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Organizational Implementation of Generative AI: The Human Experience, a Mixed-Methods Study

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Abstract

The introduction of Generative AI tools such as ChatGPT or CoPilot has rapidly transformed organizational work practices. While strategic potential is widely discussed, the human implications of Generative AI adoption remain underexplored. This study examines how employees perceive and respond to the organizational implementation of Generative AI, and how these experiences shape their psychological empowerment and perceived performance. An integrated framework combining Unified Theory of Acceptance and Use of Technology (UTAUT), user adaptation theory, and psychological empowerment was developed and empirically tested. A sequential explanatory mixed-methods design was employed, combining survey data from 363 employees with 14 follow-up interviews. Structural equation modeling (SmartPLS) tested hypothesized relationships, and qualitative analysis explored underlying experiences. The study contributes an integrated perspective on the human side of Generative AI implementation, extending technology acceptance models with affective and empowerment mechanisms and that psychological empowerment functions as the primary mechanism linking Generative AI use to performance outcomes. This study demonstrated that the relationship between adaptation, psychological empowerment, and perceived performance is significantly positive. In other words, when employees actively engage with Generative AI, they tend to feel more empowered in their work, experiencing greater autonomy, competence, and impact, which in turn enhances their perceived performance. This finding highlights that adaptation is not merely a form of compliance but a psychologically beneficial process through which employees come to view Generative AI as a meaningful and value-adding tool. Practically, organizations should prioritize creating conditions for employee empowerment, through experimentation opportunities, role-specific support, and transparent governance, rather than focusing solely on technology deployment and mandating universal use.

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1 Introduction

At the end of 2022, OpenAI launched ChatGPT, providing the public with an easy-to-access interface to large language models. This release has been credited with catalyzing global interest in Generative Artificial Intelligence. What began as an experimental chatbot quickly evolved into one of the most transformative technologies of the decade. Within months, Generative AI shifted from a technological curiosity to an organizational necessity, forcing organizations and employees to rethink their current way of working.

Generative AI represents a new phase of digital transformation. A transformation that is characterized not only by automation of tasks but also by the creation of new content, ideas, and solutions. Unlike traditional forms of AI, Generative AI can produce original text, images, or code, effectively augmenting human creativity and decision-making. As major technology companies integrate these capabilities into everyday software, organizations across sectors are exploring how such tools can enhance productivity, efficiency, and innovation. However, alongside these opportunities come significant challenges. The probabilistic and opaque nature of Generative AI introduces new forms of uncertainty, ethical concerns, and workflow disruption, requiring employees to continuously adapt their skills, roles, and ways of working.

While the strategic potential of Generative AI has been widely discussed in both research and industry, much less is known about its human implications. Existing literature has primarily focused on the organizational and technical aspects of (generative) AI adoption, examining performance gains, governance frameworks, and strategic readiness. However, as previous digital transformation research has shown, technological change succeeds or fails not solely because of its technological merits, but because of how people experience and respond to it. Employees' perceptions, emotions, and behaviors ultimately determine whether Generative AI becomes a tool for empowerment or a source of anxiety, alienation, and resistance.

These gaps highlight the need to better understand the human experience of Generative AI implementation in organizational contexts. Specifically, there is limited empirical evidence on how employees perceive and adapt to these tools once they become embedded in daily work practices. Moreover, current research often adopts a single theoretical lens, such as technology acceptance, behavioral adaptation, or psychological empowerment, without integrating these perspectives into a coherent framework that captures the full cognitive, emotional, and behavioral spectrum of employee responses to digital transformations.

Addressing this gap, the present study investigates how employees experience the implementation of Generative AI within their workplace. The research aims to explore how employees perceive, respond to, and are psychologically affected by the introduction of Generative AI tools, and how these experiences shape their sense of empowerment and perceived performance. To achieve this, the study develops and empirically tests an integrated framework that combines the Unified Theory of Acceptance and Use of Technology (UTAUT), the coping model of user adaptation and resistance, and the theory of psychological empowerment. By linking technology perceptions, affective reactions, and behavioral responses to empowerment and performance outcomes, this research provides a multidimensional understanding of the human side of the implementation of Generative AI. Accordingly, this study is guided by the following research question:

“How do employees experience and respond to the organizational implementation of Generative AI, and how do these experiences shape their psychological empowerment and perceived individual performance?”

To operationalize this question, the study addresses five sub-questions:

1. How do employees evaluate generative AI in terms of performance expectancy, effort expectancy, social influence, and facilitating conditions, and how do they appraise it affectively (trust, AI anxiety, trialability) in their day-to-day work?
2. How are these technology perceptions and affective appraisals associated with employees' behavioral responses to implementation?
3. In what ways are employees' adaptation and resistance to Generative AI related to their sense of psychological empowerment?
4. How do employees' responses to Generative AI and their resulting sense of psychological empowerment influence their perceived individual performance?
5. To what extent do organizational and individual conditions moderate these relationships and enable or hinder effective, responsible implementation and use of Generative AI in the workplace?

Methodologically, the study adopts a mixed-methods design that combines quantitative and qualitative approaches. The quantitative phase captures patterns and relationships between key constructs across a large employee sample, while the qualitative phase explores employees' lived experience in greater depth, uncovering the nuances and emotions behind those patterns. This sequential explanatory design allows for both generalizable insights and rich contextual understanding of how employees navigate Generative AI implementation in practice.

The remainder of this study is structured as follows. Chapter 2 reviews the relevant literature and develops the conceptual model and hypotheses. Chapter 3 describes the research methodology. Chapter 4 presents the quantitative and qualitative results. Chapter 6 integrates and discusses these results, outlines theoretical and practical implications, and goes into the limitations and suggestions for further research. Chapter 7 concludes the study by summarizing the key findings, answering the central research question and reflecting on the overall contribution of the research.

2 Theory

2.1 Literature review

2.1.1 Generative AI: Technology and organizational context

Artificial Intelligence (AI) refers to the ability of computer systems or machines to perform tasks that would normally require human intelligence (McCarthy, 2006). Traditional AI relies on explicit rules and logical reasoning to perform tasks. Generative AI is a subfield of AI that focuses on creating new and realistic content, such as text, images or code, based on user prompts or learned patterns. It produces original outputs that mimic the style or structure of its training data (Bahn & Strobel, 2023). The public release of ChatGPT demonstrated the power of Generative AI to a wide audience. Generative AI represents a transformative leap in AI, shifting from data analysis to content creation, which opens up new capabilities and offers many possibilities. There are different types of Generative AI, including text generation (e.g. ChatGPT), image and video creation (e.g. DALL-E), audio generation (e.g. VALL-E) and code generation (e.g. GitHub CoPilot.) While these tools vary in application, they share a common foundation in deep learning techniques that enable content creation rather than mere data analysis. Unlike previous workplace technologies, Generative AI represents a discontinuous innovation that fundamentally alters the nature of work tasks. Traditional automation replaced manual labor with mechanical processes following explicit rules; Generative AI instead produces content that appears human-like yet lacks human understanding or intentionality (Dwivedi, et al., 2023). This creates unique implementation challenges: outputs may be plausible but inaccurate, creative but unoriginal and efficient but requiring verification. The technology operates probabilistically rather than deterministically, meaning identical inputs may produce different outputs, complicating quality assurance and reliability assessments.

Organizations began adopting Generative AI starting late 2022. This happened after the public release of OpenAI's ChatGPT on November 30, 2022 (Dwivedi, et al., 2023). Within five days of the launch ChatGPT had reached one million users. This marked the moment where Generative AI moved from research labs and niche applications to general (business) use. In the following period, major technology companies, including Microsoft, Amazon, and Meta started integrating Generative AI capabilities into their core products and cloud services, accelerating organizational adoption (Wilkinson, 2023). Organizations are not embracing Generative AI merely due to the surrounding hype. Research shows that its implementation comes with tangible benefits. Empirical research demonstrates significant productivity increases in practice (Noy & Zhang, 2023; Peng, Kalliamvakou, Cihon, & Demirer, 2023). In addition, Brynjolfsson et al. (2023) provide empirical evidence that Generative AI contributes to higher-quality communication. Several conceptual papers propose that Generative AI can enhance organizational performance through increased creativity, employee empowerment, efficiency and decision-making support (Al Naqbi, Bahroun, & Ahmed, 2024; Hernández, 2024). While these benefits provide a useful strategic lens, further empirical research is needed to validate their realization in practice. Increased efficiency and productivity help

organizations to produce more value with equal or fewer resources, but in addition to that previous studies on Artificial Intelligence adoption show that firms investing in AI also achieve significantly higher growth in sales, employment and market valuation compared to firms that do not (Babina, Fedyk, He, & Hodson, 2020). These findings suggest a promising future for Generative AI, although similar firm-level effects from the adoption of Generative AI are still emerging in literature. Early evidence does suggest strong potential: in the two weeks following the release of ChatGPT, firms with higher exposure to Generative AI experienced daily excess returns of approximately 0.4%, indicating that investors believe that organizations with high exposure to Generative AI have better prospects than the market average (Eisfeldt, Schubert, & Zhang, 2023). However, the potential benefits must be weighed against significant risks and challenges that complicate organizational implementation. A major concern is that people become over reliant on AI-generated outputs, which can weaken their critical thinking. Over reliance can lead users to accept answers without verification or to overestimate the tool's capabilities (Dell'Acqua, et al., 2023; Peng, Kalliamvakou, Cihon, & Demirer, 2023). Verification of the output of Generative AI is critical due to its ability to "hallucinate", producing content that is factually incorrect or misleading. Unlike deterministic software, a Generative AI tool might confidently generate an answer that looks plausible but is completely wrong or fabricated. If organizations would rely on such outputs, there are cognitive risks associated with making decisions based on faulty information (Wach, et al., 2023). Furthermore, Generative AI models on internet data are vulnerable to producing biased or discriminatory content, reflecting societal prejudices embedded in the training data. This risk is present during both model training and real-time inference, potentially leading to misleading outputs that can affect decision-making or offend stakeholders (Bahn & Strobel, 2023; Deng & Lin, 2022). Besides bias, there are many more ethical and societal concerns, including concerns about plagiarism and intellectual property. Generative AI can generate content that is very similar to existing works, making authorship and originality a complicated issue (Bahn & Strobel, 2023). This raises legal and ethical questions about who owns the generated content. Organizations implementing Generative AI must deal with the ethical governance of these tools, establishing guidelines on acceptable use, ensuring that outputs align with ethical standards, and preventing misuse (Dwivedi, et al., 2023). Another concern that is highlighted in existing literature is work alienation, where employees may feel a sense of detachment, loss of meaning, or reduced personal significance in their work when collaborating intensively with Generative AI. Hai et al. (2025) found that heavier reliance on Generative Ai at work can correlate with higher feelings of alienation, which in turn may lead to lower engagement and even unethical work behaviors. This dark side of employee-AI collaboration highlights the importance of monitoring employee well-being and ensuring that jobs are redesigned in a way that people continue to feel valuable and connected to work. Finally, existing studies have pointed to security and data privacy risks. Generative Ai systems often require large amounts of data, some of which may be sensitive organizational or personal data. There are concerns that proprietary or confidential information could unintentionally be exposed through AI systems (Reznikov, 2024). These challenges and fundamental changes alter how work tasks are carried out, consequently changing the nature of employees' work and how they interact with technology. Despite the strategic attention Generative AI has received, less is known about how employees perceive, respond to, and experience these tools in their daily work. Understanding this human side of using Generative AI is critical, as it shapes not only how effectively the technology is integrated, but also its broader psychological and performance impacts.

2.1.2 Digital Transformation and Employee Responses

Implementing Generative AI into an organization is not just a technical installation; it is a socio-technical change that affects technology infrastructure, business processes, and people. Effective implementation of Generative AI, therefore needs to be approached as part of an organization's broader digital transformation strategy, with attention to organizational change management and employee acceptance. Organizations often find that they must restructure workflows and redefine roles to accommodate to the introduction and implementation of Generative AI tools (Hernández, 2024). A socio-technical perspective is crucial, and organizations must consider how the technology will fit into existing workflows and what new workflows its implementation may require (Bostrom & Heinen, 1977; Pasmore, 1988).

Employees play a determining role in whether digital transformations succeed or fail. Organizational change literature consistently demonstrates that technological availability does not guarantee effective use. Instead employees' acceptance, engagement, and adaptation behaviors create the critical difference between successful and unsuccessful implementations (Klein et al., 2024; Weber et al., 2022). Employees may act as powerful enablers when engaged, amplifying intended benefits through innovative and peer influence. Conversely, they may become significant barriers when resistant, undermining initiatives through minimal compliance, workarounds, or active opposition (Oreg, 2006; Lapointe & Rivard, 2005). This dual role as both potential champions and obstacles, make employee centered research essential for understanding the dynamics of change and implementation, also in the context of Generative AI, whose rapid evolution, creative capabilities and probabilistic nature boost both the opportunities for employee innovation and the risks of resistance.

Classical organizational change management frameworks emphasize employee engagement, communication, and leadership support as critical success factors (Kotter, 2009; Hiatt, 2006). However, these principles, developed from traditional change initiatives, face new challenges in Generative AI contexts, where the technology has a probabilistic nature and where its opacity and rapid evolution create unique uncertainties and anxieties among employees. Employees must learn to trust outputs whose reliability can vary, adapt workflows around evolving capabilities and reconcile the technology's creative potential with its opacity. To address the unique challenges of Generative AI, several new or adapted frameworks have been proposed that emphasize responsible and human-centered approaches to guide organizations in responsible implementation. Hernández (2024), proposes an action-based organizational framework emphasizing staff training, ethical use, innovation culture and human-machine collaboration to integrate Generative AI responsibly within organizations. Sherson (2024) introduces a hybrid intelligence adoption ladder and change model that supports human-AI collaboration, cultural readiness, and strategic alignment. Reznikov (2024) outlines three strategic Generative AI adoption paths: incremental, transformational, and collaborative, framed within the TOE and Gartner maturity models. Nah et al. (2023) propose a Human-Centered AI (HCAI) framework that promotes ethical alignment, transparency, inclusivity, and collaborative human-AI decision-making, where Wang et al. (2024) suggest a Social-Centered AI (SCAI) framework because they find that current evaluation frameworks fail to consider the distribution of benefits of AI systems situated in group and institutional contexts. While these frameworks help to guide the responsible implementation of Generative AI, they exhibit one common limitation: they describe what organizations should do, but offer limited insight into what employees experience throughout this process. These models focus on organizational responses, policies, and processes, but pay insufficient attention to individual psychological responses, behavioral

adaptations, or the real-life experiences of employees navigating AI-Augmented work. Existing research suggests that for employees, the introduction of Generative AI often entails navigating significant changes to their daily work practices and sense of place at work. For example, some studies find that AI-aligned roles can challenge worker's sense of meaning and connection (Hai et al., (2025).). While Generative AI tools may enable new forms of task completion and capability, they also introduce uncertainty risks relating to control and agency (Bankins, Ocampo, Marrone, Restuborg, & Woo, 2023; Beaudry & Pinsonneault, 2005). These psychological and behavioral responses shape a spectrum of behavioral outcomes, from active engagement and exploration to minimal compliance or complete resistance (Beaudry & Pinsonneault, 2005; Lapointe & Rivard, 2005).

