we applied procedural remedies, including assurances of respondent anonymity, and conducted Harman's single-factor test to assess the extent of common method variance (Kamboj et al., 2018). Future research could adopt longitudinal designs and field experiments to track how perceptions and organisational responses to GenAI evolve over time. As regulations mature, examining the impact of the evolving policy landscape will also be important. Given this study primarily reflects organisations at the early stages of GenAI engagement, future studies should explore organisations with more advanced GenAI integration to capture the dynamics of scaled or mature implementations.

To further strengthen this research future studies could explore additional constructs within each TOE domain. For example, in the organisational context, variables such as leadership support, innovation culture, or data governance maturity may deepen our understanding of internal dynamics. In the technological context, measures of AI maturity—such as the level of integration, tooling, or interoperability—could help differentiate between pilot use and scaled adoption. Within the environmental context, growing attention to ethical, legal, and societal implications (ELSI) of GenAI suggests the need to explore how external expectations, public sentiment, and AI policy influence adoption trajectories. Moreover, as AI-related regulatory frameworks continue to evolve (e.g., the EU AI Act or emerging national standards), the role of regulatory pressure is likely to become more prominent over time. This underscores the importance of conducting longitudinal research that can capture shifts in adoption behaviour as compliance requirements become more clearly defined and enforced. Finally, integrating TOE with complementary theories—such as the technology acceptance model (TAM), Institutional Theory or dynamic capabilities theory—may provide a more granular understanding of how organisations adapt, absorb, and institutionalise GenAI technologies. These expanded models could also support comparative studies across industries, regions, or organisational sizes, offering valuable insights into the broader AI focused digital transformation landscape.

7. Conclusions

This study contributes to the emerging body of research on GenAI by applying the TOE framework to examine the key factors influencing its adoption within organisations. Although AI and automation have been widely studied, the rise of GenAI introduces novel capabilities and challenges that remain poorly understood in current literature. By focusing directly on GenAI, this study provides timely insights into a technology that is quickly reshaping professional and industrial landscapes. The study also demonstrates the value of a mixed methods approach, combining qualitative depth with quantitative validation to generate theory-informed and practice-relevant insights. The findings highlight the central role of perceived relative advantage and staff skills in driving GenAI use, while complexity remains a notable barrier. The moderating role of organisational change capacity further illustrates the importance of internal adaptability in managing both technical challenges and skill dependencies. While regulatory concerns were acknowledged, they did not significantly influence adoption at this early stage, pointing to a potential lag between environmental pressures and organisational response. Overall, the research provides a foundational understanding of how organisations are approaching GenAI and offers a springboard for future studies exploring long-term adoption, governance, and impact.

CRediT authorship contribution statement

Yogesh K Dwivedi: Writing – review & editing, Visualization, Validation, Conceptualization. **Senali Madugoda Gunaratnege:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation. **Tegwen Malik:** Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Fern Davies:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Data curation. **Keyao Li:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Laurie Hughes:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used OpenAI ChatGPT 4o in order to check language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Interview Questions

The full set of semi-structured interview questions are outlined below.