Classical technology acceptance research has traditionally framed adoption as a voluntary decision (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003). In the context of Generative AI, however, this distinction between adoption and non-adoption is increasingly difficult to define. Generative AI is embedded in ubiquitous tools such as Microsoft Office and enterprise platforms; therefore employees cannot entirely avoid contact with it. The central question is therefore less about whether employees adopt to Generative AI, and more about if and how they adapt their work practices and behaviors once the technology is introduced. Beaudry and Pinsonneault (2005) conceptualize this as user adaptation in response to IT events, highlighting the need to examine behavioral adjustments and coping responses beyond initial acceptance. As Bankins et al. (2023) note, there remains a pressing need for research that captures employees' evolving relationships with Generative AI technologies. The following sections will examine how employees perceive Generative AI (section 2.1.3), how they adapt to it (2.1.4) and how these responses shape empowerment and performance (2.1.5).

2.1.3 Employee perceptions of Generative AI

Employees' perceptions of Generative AI strongly shape their willingness to engage with it and how they may integrate it into their work practices. These perceptions, conceptualized in both classical technology acceptance theories and more recent AI-specific research, provide critical insight into what happens before adaptation and resistance.

The technology acceptance model (TAM; Davis 1989) has become the dominant framework for understanding how individuals evaluate and adopt new technologies. Within organizational contexts, TAM helps to identify psychological barriers to change, enabling organizations to develop targeted interventions to improve user acceptance. Recent research continues to demonstrate its relevance in AI contexts, both Chen et al. (2025) and Korzynski et al. (2023) show that perceived usefulness and ease of use remain critical determinants of user acceptance of AI technologies. Venkatesh et al. (2003) extended TAM by developing the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies four core determinants of technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. Although initially focused on voluntary adoption decisions, its core constructs remain highly relevant even as technologies become deeply embedded into everyday work tools and processes. Numerous studies have extended and applied UTAUT beyond its original scope, for example, to continuance behavior in digital health systems (Bai & Guo, 2022) and technology use among health professionals (Ngusie, et al., 2024), illustrating its flexibility and enduring value in evolving technological contexts. Moreover, Wagman et al. (2025) apply UTAUT directly to Generative AI, showing that these constructs continue to predict user perceptions and behaviors even in rapidly evolving Generative AI-enabled work environments. This adaptability makes UTAUT a suitable lens for examining employee perceptions and behavioral responses in the context of Generative AI. Performance

expectancy refers to the belief that using a system will enhance job performance (Venkatesh, Morris, Davis, & Davis, 2003). In the context of Generative AI, this extends beyond efficiency and includes communication and output quality gains that have been observed in field and lab studies (Brynjolfsson, Li, & Raymond, *Generative AI at work*, 2023; Noy & Zhang, 2023). In addition, organizations increasingly frame Generative AI as enabling higher-order work, including creativity, decision-making, and problem-solving capabilities (Ishaq, Gorski, Butt, Umair, & Tajammal, 2025). Empirical studies show that employees perceive Generative AI tools such as ChatGPT and GitHub Copilot as increasing productivity and enabling higher-quality outputs (Noy & Zhang, 2023; Brynjolfsson, Li, & Raymond, *Generative AI at work*, 2023; Peng, Kalliamvakou, Cihon, & Demirer, 2023). However, because outputs are probabilistic and can be inaccurate, performance benefits depend not only on the system's capabilities but also on employees' ability to verify and refine outputs (Dwivedi, et al., 2023). Consistent with UTAUT, higher performance expectancy is associated with more proactive engagement and integration of Generative AI into workflows, whereas lower expectations may lead to superficial use or resistance. Effort expectancy is defined as the perceived ease of learning and using a system (Venkatesh, Morris, Davis, & Davis, 2003). It captures how intuitive, accessible, and manageable a technology is perceived by its users. Generative AI tools often feature conversational interfaces and seamless integration into familiar platforms such as Microsoft Office, lowering barriers of initial use. Empirical studies find that effort expectancy is a significant predictor of the behavioral intention to use Generative AI tools. Employees in Korean companies reported that perceived ease of use strongly influenced their willingness to adopt Generative AI systems (Kim, Blazquez, & Oh, 2024), while cross-country studies of ChatGPT users showed similar effects (Budhathoki, Zirar, Njoya, & Timsina, 2024). High effort expectancy can encourage employees to experiment with and integrate Generative AI in their workflows, whereas perceptions of complexity or cognitive burden may discourage use or lead to resistance. Organizational interventions such as training, prompt engineering, and user support can help reduce perceived effort and foster deeper adaptation (Venkatesh, Morris, Davis, & Davis, 2003; Kim, Blazquez, & Oh, 2024). Social Influence refers to the degree to which individuals perceive that important others, such as managers, colleagues, or clients, believe they should use a technology (Venkatesh, Morris, Davis, & Davis, 2003). In workplace contexts, peer enthusiasm, leadership endorsement, and visible success stories strongly shape employee attitudes towards Generative AI; for example, social influence significantly predicts intention to use Generative AI systems in organizational (Kim, Blazquez, & Oh, 2024; Patterson, Frydenberg, & Basma, 2024) and early adopters' enthusiasm can encourage wider adoption among peers (Cardon, Fleischmann, & Aritz, 2023). These social dynamics are fundamental as Generative AI tools have become embedded into standard workflows, where adoption is less about voluntary choice and more about aligning with evolving team norms (Chen, et al., 2025). Positive social signals, such as collaborative experimentation or encouragement from management, can lower uncertainty and accelerate integration (Budhathoki, Zirar, Njoya, & Timsina, 2024), while skepticism or fear among colleagues can reinforce resistance (Oreg, 2006; Lapointe & Rivard, 2005). Social influence thus plays a key role in shifting perceptions and building confidence, which in turn promotes adaptation and reduces passive resistance. Facilitating conditions are defined as the degree to which individuals believe that organizational and technical infrastructures support technology use (Venkatesh, Morris, Davis, & Davis, 2003). In the case of Generative AI, these conditions include access to appropriate tools, reliable infrastructure, governance policies, ethical guidelines, and targeted training programs (Reznikov, 2024; Chen, et al., 2025; Deshmukh & Mehta, 2024). Clear policies on data privacy, intellectual property, and acceptable use reduce ambiguity and personal risk, while resources such as prompt libraries, safe testing environments, and quality assurance help employees integrate Generative AI into core tasks (Reznikov, 2024; Chen, et al., 2025). The absence of such conditions can heighten uncertainty and lead to workarounds or disengagement (Lapointe & Rivard, 2005). Strong facilitating conditions support confident

experimentation and sustained adaptation behaviors (Patterson, Frydenberg, & Basma, 2024).

While UTAUT clarifies how employees perceive Generative AI in terms of usefulness, ease, social cues, and organizational support, Generative AI's probabilistic outputs, opacity, and rapid evolution introduce additional perceptions that shape employees' behavioral responses. Research consistently finds that higher trust in automated and AI systems enhances user acceptance (Glikson & Woolley, 2020; Schaefer, Chen, Szalma, & Hancock, 2016), and studies of attitudes towards AI similarly link trust with more favorable adoption orientations (Schepman & Rodway, 2022; Korzynski, et al., 2023). At the same time, qualitative evidence indicates that distrust can restrain engagement with Generative AI in organizational settings (Hartyándi, 2025). The conceptualization of trust as comprising both cognitive and emotional dimensions is well established in organizational and human-computer interaction research (McAllister, 1995; Nass & Moon, 2002; Lee & See, 2004). Building on this dual structure, De Duro et al. (2025) developed the TILLMI scale and extended the distinction between cognitive and emotional trust to the context of Generative AI.

Another factor shaping employees' response to Generative AI is AI-anxiety, which is defined as the apprehension or fear individuals experience about artificial intelligence and its implications for their work. In parallel, research on technostress shows that new digital systems can create strain, overload, and uncertainty, which in turn trigger avoidance or resistance behaviors (Ragu-Nathan, Tarafadar, Ragu-Nathan, & Tu, 2008; Chang, Zhang, Guo, & Cai, 2024). These findings suggest that anxiety about emerging technologies, including Generative AI, can act as a stressor that shapes employees' coping responses and dampens their willingness to engage with new tools (Tarafadar, Tu, Ragu-Nathan, & Ragu-Nathan, 2011). In workplace settings, this anxiety often manifests in two related dimensions: job insecurity, reflecting concerns about technological replacement, and learning anxiety, reflecting uncertainty about acquiring new competencies to work effectively with AI systems (Tong, Yu, & Shou, 2025). Drawing on Social Cognitive Theory and the Transactional Model of Stress and Coping, Tong et al. (2025) show that employees respond to AI-related anxiety through behavioral coping strategies such as avoidance, resistance, or active adaptation. Consistent with these frameworks, recent empirical studies and industry surveys confirm that AI anxiety is widespread and consequential. For instance, an EY (2023) survey of 1,000 U.S. workers reported that 71% of expressed concern over AI's growing role in the workplace. Empirical evidence increasingly indicates that such anxiety constrains technology engagement employees may recognize a tool's potential yet limit their usage, producing a push-pull tension that restrains adaptation (Nastjuk, Trang, Grummeck-Braamt, Adam, & Tarafdar, 2022). Although validated instruments such as the Artificial Intelligence Anxiety Scale (Wang & Wang, 2022) now enable systematic measurement, the literature remains in early stages. It provides limited insight into how AI anxiety shapes behavioral responses in organizational contexts where exposure to Generative AI has become unavoidable.

Trialability, referring to the degree to which a technology can be experimented with before full adoption, has long been recognized as a key determinant of innovation diffusion (Moore & Bensabat, 1991; Rogers, 2003). It captures the extent to which employees can safely explore a new technology's functions and potential benefits before it becomes mandatory. Empirical studies across digital and AI contexts confirm that trialability positively influences intention to use and exploratory behaviors (Jilani, Moniruzzaman, Dey, Alam, & Uddin, 2022; Liu, Son, & Cao, 2023). In organizational contexts, trialability facilitates learning and exploratory use, which promotes deeper integration into work practices (Rogers, 2003). Regarding Generative AI, trialability often takes the form of pilot projects, sandbox environments, or informal experimentation by early adopters, as frequently documented in

enterprise reports on Generative AI (Deloitte, 2025; TechTarget, 2024; McKinsey & Company, 2023). Despite its conceptual relevance, empirical research has yet to clarify how trialability shapes employees' ongoing adaptation once Generative AI systems become embedded in everyday workflows.

Taken together, classic acceptance beliefs (UTAUT), and Generative AI-salient perceptions (trust, AI-anxiety, trialability) shape how employees appraise and cope with Generative AI, once it is being implemented in everyday work. In embedded rollouts, the central questions shift increasingly from whether employees adopt to how deeply and effectively they engage. These perceptions indicate that the implementation of Generative AI can yield different trajectories for employees, ranging from active adaptation to various forms of resistance. However, current research rarely connects these perceptions to concrete post-implementation behaviors in organizational GenAI settings.

2.1.4 Behavioral responses: Adaptation vs. Resistance

While the previous section examined the perceptual antecedents of employee responses to Generative AI, this section focuses on the behavioral outcomes of those perceptions, which are central to understanding successful implementation. In the context of technology implementation, behavioral outcomes represent how employees act upon or cope with new technologies following their cognitive and emotional appraisals. According to the coping model of user adaptation (Beaudry & Pinsonneault, 2005), individuals evaluate technology adoption as either an opportunity or a threat, leading to distinct behavioral coping responses. When a technology is appraised as an opportunity, employees typically engage in benefit-maximizing behaviors, such as exploration or integration, forms of adaptation that enhance the technology's value. Conversely, when a technology is perceived as a threat, employees may adopt disturbance-handling behaviors, such as avoidance, minimal use, or active resistance (Beaudry & Pinsonneault, 2005; Oreg, 2006).

Adaptation refers to employees' active efforts to adjust their work practices and attitudes in ways that capitalize on the opportunities introduced by new technologies. Drawing on Beaudry and Pinsonneault's (2005) coping model of user adaptation, adaptation constitutes a benefit-maximizing response in which individuals modify their behaviors, cognitions, and emotions to exploit the advantages of a technology they evaluate as an opportunity. They link adaptation to active engagement and indicate that adaptation involves learning-by-doing and proactive experimentation, through which employees refine their skills and align new technological possibilities with task demands. In the context of Generative AI, active engagement frequently emerges through bottom-up experimentation and participatory learning. Kochan et al. (2024) emphasize that successful implementations encourage workers to experiment with Generative AI tools and collaboratively redesign workflows. Similarly, Dong et al. (2024), Budhathoki et al. (2024), and Rafi et al. (2024) indicate that employees who perceive Generative AI as useful and trustworthy engage in exploratory and integrative behaviors, embedding these tools into daily work practices. Through such adaptive engagement, employees translate uncertainty into capability, improving creativity, productivity, and job satisfaction. These behaviors foster a sense of psychological empowerment, as workers gain control and confidence in using Generative AI systems (Dong, Liu, Li, & Lee, 2024; Rafi, Aitken, Fatah, & Mailangkay, 2024). However, not all employees experience Generative AI as an opportunity. For some, the technology triggers feelings of threat, leading to defensive and resistant coping responses. It is important to distinguish between rejection of something and resistance to something. Rejection is a pre-adoption decision not to accept or use a technology. It occurs before the implementation, when

individuals choose not to adopt at all (Rogers, 2003). Resistance refers to the intentional or unintentional behaviors that reflect opposition, skepticism, or reluctance to adopt or engage with a new system or technology (Oreg, 2006; Lapointe & Rivard, 2005). Meissonier and Houzé (2010) emphasize that “resistance is not rejection; it’s the expression of conflict in action. This means resistance can co-exist with formal or passive use but in constrained, minimal, or defensive ways. In the context of Generative AI, resistance often reflects perceived risks, loss of control, or anxiety about automation and evaluation, but Hartsyáandi (2025) also highlights that some employees perceive Generative AI as a “Janus-faced” presence, simultaneously promising and threatening. This conflicting feeling can create disillusionment and mistrust when initial expectations remain unmet. Lozie et al. (2024) add that anxieties about role redundancy and diminished job meaning often surface when Generative AI is introduced without sufficient framing or organizational support. Similarly, ethical concerns, heightened surveillance, and ambiguous data policies contribute to security-driven hesitation, particularly in organizations that lack transparent guidelines or regular training. This is also highlighted by Rafi et al. (2024), who show that even when employees perceive Generative AI as useful, resistance may still emerge when technical support, training, or infrastructure are insufficient, thereby constraining effective use. Collectively, these concerns reinforce perceptions of uncertainty and loss of control, prompting defensive engagement and cautious, minimal use patterns characteristic of resistant coping responses. As outlined in the previous section, employees’ perceptions of usefulness, ease of use, social influence, and organizational support, together with trust, trialability, and AI anxiety, determine whether they engage in adaptive exploration or display resistant, defensive use patterns.

2.1.5 Psychological empowerment and performance implications

As organizations increasingly integrate Generative AI into their workflows, it becomes critical to examine the psychological impact this technological shift may have on employees, beyond merely focusing on why they might adapt or not. To understand how individuals respond to such transformational changes in their work environment, Spreitzer’s (1995) Psychological Empowerment Theory offers a valuable framework. This theory conceptualizes empowerment as a multidimensional construct composed of meaning, competence, autonomy, and impact, capturing the extent to which employees feel intrinsically motivated and capable of influencing their work context. Autonomy concerns the degree of choice and freedom employees experience in performing tasks; competence reflects self-efficacy and confidence in one’s work role; meaning represents the alignment between one’s work and personal values; and impact captures the extent to which individuals feel able to influence outcomes at work. As Generative AI reconfigures workflows and decision autonomy, it has the potential to both enhance and undermine empowerment. When employees use Generative AI to expand creative control or overcome skill limitations, they may experience heightened competence or autonomy. When use is imposed or opaque, it can diminish perceived control and meaning. Psychological Empowerment is consistently linked to desirable work outcomes; a meta-analysis shows positive effects on performance and satisfaction (Seibert, Wang, & Courtright, 2011).

Perceived performance encompasses employees’ subjective evaluation of their performance in the workplace. Employee performance is commonly assessed through a combination of different factors. Three aspects that come forward in business research are productivity, reflecting output and efficiency (Phina, Arinze, & Chukwuma, 2015; Tatum, Nebeker, & Sorensen, 1991), quality and task performance, which emphasize the accuracy and completeness of core job duties (Kahya, 2009), and creativity, which is seen as a critical

dimension of performance, contributing to innovation and problem-solving capacity, especially in knowledge-intensive or adaptive roles (Maarofi & Navidinya, 2011; Nurhaeda, Maryadi, Salim, & Kitta; Arifin, Mujahid, & Suyuthi, 2023). Perceived productivity is the subjective evaluation by employees of their own productivity in the workplace. It refers to their self-assessed sense of how efficiently they perform their jobs, the quantity of work they produce at a certain speed (Koopmans, et al., 2013). Perceived task performance refers to how employees perceive the quality of their work. Where perceived productivity is about the amount of work done in a certain amount of time, perceived task performance is about the effectiveness, accuracy, and goal attainment (Koopmans, et al., 2013). Perceived creativity reflects employees' beliefs about their capacity for original problem solving and idea generation. The construct is rooted in Amabile's componential theory of creativity (Amabile, 1996). This theory defines creativity as the result of domain-relevant skills, creativity-relevant cognitive processes, and intrinsic task motivation. Generative AI tools directly reshape how employees experience productivity, performance quality, and creativity. They automate routine tasks (Noy & Zhang, 2023; Brynjolfsson, Li, & Raymond, Generative AI at work, 2023), enabling higher efficiency; augment analytical and writing tasks, improving quality and accuracy (Peng, Kalliamvakou, Cihon, & Demirer, 2023), and provide idea generation capabilities that stimulate creative problem solving. While Generative AI tools promise to enhance employee performance, their effects are not universally positive. Generative AI outputs are probabilistic; therefore, they may contain factual inaccuracies or lack contextual nuance. Consequently, their performance-enhancing effects are not guaranteed. Net performance depends on users' verification practices, task criticality, and the presence of organizational safeguards such as training, oversight, and usage protocols (Kim, Blazquez, & Oh, 2024; Vaishnav, Singh, & Cornell, 2024). In addition, over-reliance can diminish critical thinking and decision ownership, particularly in routine evaluative tasks (Dell'Acqua, et al., 2023). Employees in less cognitively demanding roles may experience skill degradation or role disempowerment when creative or judgment-intensive tasks are taken over by Generative AI (Peng, Kalliamvakou, Cihon, & Demirer, 2023; Hai, Long, Honora, Japutra, & Guo, 2025). Hence, the psychological and performance impacts of Generative AI are contingent, not uniform, requiring nuanced implementation approaches.

2.1.6 Gaps and contributions

Across the reviewed literature, Generative AI is increasingly positioned as a transformative force in organizational digital transformation. Studies highlight its capacity to enhance productivity, creativity, and efficiency (Brynjolfsson, Li, & Raymond, Generative AI at work, 2023; Noy & Zhang, 2023), while also surfacing ethical, psychological, and managerial challenges (Dwivedi, et al., 2023; Hai, Long, Honora, Japutra, & Guo, 2025). While these studies establish a solid understanding of Generative AI at the organizational level and technical perspectives, focusing on adoption frameworks, governance models, and firm-level outcomes, they offer limited insight into how employees personally navigate, interpret, and adapt to these technologies in their daily work context.

Scholars consistently recognize that employees' perceptions and behaviors determine whether digital transformation initiatives succeed or fail (Klein, Spieth, & Söllner, 2024; Weber, Büttgen, & Bartsch, 2022). Yet, empirical research exploring employees' psychological and behavioral responses to Generative AI remains scarce. Existing research often adopt single theoretical perspectives to study the human-AI interaction, such as the Technology Acceptance Model (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), or the psychological empowerment theory (Spreitzer, 1995), but these perspectives have rarely been integrated to capture the full spectrum of cognitive, behavioral and motivational employee responses. The following

section, therefore, synthesizes the main gaps identified across this literature and delineates how the present study seeks to address them.

While the organizational adoption and strategic integration of Generative AI have received growing scholarly attention, the individual-level experience of employees during the implementation remains underexplored. Most existing research emphasizes organizational readiness, governance frameworks, and digital transformation strategies (Dwivedi, et al., 2023; Reznikov, 2024; Hernández, 2024), focusing on how firms can integrate Generative AI responsibly within their current technological infrastructure. However, these perspectives pay limited attention to how employees perceive, adapt to, and emotionally respond to the introduction of Generative AI in their daily work practices. Classical socio-technical theory already established that technological change is enacted through people (Bostrom & Heinen, 1977; Pasmore, 1988), yet empirical evidence on employees' responses to Generative AI remains scarce. Recent scholars have called for a stronger understanding of the human side of AI-driven transformation, emphasizing the importance of trust, emotional engagement, and sensemaking in shaping adoption outcomes (Bankins, Ocampo, Marrone, Restuborg, & Woo, 2023; Klein, Spieth, & Söllner, 2024; Hai, Long, Honora, Japutra, & Guo, 2025). Addressing this gap requires moving beyond conceptual discussions to empirically capture employees' perceptions, emotions, and behavioral responses as they evolve during implementation.

A second gap in the existing literature concerns the fragmented theoretical approaches used to study employee responses to Generative AI. Most studies adopt a single theoretical lens, focusing on either technology acceptance, behavioral adaptation, or psychological outcomes, without connecting these perspectives into a coherent explanatory model. Yet, Generative AI introduces changes that simultaneously affect how employees think about, interact with, and feel about their work (Bankins, Ocampo, Marrone, Restuborg, & Woo, 2023; Klein, Spieth, & Söllner, 2024). Only a few conceptual frameworks, such as Human-Centered AI (Nah, Zheng, Cai, Siau, & Chen, 2023) or Hybrid Intelligence models (Sherson, 2024), have begun to acknowledge this multidimensionality, but these remain largely prescriptive and lack empirical validation. Theoretical integration is needed to explain how employees' perceptions of Generative AI shape their behavioral responses and psychological states.

Another critical gap concerns the limited empirical research capturing employees' experiences of Generative AI implementation as it happens in real organizational contexts. Much of the current literature remains conceptual or speculative, emphasizing potential applications and strategic implications rather than direct observations of employee responses (Dwivedi, et al., 2023; Reznikov, 2024; Bahn & Strobel, 2023). Quantitative studies that do collect data typically examine intentions to use or attitudes toward AI in general, offering limited insight into how employees actually adapt their work practices once the technology is introduced. This study addresses this gap by examining an ongoing organizational-wide rollout, allowing real-time investigation of how employees perceive, respond to, and are psychologically affected by Generative AI.

Moreover, limited attention is paid to the psychological and emotional mechanisms through which employees experience Generative AI at work. However, recent research has begun to highlight the importance of emotional and psychological variables such as trust in AI systems (De Duro, Veltri, Golino, & Stella, 2025; Schepman & Rodway, 2022), AI anxiety (Wang & Wang, 2022), and psychological empowerment (Spreitzer, 1995; Hai, Long, Honora, Japutra, & Guo, 2025). These mechanisms influence whether employees feel empowered or alienated, secure or threatened, when working alongside AI. High cognitive trust and emotional comfort can foster openness and experimentation, whereas anxiety or perceived loss of control may trigger avoidance and resistance behaviors (Bankins, Ocampo, Marrone, Restuborg, & Woo,

2023; Klein, Spieth, & Söllner, 2024). Despite their theoretical relevance, few empirical studies have systematically modelled these psychological constructs within technology-acceptance or transformation frameworks in the context of live Generative AI implementation. This study contributes by integrating these affective and motivational mechanisms into a unified framework that explains how employees' perceptions of Generative AI translate into behavioral and performance outcomes.

A final gap in the current literature concerns the limited attention given to contextual and demographic moderators that shape how employees experience Generative AI implementation. Even studies that examine individual attitudes or psychological outcomes often treat employees as a uniform group, overlooking variation in how contextual factors influence adoption and empowerment. However, organizational context and personal characteristics fundamentally shape how employees interpret, engage with, and derive value from new technologies (Fadel et al., 2015; Venkatesh et al., 2016). Prior research in digital transformation and technology adoption has shown that variables such as organizational role, technological competence, and tenure can moderate key relationships between perceptions, behavioral responses, and performance outcomes (Klein, Spieth, & Söllner, 2024). The present study addresses this gap by examining the moderating effects of role, digital literacy, training, tenure, and age, thereby offering a more differentiated understanding of the human experience of Generative AI implementation. By incorporating these contextual variables, the study moves beyond generalized acceptance models toward a more situated understanding of AI-driven transformation.

Taken together, the reviewed literature demonstrates that Generative AI represents a large technological and organizational transformation, yet our understanding of its human implications remains limited. The present study responds to this need by developing and empirically testing a multidimensional framework that integrates technology acceptance constructs, behavioral reactions, and psychological empowerment as pathways to perceived individual performance. The following section presents this theoretical framework and the proposed relationships that underpin the study's conceptual model.

2.2 Theoretical Framework

Building on the gaps identified in the preceding section, this theoretical framework aims to explain how employees experience the implementation of Generative AI in their work. While prior research largely examined Generative AI from strategic and technological perspectives, little is known about the cognitive, emotional, and behavioral mechanisms through which employees respond to such transformations. The purpose of this framework is therefore to integrate complementary theoretical perspectives to capture the human experience of Generative AI implementation, specifically how employees' perceptions, affective evaluations, and behaviors interact to shape their sense of empowerment and perceived individual performance.

The framework draws primarily on three theoretical foundations: the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) to explain cognitive appraisals of the technology; adaptation and resistance theories (Beaudry & Pinsonneault, 2005; Oreg, 2006) to account for behavioral responses to change; and the psychological empowerment theory (Spreitzer, 1995) to capture motivational and emotional outcomes. Together, these frameworks form an integrated model linking technology perceptions and affective reactions to behavioral responses, which subsequently influence psychological empowerment and perceived individual performance.

The framework operates at the individual level of analysis, focusing on employees experiencing a live implementation of Microsoft Co-pilot within a knowledge-intensive organization. It includes contextual moderators to account for differences in how employees experience Generative AI. The framework does not aim to evaluate organizational performance or technical effectiveness, but rather the human impact of implementation. The following sections define the key constructs and outline the hypothesized relationships that form the conceptual model guiding this study.

2.2.1 Construct specifications

To explain the human impact of Generative AI implementation at the individual level, the framework comprises technology perceptions (UTAUT), affective appraisals (trust, AI Anxiety, trialability), behavioral responses (adaptation, resistance), psychological empowerment, and perceived individual performance, as well as a set of exploratory contextual moderators that may shape these relationships. Each construct is defined conceptually below to establish theoretical clarity and ensure consistent usage throughout the study; operational definitions are provided in Chapter 3.

2.2.1.1 Technology Perceptions (UTAUT and Trialability)

The first construct group, technology perceptions, captures employees' cognitive appraisals of Generative AI as introduced in the UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003). These perceptions determine initial reactions to the technology and shape willingness to experiment with its features. The four core perceptions are performance expectancy, effort expectancy, social influence, and facilitating conditions with the addition of trialability. Performance expectancy concerns the belief that Generative AI improves job outcomes (speed, quality, communication). This reflects expectations that Generative AI will streamline routine tasks and enhance deliverables. Higher expectations typically foster experimentation and deeper integration. Effort expectancy refers to the ease associated with using Generative AI. It reflects how easy or difficult an individual believes Generative AI will be to learn and use. When employees find the system straightforward to use, perceived barriers to experimentation decrease, supporting smoother adoption and adaptation. Social Influence refers to the degree to which individuals believe that important other people think they should use Generative AI. It reflects perceived social norms, professional expectations, and the value attached to adopting this new technology within a workplace culture. Regarding Generative AI, a stronger social influence can increase employees' motivation to experiment with the technology and align their behaviors with organizational transformation goals. Facilitating conditions refer to the extent to which an individual believes an organizational and technical infrastructure exists to support the use of Generative AI. When employees perceive strong facilitating conditions, they are more likely to integrate Generative AI tools confidently into their workflows, reducing uncertainty and resistance during implementation. Although UTAUT was originally developed to explain adoption behaviors, prior research shows its constructs can also be applied to continuance or post-adoptive use contexts. However, it remains unclear whether UTAUT's predictors retain the same explanatory power when employees are already interacting with an embedded technology such as Generative AI. This study therefore extends UTAUT into a post-adoptive adaptation context to examine whether its determinants continue to shape behavioral responses during real-world implementation. Training participation is included to assess the role of organizational support in shaping employees' adoption and effective use of Generative AI. Prior research in technology adoption (Venkatesh, Morris, Davis, & Davis, 2003) emphasizes the importance of training as part of 'facilitating conditions', which directly impacts perceived ease of use and behavioral intention. Measuring training participation allows for testing whether employees who have received structured

support experience a positive feeling toward adoption, greater empowerment and report higher perceived performance gains. Trialability refers to the degree to which employees perceive they can experiment with Generative AI before its full integration into daily work (Rogers, 2003). It captures perceived opportunities to explore, test, and learn from the technology in a low-risk environment. Higher trialability allows employees to form accurate judgments about usefulness and ease of use, fostering trust and willingness to adopt Generative AI tools.

2.2.1.2 Affective appraisals

The second group, affective appraisals, captures the emotional and evaluative reactions employees form toward Generative AI. While technology perceptions describe beliefs about the usefulness and ease of the technology, affective appraisals reflect emotions and feelings that accompany its use. These emotional responses are central to how employees experience technological change and determine whether cognitive perceptions translate into constructive or defensive behaviors. This study focuses on three affective appraisals that are particularly relevant to Generative AI in the workplace: cognitive trust, emotional trust, and AI anxiety. Cognitive trust is the willingness to be vulnerable to the actions of another based on the expectation that they will perform a particular action important to the trustor (Mayer, Davis, & Schoorman, 1995). Translating this to the Generative AI context, cognitive trust develops when users perceive that the tool provides reliable outputs and supports work performance effectively, fostering willingness to engage and adapt. Emotional trust refers to the sense of comfort, security and assurance employees feel when using Generative AI. It is built on emotional bond and interpersonal closeness, not just rational evaluation (McAllister, 1995). Emotional trust emerges when employees perceive the technology as non-threatening, helpful, and aligned with their values or professional goals. High emotional trust can strengthen acceptance and reduce resistance to Generative AI implementation. AI Anxiety describes feelings of tension, apprehension, or worry associated with using or being expected to use Generative AI systems (Wang & Wang, 2022). It involves concerns about personal capability, potential job displacement, and uncertainty about ethical or privacy implications. Within the implementation of Generative AI, heightened anxiety can reduce willingness to experiment with the technology and increase avoidance or resistance behaviors. Managing this anxiety through transparent communication and training is therefore critical for successful adoption. Together these constructs constitute the emotional lens through which employees interpret the implementation of Generative AI, shaping whether cognitive perceptions evolve into positive adaption or defensive resistance.