TOE Alignment	Questions
General	**Q1**. How do you personally feel about generative AI (GenAI) and its widespread adoption at a societal level.
General	**Q2**. Has the organisation started to look at the potential for GenAI?
	Sub question: if yes - which specific areas (business functions) of the organisation could use the technology effectively?
	Sub question: If already using GenAI - gauge the current level of maturity of AI adoption. (Gartner scale 1–5)?
Technology	**Q3**. Can you describe the specific GenAI technologies/platforms your organisation is currently using and how the technology is being used?
Technology	**Q4**. Describe some of the challenges you envisage or have experienced from implementing (or using) GenAI.
	Sub question: has the technology been integrated with existing systems and processes or is it standalone?
	Sub-question: Is there any reliance on specific platforms or vendors (e.g. Microsoft or OpenAI) and has this impacted innovation and independent adaptation.
	Sub-question: What are your thoughts on the potential for over-reliance on GenAI and the needs for balancing automated decision-making with GenAI and maintaining human oversight?
Organisational	**Q5**. What are your thoughts on the impact that GenAI has or may have on employees within the organisation and the main challenges in this area?
	Sub question: What form do you think that impact will take?
	Sub-question: Do you feel that there is likely to be some level of "resistance" amongst staff and what do you feel is the underlying reason for this?
Organisational	**Q6**. Have there been any ethical challenges that the organisation has faced or may face for the adoption of GenAI.
	Sub question: how has this negatively impacted staff?
Organisational	**Q7**. Describe some of the main challenges that may arise around your organisation's allocation of resources (financial, human, technical) for the implementation of GenAI?
	Sub question: Any challenges related to existing GenAI knowledge/skills within the organisation?
Environmental	**Q10**. What are your thoughts on the challenges in facing the organisation in the context of regulatory, compliance or legal issues when adopting GenAI?
	Sub-question: Has the organisation assessed the data privacy and data security aspects?
	Sub-question: Has the organisation assessed the challenges around legal liability from GenAI outputs, what are thoughts on this?
Environmental	**Q11**. What are the key challenges from increased use of GenAI that could impact the sector as a whole and therefore, your organisation?
	Sub question: Are there any sector dynamics (sector wide factors) that may impact existing business models?
Environmental	**Q12**. What is your view on the impact from competitive pressures (from the sector or other organisations), to adopt GenAI and how has this shaped organisational policy?
	Sub question: What have been the main challenges here in responding to market pressures?
	Sub question: What about the internal pressures and challenges from an executive that is keen to "fast track" GenAI use to keep up with the competition?
General	**Q13**. What proactive measures has your organisation taken to mitigate potential negative impacts from GenAI?
Final question	**Sub question**: Are there any other issues you have experienced in your organisation or in the sector that you have not had a chance to share?

Survey constructs

Operationalisation of constructs

The constructs used in the quantitative phase were operationalised using established measurement items adapted from prior studies on technology adoption, particularly those applying the TOE framework. Where necessary, item wording was refined to reflect the specific context of GenAI adoption, ensuring content relevance while preserving the conceptual integrity of each construct. Adaptations were minimal and focused primarily on terminology updates to maintain contextual alignment with the original scale structures and properties.

TOE Construct	Item	Source(s)
Technology	*Complexity*	Wang et al. (2016)
	CX1: To what extent do you feel that the implementation of GenAI to existing systems are complex to achieve?	
	CX2: To what extent do you believe the complexity of integrating GenAI into existing work practices is difficult?	
Organisational	*Perceived Relative Advantage*	Siew et al. (2020)
	RA1. To what degree do you believe GenAI will increase the firms productivity?	Iranmanesh et al. (2023)
	RA2. To what extent will the adoption of GenAI improve the efficiency of your organization's operations?	
	RA3. To what extent do you think GenAI will enhance the quality of the products or services offered by your organization?	
	RA4. To what extent do you believe that the adoption of GenAI is advantageous in the existing marketplace?	
Organisational	*Staff Skills and Competency*	Gangwar & Date (2015)
	SC1. To what extent does your organization recruit personnel with the necessary skills to use GenAI effectively?	Siew et al. (2020)
	SC2. How sufficient is the training provided to staff in using GenAI?	Singh et al. (2024)
	SC3. Do employees in your organisation have sufficient experience and competency with GenAI?	Mikalef and Patelli (2017)
	Change Capacity	
	CC1: To what extent does the organisation possess the transformational abilities to help integrate the necessary processes for GenAI?	
	CC2: My organisation has the capacity to easily adapt to changes driven by Generative AI adoption?	
Environmental	*Regulatory Pressure*	Pan et al. (2021)
	RP1. To what extent is the use of GenAI impacted by government procedure?	
	RP2. To what extent is the use of GenAI driven by incentives provided by the government?	

Data availability

Data will be made available on request.

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