2.2.1.3 Behavioral responses: adaptation and resistance

The third construct group, behavioral responses, reflects the actions and coping strategies employees adopt in response to the implementation of Generative AI. Drawing on the coping model of user adaptation and research on technological resistance, these responses can be broadly divided into two contrasting forms: adaptation and resistance. Together they describe the behavioral continuum that characterizes employees' engagement with Generative AI during organizational change. Adaptation refers to the process of actively adjusting to new technology, including learning, integrating it into work processes, and experimenting to improve outcomes (Beaudry & Pinsonneault, 2005). It encompasses experimentation, learning, and modification of work processes to leverage Generative AI effectively. It is often driven by positive appraisals, such as high-performance expectancy, and is associated with constructive coping and innovation-oriented behavior. Resistance represents the defensive or avoidance-oriented behaviors employees display when they perceive Generative AI as threatening, unnecessary, or misaligned with their work practices (Oreg, 2006; Lapointe & Rivard, 2005). Resistance can manifest as reluctance, skepticism, or active avoidance of the

technology. It may stem from negative appraisals, such as AI anxiety or low trust, and can slow or disrupt implementation efforts. However, resistance is not inherently negative; it can signal legitimate concerns or unmet needs in the change process. In this study, resistance captures employees' behavioral opposition to, or disengagement from, the use of Generative AI tools. Together, adaptation and resistance capture the behavioral responses of employees' to Generative AI, mediating the relationship between their perceptions and emotions on the one hand and their psychological empowerment and performance outcomes on the other.

2.2.1.4 Psychological empowerment

The fourth construct group, psychological empowerment, represents the motivational and psychological state through which employees experience meaning, competence, autonomy, and impact in their work. Drawing on Spreitzer's (1995) conceptualization, psychological empowerment is understood as a four-dimensional construct reflecting an individual's active orientation toward their work role. It reflects whether the integration of Generative AI enhances employees' intrinsic motivation and sense of agency in their roles. Meaning refers to the sense that work conducted with Generative AI remains purposeful and aligned with one's professional values (Spreitzer, 1995). When using GenAI allows employees to focus on tasks they find significant or creative, it enhances perceived meaning; if it reduces human judgment or craftsmanship, meaning may decline. Competence denotes the confidence employees gain in their ability to perform work tasks effectively using Generative AI (Spreitzer, 1995). It reflects a sense of self-efficacy and mastery developed as employees learn to interact with and apply the technology in meaningful ways. Importantly, competence in this context also involves overcoming skill gaps created by the introduction of new digital tools. Employees feel empowered when they can bridge these gaps and maintain relevance in an evolving technological environment. When employees perceive that using Generative AI enhances their professional capability, they experience greater motivation and engagement in their work. Autonomy reflects the degree of freedom and control employees experience when using Generative AI in their work. In this study, it refers to the sense that AI tools enable employees to make their own choices about how, when, and to what extent to use the technology. Generative AI can enhance perceived autonomy by reducing dependence on supervisors or colleagues for information and by allowing employees to structure tasks, explore creative approaches, and complete work at their own pace. Impact represents the extent to which using Generative AI makes employees feel that their work contributes meaningfully to team or organizational outcomes (Spreitzer, 1995). When employees perceive that their effective use of GenAI leads to visible improvements in productivity, innovation, or decision-making, they experience a stronger sense of empowerment and value.

2.2.1.5 Perceived performance

The final construct group, perceived individual performance, represents employees' subjective assessment of how the use of Generative AI affects their work outcomes. It captures whether employees feel that integrating AI tools improves the quality, efficiency, and creativity of their performance. While organizational performance is often used to evaluate technology at macro level, perceived individual performance focuses on the micro-level experience: how employees themselves evaluate the contribution of Generative AI to their daily work. In this study, perceived individual performance is conceptualized through three interrelated dimensions: productivity, task performance and creativity. Productivity refers to the perceived efficiency and output improvements employees experience because of using Generative AI (Brynjolfsson & McAfee, *The Second Machine Age: Work progress and prosperity in a time of brilliant*, 2014). It reflects the extent to which employees believe that Generative AI tools help them complete tasks faster, manage workload more effectively, or handle greater volumes of information with less effort. When employees perceive that Generative AI streamlines

repetitive or time-consuming tasks, they report higher productivity and a stronger sense of personal accomplishment. Task performance concerns the perceived quality, accuracy and completeness of employees' core work activities supported by Generative AI (Koopmans, et al., 2013). It captures whether the technology helps them produce higher-quality deliverables, make better decisions, or reduce errors. For many professionals, Generative AI support can improve decision-making and problem-solving by offering rapid access to relevant information or alternative solutions. As such, higher task performance reflects employees' belief that the technology enhances the quality of their work. Creativity represents the extent to which using Generative AI enhances employees' capacity to generate new ideas, insights, or solutions (Amabile, 1996). It reflects the perception that Generative AI tools stimulate divergent thinking, support brainstorming, or free up cognitive resources for innovation. When employees experience Generative AI as a collaborator in idea generation, helping them explore options, reframe problems, or test novel approaches, they perceive higher creativity in their work. Conversely, when AI use feels constraining or formulaic, creativity may decline. Together, these three dimensions capture employees' perceived performance benefits derived from using Generative AI, providing an outcome-focused perspective on the human impact of technological implementation.

2.2.1.6 Contextual exploratory moderators

Gender

Research building on TAM/UTAUT has consistently shown that males report higher perceived ease of use, greater self-efficacy, and more favorable attitudes toward technology compared to females, who often report higher levels of computer anxiety and lower digital self-confidence, which could negatively affect their adoption to Generative AI (Goswami & Dutta, 2016). In addition, a working paper by Otis et al. (2024) confirms that there is a persistent gender gap in the usage of Generative AI, where women are 20% less likely than men to use Generative AI tools, even when access to the tools is equal.

Age

There is large variation in generational digital familiarity (Park, Jeon, Ahn, Chung, & Park, 2025). According to (Morris & Venkatesh, 2006) age influences technology adoption behavior and older employees often rely more on social influence and perceived control than younger employees when deciding whether to adopt new technologies.

Role

Different job roles define different types of access, responsibilities and impact of new tools. E.g. managers might adopt to Generative AI differently than support staff. Research by Zirar et al. (2023) on workplace AI suggests that there is role-based variance in access and outcomes, impacting productivity and satisfaction. Including this demographic will help to explain differences in the impact of Generative AI on different types of employees.

Educational Background

Higher education correlates with better digital literacy and tech-acceptance attitudes (Nikou, De Reuver, & Mahboob Kanafi, 2022).

Tenure

Beaudry and Pinsoneault (2005) argue that individuals' responses to new IT vary by tenure, with longer-tenured employees more likely to exhibit avoidance or resistance behaviors. Oreg (2006) also notes that tenure is positively related to dispositional resistance to change, especially in knowledge-based organizations. This demographic helps to explain the variation

in openness to change and by controlling for tenure we avoid misinterpreting Generative AI resistance or low adoption as caused by Generative AI itself, when it could be about employee experience.

Digital Literacy

Digital literacy is the ability to operate digital devices, use digital content and strategically, adapt to new technologies in context (van Deursen & van Dijk, 2013). Studies show that digital and information literacy increase perceived ease of use, indicating that the adoption of Generative AI and its impact on perceived performance is dependent on user literacy levels (Nikou, De Reuver, & Mahboob Kanafi, 2022). Including digital proficiency/literacy can help us to adjust for skill differences in adoption, empowerment and perceived performance. We can test whether digital proficiency directly increases the adoption of Generative AI or whether it increases empowerment through Generative AI.

Frequency of use

Frequency of GenAI use reflects the level of user exposure and engagement with it. While adoption captures whether an employee uses GenAI, frequency provides a more continuous measure of how intensively they use it in their daily work. According to post-adoption models (Bhattacharjee, 2001), frequency of use is strongly associated with the degree of ongoing use of a system is a critical indicator of successful integration into work practice. Including frequency of use allows for exploring how the depth of engagement with Generative AI influences outcomes like perceived performance and empowerment. Furthermore it helps distinguish between light users (occasional/experimental use) and heavy users (regular, integrated use), which can support targeted implementation strategies.

Collectively, these exploratory moderators enable a more nuanced understanding of for whom and under what conditions Generative AI implementation is most beneficial. Although no directional hypotheses are proposed, examining these moderators empirically provides valuable insight into potential boundary conditions of the proposed framework and informs future theory development on AI adoption in the workplace.

2.2.2 Theoretical model and proposed relationships

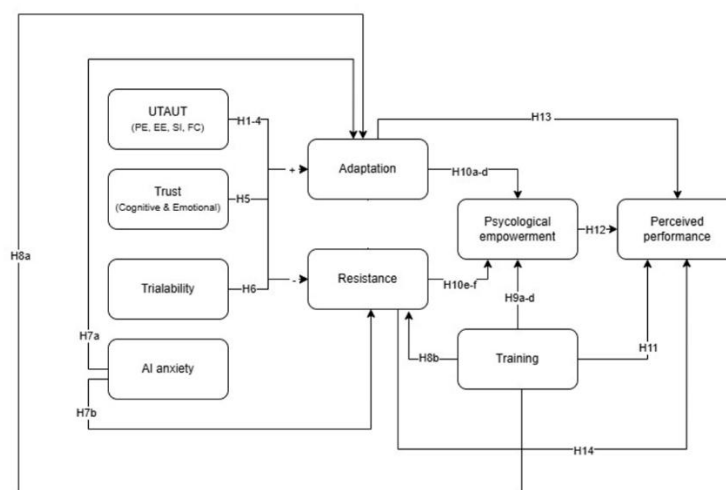


Figure 1: Conceptual model of employees' experience of the implementation of Generative AI

Figure 1 presents the proposed framework. Employees' behavioral responses to Generative AI, adaptation, and resistance, are modeled as the immediate outcomes of several antecedents: technology perceptions (UTAUT, Trialability), affective appraisals (trust and AI anxiety), and training participation as part of facilitating conditions. These behavioral responses, in turn, shape psychological empowerment and together influence perceived individual performance. The following subsections justify each relationship and state the corresponding hypotheses.

Technology perceptions (UTAUT factors)

Employees' perceptions of Generative AI influence their engagement behaviors. When employees view the technology as useful, easy to use, socially supported, and adequately resourced, they are more likely to experiment with and integrate it, and less likely to resist it (Venkatesh, Morris, Davis, & Davis, 2003).

- H1a. Performance expectancy is positively associated with adaptation.
- H1b. Performance expectancy is negatively associated with resistance.
- H2a. Effort expectancy is positively associated with adaptation.
- H2b. Effort expectancy is negatively associated with resistance.
- H3a. Social influence is positively associated with adaptation.
- H3b. Social influence is negatively associated with resistance.
- H4a. Facilitating conditions are positively associated with adaptation.
- H4b. Facilitating conditions are negatively associated with resistance.

Trust

Trust in generative AI reduces uncertainty and encourages engagement (Schaefer et al., 2021). Both cognitive trust (belief in Generative AI reliability) and emotional trust (comfort with Generative AI use) promote constructive engagement.

- H5a. Cognitive trust is positively associated with adaptation.
- H5b. Cognitive trust is negatively associated with resistance.
- H5c. Emotional trust is positively associated with adaptation.
- H5d. Emotional trust is negatively associated with resistance.

Trialability

Opportunities to experiment with Generative AI in a low-risk setting foster familiarity and confidence (Rogers, 2003), which promote adaptation and discourage resistance.

- H6a. Trialability is positively associated with adaptation.
- H6b. Trialability is negatively associated with resistance.

AI Anxiety

Fear or discomfort regarding Generative AI can inhibit experimentation and encourage avoidance (Chang, Zhang, Guo, & Cai, 2024).

- H7a. AI anxiety is negatively associated with adaptation.
- H7b. AI anxiety is positively associated with resistance.

Training

Structured training opportunities enhance knowledge and confidence in using Generative AI, promote adaptation, and discourage resistance (Beaudry & Pinsonneault, 2005).

- H8a. Training participation is positively associated with adaptation.
- H8b. Training participation is negatively associated with resistance.

Behavioral responses → Psychological Empowerment

Employees' behavioral engagement with Generative AI, how actively they use, explore, and integrate it into their work, shapes their sense of empowerment. When employees adapt to Generative AI by experimenting with its features, incorporating it into their tasks, and refining its use, they are likely to experience higher meaning, competence, autonomy, and impact because the technology helps them perform work more effectively and creatively. Conversely, when employees resist or avoid using Generative AI, they are less likely to benefit from these empowerment effects. Their limited engagement restricts opportunities for learning, mastery, and discretion, which may dampen or even reverse feelings of empowerment derived from the technology (Oreg, 2006; Bhattacharjee, 2001).

H9a. Adaptation is positively associated with overall psychological empowerment.

H9b. Resistance is negatively associated with overall psychological empowerment.

H9c. Adaptation is positively associated with meaning.

H9d. Adaptation is positively associated with competence.

H9e. Adaptation is positively associated with autonomy.

H9f. Adaptation is positively associated with impact.

H9g. Resistance is negatively associated with meaning.

H9h. Resistance is negatively associated with competence.

H9i. Resistance is negatively associated with autonomy.

H9j. Resistance is negatively associated with impact.

Training → Psychological Empowerment and Perceived Performance

Structured training lowers uncertainty, builds skill, and signals managerial support, all of which enhance employees' sense of meaning, competence, autonomy, and impact when working with Generative AI. Training also helps employees overcome skill gaps and exercise greater discretion in their use of AI, reinforcing an empowered stance toward their work. Training is also expected to have a direct positive effect on employees' perceived individual performance. Structured training equips employees with the knowledge and skills to use Generative AI effectively, thereby enhancing confidence, reducing trial-and-error inefficiencies, and enabling smoother integration into daily tasks. Prior research on technology adoption links organizational support and training to improved self-assessed performance and productivity (Venkatesh, Morris, Davis, & Davis, 2003; Nikou, De Reuver, & Mahboob Kanafi, 2022; Compeau & Higgins, 1995). Employees who receive clear guidance on leveraging Generative AI for their roles are more likely to perceive tangible performance gains from its use.

H10a. Training participation is positively associated with psychological empowerment.

H10b. Training participation is positively associated with perceived performance

Direct effects on perceived performance

Psychological empowerment captures whether using Generative AI enhances employees' sense of meaning, competence, autonomy, and impact in their work, which should translate into higher self-evaluations of productivity, task quality, and creativity (Spreitzer, 1995; Seibert, Wang, & Courtright, 2011). Some influences may bypass intermediate stages. Adapting practices can immediately yield performance gains; favorable perceptions may positively influence performance judgments directly (Venkatesh, Morris, Davis, & Davis, 2003; Rogers, 2003), while resistance may depress them (Lapointe & Rivard, 2005).

H11. Psychological empowerment is positively associated with perceived performance

H12. Adaptation is positively associated with perceived performance

H13. Resistance is negatively associated with perceived performance

Mediation effects

The framework proposes several mediating pathways through which employees' experiences with Generative AI influence perceived performance outcomes. Consistent with empowerment theory (Spreitzer, 1995; Seibert, Wang, & Courtright, 2011), psychological empowerment is modeled as the central mechanism linking employees' behavioral and affective experiences with their perceived individual performance. First, behavioral responses, are expected to influence perceived performance indirectly through empowerment. Employees who actively adapt to Generative AI are likely to experience greater meaning, competence, autonomy, and impact, which in turn enhance their self-evaluated performance. Conversely, resistant behaviors are expected to diminish empowerment and consequently lower perceived performance.

H14a. Adaptation → Psychological empowerment → Perceived performance (positive **indirect** effect).

H14b. Resistance → Psychological empowerment → Perceived performance (negative **indirect** effect).

Second, training participation may also exert indirect effects on performance by strengthening empowerment. Through learning opportunities and skill development, training fosters confidence and perceived control, which translate into higher performance.

H14c. Training has a positive indirect effect on perceived performance through psychological empowerment.

Finally the model considers exploratory mediators, where technology perceptions and affective appraisals influence empowerment and performance indirectly via behavioral responses.

15a–h. Antecedents (training, trust, trialability, and AI anxiety) influence psychological empowerment indirectly through adaptation and resistance behaviors, which subsequently affect perceived performance.

Collectively, these mediating pathways reflect the framework's process logic: employees' cognitive, emotional, and behavioral experiences with Generative AI shape their psychological state of empowerment, which mediates the ultimate impact on perceived individual performance.

This theoretical framework integrates cognitive (UTAUT), affective (trust and AI anxiety), and behavioral (adaptation and resistance) perspectives to explain how employees experience the implementation of Generative AI. By incorporating psychological empowerment as a mediating mechanism and perceived individual performance as the key outcome, the framework provides a holistic explanation of how employees' perceptions, emotions, and behaviors jointly shape the human impact of Generative AI in organizations. Chapter 3 describes the operationalization of constructs and the research design, including measurement development and analytical procedures. The proposed model is then empirically tested in Chapter **Error! Reference source not found..**

3 Research design

3.1 Mixed methods

In this study quantitative research is combined with qualitative research in the form of sequential explanatory analysis. The mixed-methods sequential explanatory design consists of two distinct phases, it starts with quantitative data collection and analysis then follows up with qualitative data collection and analysis for the interpretation of the quantitative results (Creswell & Creswell, 2018).

3.2 Research setting

This study is situated within TNO, a research and innovation institute, employing a highly educated, knowledge-intensive workforce. They are currently implementing Generative AI in the form of Microsoft CoPilot organization-wide. This real-time digital transformation offers the unique opportunity to study how employees respond to the implementation of Generative AI. It provides direct access to the early stages of adoption, where behavioral and psychological responses are still forming. The diversity of job roles and departments at TNO enables a rich analysis of variation in adoption, empowerment, and perceived performance across organizational context. Insights from this setting may be valuable not only for TNO, but for other organizations navigating similar technological transitions.

3.3 Research design phase 1: The quantitative study

3.3.1 Sample

Sampling method

For this part of the research a census-style distribution strategy was used, in which the survey was distributed to the entire employee population at TNO (N = 4,400) (TNO, 2025). This approach is consistent with the approach of Dillman et al., (2014), who recommend full-population survey distribution in closed organizational settings. While this approach increased inclusiveness and reach, participation was voluntary and the sample therefore constitutes a non-probability, self-selected sample. As a result, self-selection bias could have occurred, as participants may have differed systematically from non-respondents, affecting the representativeness of the sample. However, evidence from empirical research suggests that large and demographically diverse non-probability samples can still support robust descriptive and correlational analyses, particularly when the research focus is on internal organizational processes rather than external generalization (Bhaduri, 2015; Turban, Almazan, Reisner, & Keuroghlian, 2023).

Sample size

To ensure statistical validity, Cohran’s (1977) formula was used to estimate a minimum response threshold ($N = 354$), based on the total employee population at TNO ($N = 4,400$). The sample size calculation was based on the following parameters:

- A 95% confidence level, consistent with classical guidance (Cochran, 1977; Krejcie & Morgan, 1970) and recent applications in organizational research (Buckley, 2024; Taherdoost, 2018), corresponding to a Z-score of 1.96.
- A 5% margin of error (Buckley, 2024; Lee & Landers, 2022), reflecting a balance between statistical power and practical feasibility.
- An estimated proportion (p) of 0.5 (50%) used as a conservative default when the expected distribution of responses is unknown (Cochran, 1977; Bartlett & Higgins, 2001), as it maximizes the required sample size.
- The application of a finite population correction (FPC) to adjust the initial sample size due to the moderate population size ($N = 4400$), as the target sample exceed 5% of the population (Cochran, 1977).

Although the sample was not strictly random, the approach supported comprehensive coverage of employee perspectives across departments, usage levels, and tenure. In total, 392 responses were received. Respondents who did not provide consent to use their data were excluded, as were respondents with more than one missing Likert-scale response, to preserve data quality. After applying these exclusion criteria, 363 valid cases remained, resulting in an effective response rate of 8.2%. The demographic characteristics of the final sample are presented in section 4.1.1.

3.3.2 Instrument

The survey consisted of two parts: (1) a set of validated scales measuring the theoretical constructs in the conceptual model, and (2) demographic and contextual questions. All construct items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items loading the constructs were adapted from existing validated instruments to fit the context of the implementation of Generative AI. Demographic questions captured age, gender, educational level, organizational role, department, organizational tenure, digital literacy, and frequency of Generative AI use.

3.3.2.1 Operationalization of constructs

UTAUT

Table 1 shows the constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT; (Venkatesh, Morris, Davis, & Davis, 2003)) were included to capture core determinants of technology adoption. The survey items were adapted from the validated UTAUT constructs developed by Venkatesh et al. (2003) and have been contextualized to reflect the implementation of Generative AI, while preserving their theoretical structure and measurement integrity. Frequently TAM and UTAUT are applied prior to or during early stages of technology implementation to predict user acceptance, however recent studies have extended that application to current and post implementation contexts (Ngusie, et al., 2024; Deshmukh & Mehta, 2024; Bai & Guo, 2022).

Construct	Definition	Measurement items
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Performance Expectancy	The degree to which individuals believe that using the technology will improve job performance and outcomes	1. I find Generative AI tools useful 2. Generative AI enables me to accomplish tasks faster 3. If I use Generative AI, I will increase the quality of my work
Effort expectancy	The degree of ease associated with using the system	1. Learning to use Generative AI is easy for me 2. I find working with Generative AI tools to be clear and understandable 3. Navigating GenAI tools in my daily work is straightforward 4. It is easy for me to become skillful at using generative AI
Social influence	The degree to which individuals perceive that (important) other people believe they should use the system	1. I believe the organization expects me to start using Generative AI tools 2. I feel supported by my manager to use Generative AI tools in my work 3. My manager expects me to use Generative AI in my work 4. My colleagues think using Generative AI is beneficial 5. Colleagues believe I should adopt Generative AI in my work
Facilitating conditions	The extent to which an individual believes that an organizational and technical infrastructure exists to support use of the system.	1. I have the resources necessary to use Generative AI effectively 2. I have the knowledge necessary to use Generative AI tools 3. I have the skills necessary to use Generative AI tools 4. Generative AI is not compatible with other systems I use

Table 1: Constructs and items UTAUT

Trust

Table 2 shows that the construct cognitive trust was measured using three items adapted from the validated S-TIAS scale (Schepman & Rodway, 2022), reflecting beliefs about performance reliability and consistency. Emotional trust was measured using three items adapted from the TILLMI index (De Duro, Veltri, Golino, & Stella, 2025), reflecting psychological comfort and emotional ease in interacting with Generative AI (Table 2). While TILLMI is a preprint, its items are grounded in established trust theory (McAllister, 1995; Nass & Moon, 2002) and offer conceptually aligned coverage of the emotional/affective dimension of trust in Generative AI systems.

Construct	Definition	Measurement items
Emotional Trust	Emotional trust refers to a users' affective response to a system. It is built on emotional bonds, security, and interpersonal closeness, not just rational evaluation.	• I feel comfortable interacting with the Generative AI tool. • Using the Generative AI tool feels natural to me. • I feel that the Generative AI tool understands me or my intentions.
Cognitive trust	Cognitive trust is the willingness to be vulnerable to the actions of another based on the expectations that they will perform a particular action important to the trustor	• I believe Generative AI tools perform their tasks accurately • The output from the Generative AI tool is generally reliable • The Generative AI tool behaves consistently across different tasks

Table 2: Trust constructs and items

Trialability

Table 4 shows that trialability was measured using three items adapted from Moore and Benbasat (Moore & Bensabat, 1991), and contextualized to Generative AI implementation based on recent studies (Lee & Kim, 2023; Chawla et al., 2024).

Construct	Definition	Measurement items
Trialability	The degree to which an innovation can be experimented with on a limited basis before a full-scale adoption decision is made	• I had the opportunity to try out Generative AI tools before being expected to use them in my work. • I was able to experiment with Generative AI tools to see how they would work for me. • My organization allowed me to explore GenAI tools in a safe, low-pressure way before formal use. what is the reliability of these items?

Tabel 3: Trialability construct and items

AI Anxiety

AI Anxiety was measured using four items adapted from the validated AI Anxiety Scale (Wang & Wang, 2022) covering key aspects of job-related and learning-related concerns (Table 4).

Construct	Definition	Measurement items
AI Anxiety	AI anxiety is the fear, stress or apprehension individuals feel about artificial intelligence and its impact on their lives and work.	- I am worried that AI tools will replace parts of my job - I feel insecure about my job because of using Generative AI - I feel overwhelmed when I think about having to learn how to use new Generative AI tools - I am afraid I won't be able to keep up with the growing use of Generative AI in my work.

Table 4: AI Anxiety construct and items

Psychological Empowerment

Items were adapted from Spreitzer's (1995) psychological empowerment scale to reflect the use of Generative AI in the workplace (Table 5). While the core constructs remained unchanged, item phrasing was modified to contextualize them to GenAI implementation. This approach follows prior studies adapting validated scales to novel technology contexts (Ngusie, et al., 2024; Masrek, Anuar, & Mazlan, 2024).

Construct	Definition	Measurement items
Autonomy	The degree of autonomy and control an individual feels over how they carry out their job tasks.	- Generative AI gives me more freedom in how I perform my work - I can decide how and when to use GenAI, which increases my sense of autonomy - Using GenAI allows me to tailor how I approach my tasks
Competence	The individual's confidence in their ability to successfully perform work-related tasks.	- GenAI helps me overcome skill or knowledge gaps in my work - Using Generative AI makes me feel more capable in my job - Since using Generative AI, I feel more confident in handling my work tasks
Meaning	The extent to which an individual perceives their work as personally important and consistent with their values and beliefs.	- Because of Generative AI, I find my work more meaningful - Using Generative AI helps me focus on aspects of my job that matter most to me - Generative AI supports me in doing work that aligns with my values or interest
Impact	The extent to which an individual feels they can influence organizational outcomes and decisions at work.	- Using Generative AI enables me to make bigger impact in my work or team - I feel that my use of Generative AI contributes to my organization's success - Generative AI helps me influence the quality and outcomes of my work more effectively

Table 5: Psychological Empowerment constructs and items

Behavioral Response

To measure the behavioral response of employees to the implementation of Generative AI items for adaptation and resistance were adapted from established measures of employee adaptation and technology resistance behaviors (Beaudry & Pinsonneault, 2005; Lapointe & Rivard, 2005; Oreg, 2006) (Beaudry & Pinsonneault, 2005; Oreg, 2003; Lapointe & Rivard, 2005; Roy & Neeshan, 2023; Ferlie et al., 2005). This construct captures the range of employee reactions to the implementation of Generative AI in the workplace, encompassing both **adaptation** and **resistance**.

Construct	Definition	Measurement items
Adaptation	Adaptation is the process of actively adjusting to a new technology, including learning, integrating it into work processes, and experimenting to improve outcomes	- I have made changes to how I do my work because of Generative AI - I experiment with different GenAI tools to improve my work processes - I actively seek ways to integrate GenAI into my daily work tasks - I feel comfortable exploring Generative AI features without formal instructions
Resistance	Resistance refers to the intentional or unintentional behaviors that reflect opposition, skepticism, or reluctance to adopt or engage	- I feel reluctant to use Generative AI tools, even when available - I avoid using Generative AI unless I am explicitly required to - I am skeptical about whether GenAI is beneficial for my job - I have delayed learning to use Generative AI tools even when training was available

	with a new system or technology	I have voiced concerns or criticisms about the use of Generative AI in our organization
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Tabel 6: Behavioral response constructs and items

Perceived Performance

Items for perceived performance were adapted from established measures of workplace productivity and task performance (Koopmans, et al., 2013) and creativity (Amabile, 1996; Zhou & George, 2001; Hackman & Oldham, 1976; Tierney & Farmer, 2002).

Construct	Definition	Measurement items
Productivity	Perceived productivity is the subjective evaluation by employees of their own productivity at the work place.	- Generative AI improves the efficiency of my work - With the help of Generative AI, I feel like I am getting more done during my workday - Using generative AI increases my productivity
Task Performance	Perceived task performance refers to how employees perceive the quality of their work.	- Generative AI improves the accuracy of my work - I am able to meet my work goals more easily with the help of Generative AI - Generative AI helps me manage complex tasks more successfully
Creativity	Perceived creativity reflects employees' beliefs about their capacity for original problem solving and idea generation.	- Generative AI tools help me think about problems in novel ways - Using Generative AI enhances my ability to generate original ideas - The use of generative AI encourages experimentation and innovation in my tasks - I often come up with new and practical ideas at work when using GenAI

Pilot

Before distributing the final survey, a pilot survey was conducted with 8 participants to evaluate the clarity, flow and technical functionality of the questionnaire. Feedback from the pilot informed minor adjustments to question wording and the structure of the questionnaire. Due to the small sample size, no statistical reliability analysis was performed at this part of the process.

3.3.3 Data collection

The survey was distributed on the 30th of June 2025 through various internal communication channels within the organization and remained open until the 28th of July 2025, resulting in a data collection period of 4 weeks. The survey platform that was used was Microsoft Forms. After the initial launch two reminders were sent to encourage participation. Additionally, employees were encouraged to share the survey with their colleagues to start a snowballing effect and increase the overall reach within the organization.

3.3.4 Data analysis

Analysis approach

The quantitative phase of the study was analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4.0. This approach is suitable for predicted-oriented research, complex models with many constructs, and studies with relatively modest sample sizes. The analysis happened in two stages, first the evaluation of the measurement model to ensure reliability and validity of the constructs, followed by the evaluation of the structural model for hypothesis testing.

Data cleaning

Prior to analysis, the raw survey data were cleaned and prepared. Respondents with more than one missing Likert-scale response were excluded to preserve data quality, which reduced the dataset from 392 to 363 valid cases. SmartPLS required a complete dataset, therefore the remaining missing values were imputed using column mean substitution. Given the very low rate of missing data (14 out of 23,589 cells, <0.01%) this method is unlikely to have introduced bias or meaningfully affected the results (Little & Rubin, 2019; Shrive, Stuart, Quan, & Ghali, 2006).

Measurement model evaluation

The measurement model was evaluated according to established guidelines (Hair et al., 2019). First Indicator reliability was assessed using outer loadings. The recommended threshold of 0.70 was applied. Items with loadings substantially below this threshold were excluded. However, some indicators with slightly lower values were retained to preserve content validity, provided that the construct showed acceptable internal consistency (Cronbach's α and composite reliability > 0.70) and convergent validity (AVE > 0.50).

Internal consistency reliability was examined through Cronbach's α , composite reliability (pc), and rho_A, with values between 0.70 and 0.95 considered acceptable. Convergent validity was assessed using the Average Variance Extracted (AVE), with all constructs exceeding the 0.50 threshold. Discriminant validity was examined using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio, with the majority of the pairs below the 0.90 threshold. In cases of higher values, constructs were retained based on strong theoretical justification and conceptual distinction. Finally, collinearity among the constructs was evaluated using outer VIF values, all of which fell below the recommended threshold of 5.0, indicating no multicollinearity issues.

Structural model evaluation

After establishing the reliability and validity of the measurement model, the structural model was evaluated, also according to Hair et al.'s (2019) established guidelines. To assess collinearity among predictor constructs, inner VIF values were examined. All values fell below the threshold of 5.0, indicating that multicollinearity was not a concern at the construct level. The explanatory power of the model was then examined through R^2 values of the constructs, with thresholds of 0.25 (weak), 0.50 (moderate), and 0.75 (substantial) explanatory power. To further evaluate the contribution of individual predictors, effect sizes (f^2) were calculated, where values of 0.02, 0.15, and 0.35 represent small, medium, and large effects (Cohen, 1988).

Path coefficients were estimated, and their statistical significance was tested using a non-parametric bootstrapping procedure with 5000 resamples. A significance level of $p < .05$ was adopted for hypothesis testing. In addition to direct effects, indirect effects were assessed to examine mediation, with confidence intervals obtained via bootstrapping.

Contextual covariates

To assess whether structural relationships differed significantly between groups, Permutation-Based Multi-Group Analysis (Permutation MGA) was conducted. This non-

parametric approach evaluates group differences in path coefficients by repeatedly permuting the data and comparing observed differences against a distribution of randomly generated group differences. As it does not assume normality, Permutation MGA is particularly suitable for PLS-SEM and small to moderate sample sizes.

3.4 Research design phase 2: The qualitative study

To elaborate on the results retrieved from the survey, the research follows up with semi-structured interviews to gain more in-depth knowledge.

3.4.1 3.4.1 Sample

For the qualitative phase of the research, survey respondents could volunteer to participate in the follow-up interviews by indicating their interest at the end of the questionnaire. From these volunteers, participants were purposefully selected to ensure diversity in terms of organizational role, department, age and gender, and attitudes toward Generative AI, capturing a broad range of perspectives on the implementation. In addition, a small number of participants were proactively approached to fill underrepresented groups in the sample, ensuring that key perspectives were not missing. In total, 14 interviews were conducted. Recruitment continued until a diverse and information-rich sample had been obtained, covering key roles, departments, demographics, and both frequent users and resistant users. After 14 interviews, no substantially new themes were emerging, suggesting that conceptual saturation had been reached.

3.4.2 3.4.2 Instrument

The interview questions were developed to explore themes identified in the survey and to provide explanatory depth for the quantitative findings. The questions derived from the research questions and the survey results and organized into thematic domains: (1) Adoption, (2) Experiences (3) Perceived impact, (4) Expectations for the future. The questions were open-ended to allow the participants to elaborate. The full interview guide is provided in Appendix A.

3.4.3 3.4.3 Data collection

The interviews were conducted online via Microsoft Teams over a period of three weeks (August, 2025). Each interview was audio-recorded with participants' consent. The Microsoft Teams automatic transcription feature produced draft transcripts during the interview which reduced the time needed for the transcription as the drafts only needed to be reviewed and corrected along with the recording, rather than completely manually transcribed. The interviews lasted between 30 and 60 minutes, depending on the level of detail provided by participants. The transcripts were anonymized, and the participants were assured of confidentiality and the voluntary nature of their participation.

3.4.4 3.4.4 Data analysis

After the interviews were conducted and transcribed, the transcripts were imported into Atlas.ti 25 to perform systematic qualitative analysis. They were analyzed using thematic analysis following Braun and Clarke's (2006) six-phase approach. To get familiarized with the

data, the transcripts were read multiple times and summarized through taking notes. Initial deductive codes were derived from the contextual framework and survey results to ensure alignment with the overall sequential explanatory research design. Subsequently, inductive codes captured additional patterns emerging from the interviews that did not fit in the existing categories. When the coding process was complete, the codes were merged into categories, creating several themes and subthemes. The analysis aimed not only to identify patterns across participants but also to explain and elaborate on the quantitative findings. In Section 4.2 **Error! Reference source not found.** illustrative quotations are presented to ground interpretations in participants' own words.

3.5 3.5 Integration strategy

The integration of the two phases of the research started during the data collection, where the quantitative survey results shaped the qualitative research phase. In the results section both the quantitative and qualitative results are presented separately, after which they are brought together during the interpretation of the results in the discussion chapter.

4 Results

This section presents both the quantitative and qualitative results of the study. They are presented separately and will be integrated further on in the discussion.

4.1 Quantitative results

This section presents the quantitative results. For the analysis PLS-SEM was used in SmartPLS 4.0 to test the proposed research model. The analysis proceeded in two stages, first validating the measurement model through assessments of reliability, variability and collinearity, followed by the evaluation of the structural model and hypothesis testing.

4.1.1 Sample and data overview

Data was collected through a Likert-scale survey. The dataset consisted of 392 respondents. Respondents with more than one missing Likert-response were excluded from the final dataset to preserve data quality. This resulted in N = 363 valid cases. This approach aligns with established best practices in survey research (Hair, Black, Babin, & Anderson, 2010). The remaining missing data were minimal with 14 out of 23,598 cells (<0.1%). Missing Likert-scale values were imputed using column mean substitution, as SmartPLS requires a complete dataset. As the rate of missing data is very low, this method is unlikely to have introduced bias or meaningfully affected the results (Little & Rubin, 2019; Shrive, Stuart, Quan, & Ghali, 2006). For the moderator variables, we applied case-wise exclusion in the subgroup comparisons. As these variables were not included in the structural model, this did not impact the results. The majority of the respondents were researchers (51.8%, predominantly male (65.6%). Roughly one third reported having received training (32.5%) and the age distribution was relatively balanced. Educational background highly skewed toward university-level (74.9%). The sample characteristics can be found in Tabel 7.

Tabel 7: Sample characteristics

Characteristic	Category	N	%
Role	Research	188	51.8%
	Managerial	57	15.7%
	Support / Professional	92	25.3%
	Other/missing	26	7.2%
Gender	Female	116	32.0%
	Male	238	65.6%
	Missing	9	2.5%
Training	Yes	118	32.5%
	No	243	66.9%
	Missing	2	0.55%
Age	Under 35	138	37.8%
	35-44	77	21.1%
	45-54	76	20.9%

<i>Digital literacy</i>	55+	71	19.5%
	Missing	1	0.3%
	Moderate	115	31.7%
	High	153	42.1%
	Very high	90	24.8%
<i>Educational background</i>	Low	4	1.1%
	Missing	1	0.3%
	University	272	74.9%
	HBO	73	20.1%
<i>GenAI usage</i>	Other/Missing	18	5.0%
	Low	47	12.9%
	Medium	152	41.9%
<i>Personal use of GenAI</i>	High	162	44.6%
	Missing	2	0.6%
	Low	115	31.7%
	Medium	204	56.2%
	High	43	11.8%
<i>Tenure</i>	Missing	1	0.3%
	Short	165	45.5%
	Medium	84	23.1%
	Long	105	28.9%
	Missing/Trainee/Intern	9	2.5%

4.1.2 Descriptive statistics and correlations

As shown in Tabel 8, the mean scores for the constructs ranged from 2.14 (AIA) to 3.78 (PE). Most constructs were close to the midpoint of 3.0, suggesting moderate overall agreement. Standard deviations ranged from 0.65 (Social Influence) to 1.02 (Impact), indicating reasonable variability across respondents.

<i>Variable</i>	Mean	SD	Min	Max	N
<i>PE</i>	3.78	0.86	1	5	363
<i>EE</i>	3.64	0.87	1	5	363
<i>SI</i>	3.17	0.65	1.2	5	363
<i>FC</i>	3.43	0.75	1	5	363
<i>CT</i>	2.64	0.75	1	5	363
<i>ET</i>	3.14	0.91	1	5	363
<i>TR</i>	3.61	0.86	1	5	363
<i>AIA</i>	2.14	0.81	1	5	363
<i>AD</i>	3.15	0.82	1	5	363
<i>RES</i>	2.55	0.85	1	5	363
<i>AU</i>	3.15	0.86	1	5	363
<i>IM</i>	3.1	1.02	1	5	363
<i>ME</i>	2.64	0.9	1	5	363
<i>COM</i>	2.99	0.99	1	5	363
<i>PR</i>	3.41	0.99	1	5	363
<i>TP</i>	2.89	0.97	1	5	363
<i>CR</i>	2.96	1.01	1	5	363

Tabel 8: Descriptive statistics first order constructs

The correlation matrix in Table 9 shows that some correlations were relatively high: Performance Expectancy and Productivity (0.846), Impact and Productivity (0.810). However, they did not exceed critical thresholds for redundancy. Discriminant validity was further confirmed through HTMT (Table 13), Fornell-Larcker (Table 14) analyses and VIF checks () reported in the following sections.

	PE	EE	SI	FC	CT	ET	TR	AIA	AD	RES	AU	IM	ME	COM	PR	TP	C R
PE																	
EE	0.50 5***																
SI	0.38 2***	0.21 3***															
FC	0.34 8***	0.63 3***	0.24 1***														
CT	0.45 9***	0.25 3***	0.25 6***	0.21 6***													
ET	0.69 0***	0.64 8***	0.34 1***	0.45 3***	0.48 7***												
TR	0.26 7***	0.33 9***	0.28 8***	0.48 1***	0.16 4**	0.30 4***											
AI	-	-	0.02	-	-	-	-										
A	0.10 0	0.33 7***	8	0.31 4***	0.01 7	0.24 7***	0.18 4***										
A	0.61 6***	0.53 3***	0.34 7***	0.42 8***	0.26 1***	0.62 2***	0.37 2***	- 0.15 8**									
RE	-	-	-	-	-	-	-	0.34 0**	-								
S	0.66 6***	0.44 7***	0.28 2***	0.36 0***	0.40 5***	0.66 3***	0.30 2***	0.57 0***									
A	0.64 8***	0.42 3***	0.28 0***	0.35 9***	0.39 6***	0.57 4***	0.30 5***	- 0.01 6	0.49 2***	- 0.46 8***							
U																	
I	0.78 4***	0.44 4***	0.40 0***	0.34 3***	0.43 4***	0.65 2***	0.28 2***	- 0.05 4	0.60 2***	- 0.60 5***	0.64 4**						
M	0.69 1***	0.40 7***	0.28 5***	0.34 2***	0.48 3***	0.62 2***	0.27 3***	- 0.06 2	0.54 4***	- 0.53 4***	0.67 2**	0.77 7**					
E																	
C	0.72 1***	0.48 3***	0.30 6***	0.36 7***	0.48 4***	0.64 8***	0.18 7***	- 0.03 2	0.54 2***	- 0.55 5***	0.68 6**	0.74 6**	0.73 0**				
O																	
M	0.84 6***	0.51 4***	0.32 9***	0.36 2***	0.38 9***	0.68 1***	0.24 8***	- 0.10 8*	0.62 8***	- 0.60 3***	0.64 0**	0.81 0**	0.69 8**	0.72 2***			
P																	
R	0.75 7***	0.41 1***	0.36 3***	0.29 8***	0.50 7***	0.64 5***	0.20 2***	0.02 4	0.60 8***	- 0.55 2***	0.65 8**	0.79 6**	0.72 7**	0.77 2***	0.799 ***		
TP																	
C	0.57 9***	0.37 4***	0.26 8***	0.32 6***	0.34 4***	0.57 1***	0.29 2***	- 0.00 8	0.51 6***	- 0.44 6***	0.65 5**	0.61 0**	0.61 5**	0.62 1***	0.556 ***	0.651 ***	
R																	

Table 9: Correlation Matrix

4.1.3 Measurement Model

To assess how the latent variables are measured by the observed indicators we examined indicator reliability. Tabel 10 presents the outer loadings of the items on their latent variables. Most of the indicators exceeded the recommended threshold of 0.70 (Hair, Hult, Ringle, & Sarstedt, 2017), indicating that they load strongly on their intended constructs. Few indicators showed lower loadings that fell below the threshold. These were retained to preserve content validity and acceptable because the overall reliability of the constructs was confirmed through internal consistency measures, reported in the next section.

Stage 1

	Outer loadings
"AD1" <- Adaptability	0.808
"AD2" <- Adaptability	0.714
"AD4" <- Adaptability	0.807

"AD5" <- Adaptability	0.601
"AIA1" <- AI Anxiety	0.634
"AIA2" <- AI Anxiety	0.717
"AIA3" <- AI Anxiety	0.907
"AIA4" <- AI Anxiety	0.866
"AU1" <- Autonomy	0.901
"AU3" <- Autonomy	0.887
"COM1" <- Competence	0.863
"COM2" <- Competence	0.931
"COM3" <- Competence	0.887
"CR1" <- creativity	0.873
"CR2" <- creativity	0.905
"CR3" <- creativity	0.903
"CR4" <- creativity	0.900
"CT1" <- Cognitive Trust	0.878
"CT2" <- Cognitive Trust	0.906
"CT3" <- Cognitive Trust	0.687
"EE1" <- Effort Expectancy	0.893
"EE2" <- Effort Expectancy	0.912
"EE3" <- Effort Expectancy	0.862
"EE4" <- Effort Expectancy	0.893
"ET1" <- Emotional trust	0.892
"ET2" <- Emotional trust	0.904
"ET3" <- Emotional trust	0.764
"FC1" <- Facilitating conditions	0.565
"FC2" <- Facilitating conditions	0.900
"FC3" <- Facilitating conditions	0.882
"FC4" <- Facilitating conditions	0.568
"IM1" <- Impact	0.914
"IM2" <- Impact	0.922
"IM3" <- Impact	0.919
"ME1" <- Meaning	0.820
"ME2" <- Meaning	0.869
"ME3" <- Meaning	0.885
"PE1" <- Performance Expectancy	0.903
"PE2" <- Performance Expectancy	0.900
"PE4" <- Performance Expectancy	0.864
"PR1" <- Productivity	0.919
"PR2" <- Productivity	0.919
"PR4" <- Productivity	0.893
"RES1" <- Resistance	0.853
"RES2" <- Resistance	0.843
"RES3" <- Resistance	0.543
"RES4" <- Resistance	0.848
"RES5" <- Resistance	0.602
"SI2" <- Social Influence	0.763
"SI3" <- Social Influence	0.687
"SI4" <- Social Influence	0.857
"SI5" <- Social Influence	0.600
"SI6" <- Social Influence	0.673
"TP1" <- task performance	0.854
"TP2" <- task performance	0.903
"TP3" <- task performance	0.889
"TR1" <- Trialability	0.917
"TR2" <- Trialability	0.934
"TR3" <- Trialability	0.703

Tabel 10 Indicator Reliability (Outer Loadings)

To check if the constructs consistently measure the same underlying concept, the internal consistency reliability was assessed using Cronbach's alpha and composite reliability (pc). Table 11 shows that all constructs exceeded the recommended threshold of 0.7 (Nunnally & Bernstein, 1994; Hair, Hult, Ringle, & Sarstedt, 2017), confirming internal consistency reliability. The values also fall below 0.95 for CR, ruling out redundancy. In addition, the pA values fell between Cronbach's alpha and the pc scores, further supporting the reliability of the measurement model.

	Cronbach's alpha	Composite reliability (pA)	Composite reliability (rho_c)
AI Anxiety	0.825	0.936	0.866
Adaptability	0.727	0.774	0.825
Autonomy	0.749	0.751	0.888
Cognitive Trust	0.779	0.867	0.867
Competence	0.874	0.879	0.923

<i>Effort Expectancy</i>	0.913	0.921	0.939
<i>Emotional trust</i>	0.815	0.835	0.891
<i>Facilitating conditions</i>	0.735	0.831	0.828
<i>Impact</i>	0.907	0.908	0.942
<i>Meaning</i>	0.822	0.836	0.894
<i>Performance Expectancy</i>	0.867	0.870	0.919
<i>Productivity</i>	0.897	0.901	0.936
<i>Resistance</i>	0.796	0.850	0.862
<i>Social Influence</i>	0.765	0.785	0.842
<i>Triability</i>	0.818	0.876	0.892
<i>creativity</i>	0.917	0.921	0.942
<i>task performance</i>	0.858	0.862	0.914

Table 11: Internal consistency reliability

The convergent validity of the measurement model was assessed using the Average Variance Extracted (AVE). AVE shows how much of the variance in the observed indicators is explained by the latent construct. Table 12 shows that all constructs achieved AVE values above the recommended threshold of 0.50 (Fornell & Larcker, 1981; Hair, Hult, Ringle, & Sarstedt, 2017).

	Average variance extracted (AVE)
<i>AI Anxiety</i>	0.622
<i>Adaptability</i>	0.544
<i>Autonomy</i>	0.799
<i>Cognitive Trust</i>	0.688
<i>Competence</i>	0.799
<i>Effort Expectancy</i>	0.793
<i>Emotional trust</i>	0.732
<i>Facilitating conditions</i>	0.557
<i>Impact</i>	0.843
<i>Meaning</i>	0.737
<i>Performance Expectancy</i>	0.790
<i>Productivity</i>	0.829
<i>Resistance</i>	0.563
<i>Social Influence</i>	0.520
<i>Triability</i>	0.736
<i>creativity</i>	0.801
<i>task performance</i>	0.779

Table 12: Convergent validity

The discriminant validity of the constructs was assessed using the HTMT ratio (Table 13) and the Fornell-Larcker Matrix (Table 14). The HTMT results show that most of the construct pairs are below the recommended threshold of 0.90 (Henseler et al., 2015), except for the pair Effort Expectancy and Productivity (0.959). This high value reflects the conceptual proximity of these constructs. Performance expectancy captures how technology will enhance job performance (Venkatesh et al., 2003), while Productivity measures perceived improvements in work output and efficiency. The substantial empirical overlap is theoretically consistent, as performance enhancement beliefs naturally correlate with productivity expectations. Both constructs were retained given their theoretical importance and distinct roles in technology acceptance research, while acknowledging their empirical overlap in this sample.

	AI Anxiety	Adaptability	Autonomy	Cognitive Trust	Competence	Effort Expectancy	Emotional trust	Facilitating conditions	Impact	Meaning	Performance Expectancy	Productivity	Resistance	Social Influence	Trialability	creativity	task performance
AI Anxiety																	
Adaptability	0.299																
Autonomy	0.112	0.659															
Cognitive Trust	0.064	0.346	0.517														
Competence	0.147	0.672	0.847	0.586													
Effort Expectancy	0.387	0.661	0.509	0.298	0.538												
Emotional trust	0.304	0.805	0.735	0.615	0.769	0.747											
Facilitating conditions	0.404	0.598	0.488	0.292	0.461	0.771	0.586										
Impact	0.148	0.732	0.781	0.517	0.838	0.487	0.759	0.424									
Meaning	0.140	0.689	0.860	0.605	0.865	0.463	0.759	0.441	0.899								
Performance Expectancy	0.167	0.768	0.800	0.556	0.824	0.565	0.821	0.443	0.883	0.813							
Productivity	0.196	0.770	0.780	0.465	0.814	0.565	0.796	0.448	0.899	0.810	0.959						
Resistance	0.422	0.753	0.603	0.508	0.663	0.527	0.821	0.493	0.713	0.654	0.803	0.716					
Social Influence	0.156	0.457	0.378	0.340	0.379	0.258	0.437	0.326	0.485	0.365	0.476	0.403	0.363				
Trialability	0.239	0.494	0.391	0.204	0.223	0.394	0.375	0.621	0.328	0.329	0.321	0.291	0.380	0.358			
creativity	0.085	0.624	0.791	0.404	0.694	0.408	0.662	0.399	0.669	0.713	0.649	0.614	0.521	0.322	0.336		
task performance	0.116	0.754	0.819	0.620	0.891	0.461	0.773	0.377	0.903	0.868	0.874	0.910	0.668	0.454	0.241	0.734	

Table 13: HTMT Ratio

	AI Anxiety	Adaptability	Autonomy	Cognitive Trust	Competence	Effort Expectancy	Emotional trust	Facilitating conditions	Impact	Meaning	Performance Expectancy	Productivity	Resistance	Social Influence	Trialability	creativity	task performance
AI Anxiety	0.789																
Adaptability	-0.228	0.737															
Autonomy	-0.064	0.517	0.894														
Cognitive Trust	-0.034	0.306	0.408	0.829													
Competence	-0.093	0.577	0.684	0.500	0.894												
Effort Expectancy	-0.427	0.534	0.425	0.271	0.486	0.890											
Emotional trust	-0.321	0.644	0.573	0.489	0.644	0.655	0.855										
Facilitating conditions	-0.410	0.464	0.371	0.217	0.375	0.685	0.488	0.747									
Impact	-0.119	0.641	0.644	0.456	0.748	0.449	0.653	0.359	0.918								
Meaning	-0.110	0.576	0.671	0.494	0.728	0.412	0.621	0.356	0.777	0.859							
Performance Expectancy	-0.161	0.652	0.646	0.479	0.717	0.512	0.692	0.368	0.782	0.686	0.889						
Productivity	-0.183	0.666	0.642	0.415	0.722	0.519	0.683	0.391	0.811	0.700	0.848	0.911					
Resistance	0.384	-0.617	-0.478	-0.426	-0.574	-0.471	-0.686	-0.386	-0.628	-0.546	-0.690	-0.630	0.750				
Social Influence	-0.018	0.371	0.279	0.272	0.309	0.220	0.342	0.220	0.401	0.285	0.383	0.328	-0.306	0.721			
Trialability	-0.232	0.358	0.310	0.166	0.201	0.362	0.317	0.457	0.288	0.274	0.282	0.258	-0.323	0.276	0.858		
creativity	-0.043	0.539	0.656	0.350	0.623	0.378	0.568	0.332	0.612	0.617	0.579	0.563	-0.455	0.269	0.287	0.895	

task performance	-0.030	0.646	0.659	0.521	0.772	0.415	0.642	0.308	0.798	0.727	0.753	0.801	-0.572	0.361	0.203	0.655	0.883
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Table 14: Fornell-Lacker Matrix

Collinearity among the predictor constructs was assessed through the inner VIF scores for the structural model. Table 15 shows that all of the scores were below 3.0, which is well under the threshold of 5.0 (Hair et al., 2019), indicating that there are no multicollinearity issues in the structural model.

	VIF
Adaptability -> Autonomy	1.615
Adaptability -> Competence	1.615
Adaptability -> Impact	2.033
Adaptability -> Meaning	1.615
AI Anxiety -> Adaptability	1.320
AI Anxiety -> Resistance	1.320
Cognitive Trust -> Adaptability	1.423
Cognitive Trust -> Resistance	1.423
creativity -> task performance	1.000
Effort Expectancy -> Adaptability	2.657
Effort Expectancy -> Resistance	2.657
Emotional trust -> Adaptability	2.784
Emotional trust -> Resistance	2.784
Facilitating conditions -> Adaptability	2.142
Facilitating conditions -> Resistance	2.142
Performance Expectancy -> Adaptability	2.154
Performance Expectancy -> Resistance	2.154
Productivity -> creativity	1.000
Resistance -> Autonomy	1.615
Resistance -> Competence	1.615
Resistance -> Impact	1.762
Resistance -> Meaning	1.615
Social Influence -> Adaptability	1.251
Social Influence -> Resistance	1.251
task performance -> Impact	1.870
Triability -> Adaptability	1.332
Triability -> Resistance	1.332

Table 15: Inner model VIF

Collinearity among the indicators the measurement model (outer model) was also examined. Tabel 16 shows that all of the outer VIF values are below the threshold of 5.0, further indicating that there were no multicollinearity issues for the model.

	VIF
"AD1"	1.361
"AD2"	1.529
"AD4"	1.625
"AD5"	1.237
"AIA1"	2.314
"AIA2"	2.463
"AIA3"	2.052
"AIA4"	2.045
"AU1"	1.559
"AU3"	1.559
"COM1"	1.910
"COM2"	3.527
"COM3"	2.925
"CR1"	2.658
"CR2"	3.366
"CR3"	3.116
"CR4"	2.936
"CT1"	1.963
"CT2"	1.870
"CT3"	1.379
"EE1"	3.711
"EE2"	4.243
"EE3"	2.319
"EE4"	2.600
"ET1"	2.275

"ET2"	2.387
"ET3"	1.467
"FC1"	1.375
"FC2"	2.899
"FC3"	2.611
"FC4"	1.253
"IM1"	2.889
"IM2"	3.129
"IM3"	2.907
"ME1"	1.723
"ME2"	1.926
"ME3"	1.940
"PE1"	2.468
"PE2"	2.418
"PE4"	2.034
"PR1"	3.340
"PR2"	3.094
"PR4"	2.307
"RES1"	2.063
"RES2"	2.067
"RES3"	1.351
"RES4"	2.080
"RES5"	1.404
"SI2"	1.747
"SI3"	1.407
"SI4"	2.161
"SI5"	1.333
"SI6"	1.540
"TP1"	1.953
"TP2"	2.423
"TP3"	2.233
"TR1"	2.924
"TR2"	3.193
"TR3"	1.394

Tabel 16: Outer model VIF

The assessment of the measurement model demonstrated satisfactory reliability and validity. These results allow for subsequent testing of the structural model.

4.1.4 Structural Model

The explanatory power of the structural model (Figure 2) was assessed using the R² values of endogenous constructs. Tabel 17: R-square values of endogenous constructs shows that the values range from 0.53 (Psychological empowerment) to 0.71 (Perceived performance). According to the guidelines of Hair et al. (2019), these values indicate moderate to substantial explanatory of the model.

	R-square	R-square adjusted
Adaptability	0.540	0.529
Perceived performance	0.708	0.706
Psychological empowerment	0.525	0.522
Resistance	0.614	0.605

Tabel 17: R-square values of endogenous constructs

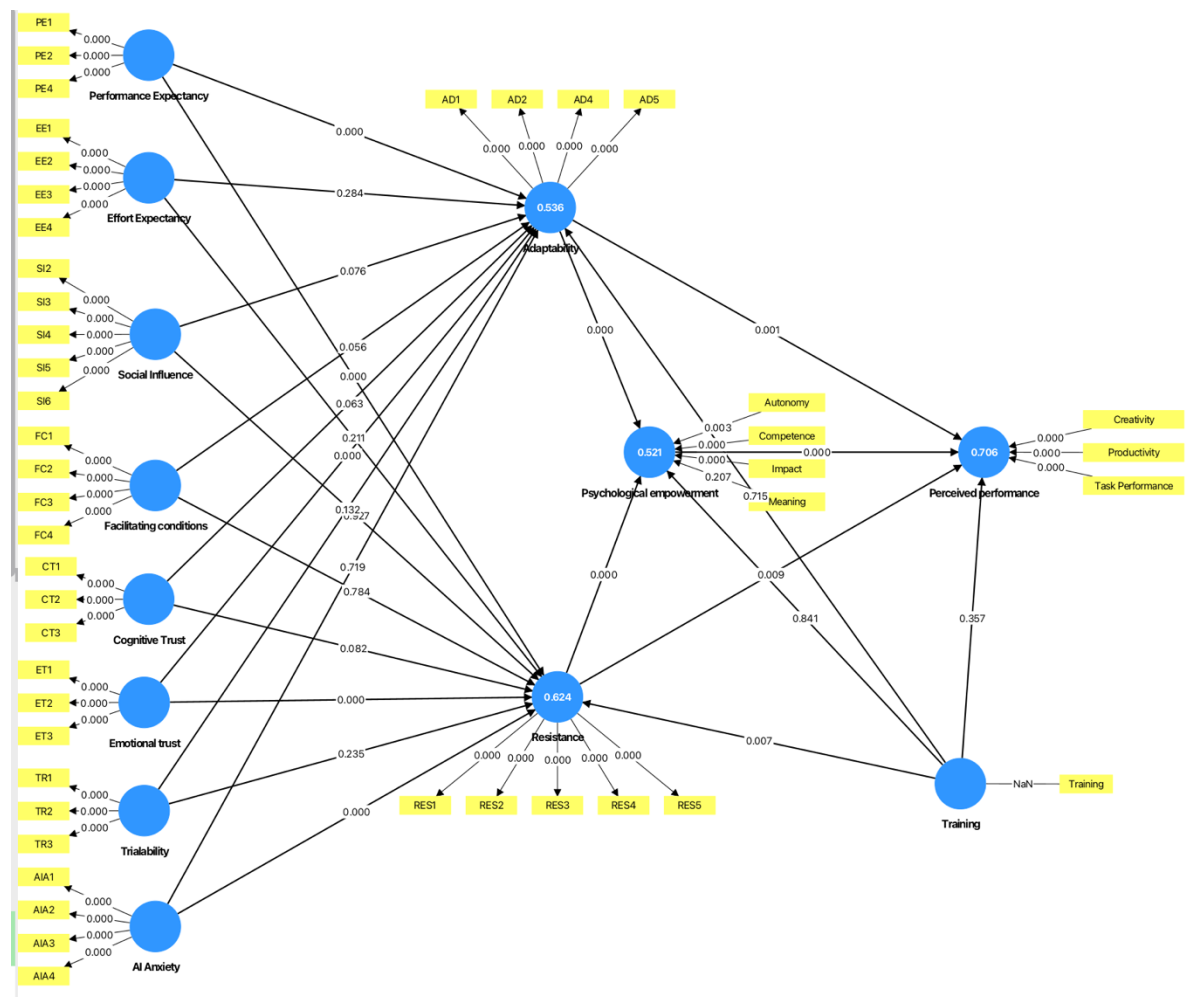


Figure 2: Structural model

Table 18 summarizes the f^2 effect size of the predictor constructs. Psychological empowerment had a large effect on Perceived performance ($f^2 = 0.688$). Adaptability, Performance Expectancy and Resistance showed medium effects ($f^2 = 0.191 - 0.231$) and several predictors demonstrated small effects. The full list of f^2 values, including negligible effects can be found in Appendix B.

	f -square
Psychological empowerment → Perceived performance	0.688
Adaptability → Psychological empowerment	0.231
Performance Expectancy → Resistance	0.216
Resistance → Psychological empowerment	0.191
Performance Expectancy → Adaptability	0.133
AI Anxiety → Resistance	0.113
Emotional trust → Resistance	0.099
Emotional trust → Adaptability	0.063
AI Anxiety → Resistance	0.113
Adaptability → Perceived performance	0.037
Resistance → Perceived performance	0.026

Table 18: Effect sizes (f^2) of predictor constructs

4.1.5 Hypothesis testing

UTAUT → Adaptability/Resistance

Table 19 shows that Performance Expectancy is a significant predictor for both outcome variables, positively predicting Adaptability ($\beta = 0.367$, $p < 0.001$) and negatively predicting Resistance ($\beta = -0.423$, $p < 0.001$), supporting both H1a and H1b. Effort Expectancy did not significantly predict Adaptability or Resistance, therefore both H2a and H2b are rejected. Social Influence positively predicts Adaptability ($\beta = 0.097$, $p = 0.044$), supporting H3a, but no significant relationship emerged with Resistance, rejecting H3b. Similarly, Facilitating Conditions positively predicted Adaptability, ($\beta = 0.117$, $p = 0.038$) supporting H4a, but also had no effect on Resistance, rejecting H4b.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supp?
H1a	Stage 1	Performance Expectancy → Adaptability	0.367	7.259	0.000	Yes
H1b	Stage 1	Performance Expectancy → Resistance	-0.423	8.299	0.000	Yes
H2a	Stage 1	Effort Expectancy → Adaptability	0.059	0.967	0.334	No
H2b	Stage 1	Effort Expectancy → Resistance	0.106	1.949	0.051	No
H3a	Stage 1	Social influence → Adaptability	0.097	2.015	0.044	Yes
H3b	Stage 1	Social influence → Resistance	-0.015	0.376	0.707	No
H4a	Stage 1	Facilitating conditions → Adaptability	0.117	2.079	0.038	Yes
H4b	Stage 1	Facilitating conditions → Resistance	0.005	0.092	0.927	No

Table 19: UTAUT predicting behavioral response

Trust → Adaptability/Resistance

Table 20 shows that cognitive trust did not significantly predict either Adaptability or Resistance, therefore we reject H5a and H5b. However, Emotional trust positively predicted Adaptability ($\beta = 0.284$, $p = 0.000$) and negatively predicted Resistance ($\beta = -0.327$, $p = 0.000$).

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H5a	Stage 1	Cognitive Trust → Adaptability	-0.09	1.894	0.058	No
H5b	Stage 1	Cognitive Trust → Resistance	-0.069	1.707	0.088	No
H5c	Stage 1	Emotional Trust → Adaptability	0.284	4.198	0.000	Yes
H5d	Stage 1	Emotional Trust → Resistance	-0.327	5.279	0.000	Yes

Table 20: Trust predicting behavioral response

Trialability → Adaptability/Resistance

Table 21 shows that trialability is no significant predictor for Adaptability as well as Resistance, consequently both H6a and H6b are rejected.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H6a	Stage 1	Trialability → Adaptability	0.081	1.619	0.106	No
H6b	Stage 1	Trialability → Resistance	-0.069	1.743	0.081	No

Table 21: Trialability predicting behavioral response

AI Anxiety → Adaptability/Resistance

Table 22 shows that AI Anxiety did not predict Adaptability, therefore we reject H7a. However, Resistance was significantly predicted by AI Anxiety, supporting H7b.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H7a	Stage 1	AI Anxiety → Adaptability	0.013	0.285	0.776	No
H7b	Stage 1	AI Anxiety → Resistance	0.239	5.225	0.000	Yes

Table 22: AI anxiety predicting behavioral response

Training → Adaptability/Resistance

As shown in Table 23 training participation did not significantly increase adaptation, therefore we reject H8a. Training participation significantly reduced resistance to GenAI ($\beta = -0.21$, $p = .007$), supporting H8b.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H8a	Stage 1	Training → Adaptability	0.033	0.365	0.715	No
H8b	Stage 1	Training → Resistance	-0.208	2.680	0.007	Yes

Table 23: Training predicting behavioral response

Resistance/Adaptability → Psychological empowerment

Table 18 shows that Adaptability positively predicted Psychological Empowerment and each of its dimensions Competence, Autonomy, Meaning and Impact, supporting H9a, H9c, H9e, H9g and H9i. Similarly, Resistance negatively predicted Psychological Empowerment and each of its dimensions, supporting Hypotheses H9b, H9d, H9f, H9h and H9j.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H9a	Stage 2	Adaptability → Psychological Empowerment	0.422	7.800	0.000	Yes
H9b	Stage 2	Resistance → Psychological Empowerment	-0.384	7.009	0.000	Yes
H9c	Stage 1	Adaptability → Competence	0.360	6.257	0.000	Yes
H9d	Stage 1	Resistance → Competence	-0.352	6.534	0.000	Yes
H9e	Stage 1	Adaptability → Autonomy	0.360	5.628	0.000	Yes
H9f	Stage 1	Resistance → Autonomy	-0.256	4.285	0.000	Yes
H9g	Stage 1	Adaptability → Meaning	0.387	6.685	0.000	Yes
H9h	Stage 1	Resistance → Meaning	-0.307	5.261	0.000	Yes
H9i	Stage 1	Adaptability → Impact	0.128	2.881	0.004	Yes
H9j	Stage 1	Resistance → Impact	-0.209	5.127	0.000	Yes

Table 1: Predicting Psychological Empowerment

Training → Psychological Empowerment and Perceived Performance

Participation in training did not significantly increase psychological empowerment or perceived performance (Table 24).

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H10a	Stage 2	Training → Psychological empowerment	-0.016	0.201	0.851	No
H10b	Stage 2	Training → Perceived performance	0.062	0.920	0.357	No

Table 24: Training influencing empowerment and performance

Predicting Perceived performance

Table 25 shows that Perceived performance was positively predicted by Psychological Empowerment ($\beta = 0.650$, $p = 0.000$) and Adaptability ($\beta = 0.147$, $p = 0.001$), and negatively predicted by Resistance ($\beta = -0.120$, $p = 0.004$).

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H11	Stage 2	Psychological empowerment → Perceived performance	0.650	15.686	0.000	Yes
H12	Stage 2	Adaptability → Perceived performance	0.147	3.178	0.001	Yes
H13	Stage 2	Resistance → Perceived performance	-0.120	2.866	0.004	Yes

Table 25: Predicting perceived performance

Mediation results

Table 26 reports the mediation results of Psychological Empowerment. Psychological Empowerment significantly mediated the relationship between Adaptation and Perceived performance ($\beta = 0.275$, $p < .001$), supporting H14a. Similarly Psychological Empowerment mediated the negative relationship between Resistance and Perceived performance ($\beta = -0.249$, $p < .001$), supporting H14b. It did not mediate the relationship between Training and Perceived performance, therefore we reject hypothesis H14c.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H14a	Stage 2	Adaptation → Psychological empowerment → Perceived performance	0.275	6.772	0.000	Yes
H14b	Stage 2	Resistance → Psychological empowerment → Perceived performance	-0.249	6.386	0.000	Yes
H14c	Stage 2	Training → Psychological empowerment → Perceived performance	-0.011	0.200	0.842	No

Table 26: Mediating perceived performance

Table 27 presents the mediation results for Adaptation and Resistance as mediator. Training had no significant indirect effects on perceived performance through both Adaptation and Resistance. Training also had no indirect significant effects on psychological empowerment. Resistance did have a significant indirect effect on psychological empowerment ($\beta = 0.081$, $p < .016$), supporting H15d. Emotional Trust had a significant positive indirect effect on Psychological Empowerment through Adaptation ($\beta = 0.120$, $p < .001$), supporting H15e. By contrast, the indirect effects of Cognitive Trust (H15f), Trialability (H15g), and AI Anxiety (H15h) on Psychological Empowerment via Adaptation were not significant ($p > .05$), and these hypotheses are therefore rejected.

H	Stage in SEM	Path	Path coefficient	t-value	P-value	Supported
H15a	Stage 2	Training performance → Adaptation → Perceived	0.005	0.344	0.731	No
H15b	Stage 2	Training performance → Resistance → Perceived	0.024	1.740	0.082	No
H15c	Stage 2	Training → Adaptation → Psychological empowerment	0.014	0.361	0.718	No
H15d	Stage 2	Training → Resistance → Psychological empowerment	0.081	2.408	0.016	Yes
H15e	Stage 2	Emotional trust → Adaptation → Psychological empowerment	0.120	3.561	0.000	Yes
H15f	Stage 2	Cognitive trust → Adaptation → Psychological empowerment	-0.038	1.895	0.058	No
H15g	Stage 2	Triability → Adaptation → Psychological empowerment	0.027	1.665	0.096	No
H15h	Stage 2	AI Anxiety → Adaptation → Psychological empowerment	0.006	0.280	0.779	No

Table 27: Behavioral response as mediator

4.1.6 Contextual covariates

Permutation-based multi-group analysis was conducted to explore group differences in the structural relationships in the model. Measurement invariance was assessed for all multi-group comparisons using the MICOM procedure. Configural invariance was ensured by applying the same model structure, indicators, and algorithm settings across groups. Compositional invariance (Step 2) was supported for all composites unless otherwise stated; complete MICOM results are presented in Appendix C.

Gender

Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed that Facilitating Conditions operate differently by gender. The direct effect of facilitating conditions on adaptability was significantly stronger for males than for females. (Female $\beta = -.059$; Male $\beta = .215$; $p = .030$). Similarly, the path from facilitating conditions to resistance differed significantly between groups, with a positive effect for females and a negative effect for males (Female $\beta = .179$; Male $\beta = -.082$; $p = .015$). Total effects also indicated stronger overall impacts of facilitating conditions on perceived performance ($\Delta\beta = -.195$; $p = .008$) and psychological empowerment ($\Delta\beta = -.195$; $p = .012$) among male respondents. No other focal paths showed significant differences between groups.

Educational background (University vs HBO)

Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA comparing HBO and University respondents revealed one significant difference, the effect of training on psychological empowerment was positive for university respondents but negative for HBO respondents ($\beta_{\text{university}} = 0.142$; $\beta_{\text{HBO}} = -0.268$; $\Delta\beta = -0.411$; $p = .042$). No other focal paths or total effects differed significantly across educational background.

Age

Under 35 vs 55+ MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Cognitive Trust and Perceived performance ($p=.022$, $p=.037$); therefore, we refrained from comparing parameters that involve those composites for this pair. MGA found no significant group differences in total effects for the remaining focal links.

Under 35 vs 45-54 Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA found no significant differences in the direct and total effects between the groups for the focal links.

Under 35 vs 35-44 Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed one focal link differed significantly Resistance $\rightarrow$ Perceived performance ($\beta_{\text{Under35}} = -0.043$; $\beta_{\text{35-44}} = -0.304$; $p = .030$). No significant differences in focal total effects.

34-44 vs 45-54 Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed significant differences in three direct links: AI Anxiety $\rightarrow$ Resistance (35-44 $\beta = .399$; 45-54 $\beta = -.058$;), $\Delta\beta = 0.341$; $p = .047$), Psychological Empowerment $\rightarrow$ Perceived performance (35-44 $\beta = .735$; 45-54 $\beta = .474$;), $\Delta\beta = 0.262$; $p = .023$) and Resistance $\rightarrow$ Perceived performance (35-44 $\beta = -.047$; 45-54 $\beta = -.304$;), $\Delta\beta = 0.257$; $p = .039$). For total effects, AI Anxiety $\rightarrow$ Psychological empowerment also differed ($\beta_{\text{35-44}} = -0.220$; $\beta_{\text{45-54}} = -0.026$; $\Delta\beta_{\text{total}} = -0.164$; $p = .040$).

35-44 vs 55+ Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed that one focal direct link differed significantly: Resistance $\rightarrow$ Psychological Empowerment (35-44 $\beta = -.556$; 55+ $\beta = -.088$;), $\Delta\beta = .467$; $p = .017$). A focal total effect also differed: Resistance $\rightarrow$ Perceived performance (35-44 $\beta = -.567$; 55+ $\beta = -.130$; $\Delta\beta = .437$; $p = .033$).

45-54-55+ Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed that one focal direct link differed significantly: Resistance $\rightarrow$ Psychological Empowerment (45-54 $\beta = .489$; 55+ $\beta = -.088$;), $\Delta\beta = .401$; $p = .031$).

Digital Literacy

Moderate vs High Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. One direct effect difference was found through permutation MGA: AI Anxiety $\rightarrow$ Adaptability (moderate $\beta = .170$; high $\beta = -.062$;), $\Delta\beta = .232$; $p = .045$). No significant differences in focal total effects.

Moderate vs Very High Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. One direct effect was found through permutation MGA: Training $\rightarrow$ Psychological Empowerment (moderate $\beta = -.231$; Very High $\beta = .266$;), $\Delta\beta = -.497$; $p = .019$). The corresponding total effect also differed significantly (moderate $\beta = -.108$; Very High $\beta = .360$;), $\Delta\beta = -.0468$; $p = .014$).

High vs Very High Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA found no significant group differences in total effects for the remaining focal links.

Role

Researcher vs Managerial MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Psychological Empowerment ($p=.025$); therefore, we refrained from comparing parameters that involve this composite for these groups. Permutation MGA found no significant group differences in total effects for the remaining focal links.

Researcher vs Support / Professional Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed that there was one significant difference in the direct effect: Resistance $\rightarrow$ Psychological Empowerment (Researcher $\beta = -.484$; Support/Professional $\beta = -.198$; $\Delta\beta = -.285$; $p = .046$). No significant differences in focal total effects.

Support/Professional vs Managerial MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Social Influence ($p=.017$); therefore, we refrained from comparing parameters that involve this composite for these groups. Permutation MGA found no significant group differences in direct effects and one significant group difference in the total effects: Adaptability $\rightarrow$ Perceived performance (Managerial $\beta = .209$; Support/Professional $\beta = .598$; $\Delta\beta = -.389$; $p = .026$).

Tenure

Short vs Long Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed two significant differences in the direct effect: Effort Expectancy $\rightarrow$ Adaptability (Short $\beta = -.093$; Long $\beta = .237$; $\Delta\beta = -.330$; $p = .040$) and Performance Expectancy $\rightarrow$ Resistance (Short $\beta = -.254$; Long $\beta = -.570$; $\Delta\beta = .317$; $p = .008$). In the total effects, significant differences between groups are Performance Expectancy $\rightarrow$ Perceived Performance (Short $\beta = .233$; Long $\beta = .427$; $\Delta\beta = .194$; $p = .032$), Performance Expectancy $\rightarrow$ Psychological Empowerment (Short $\beta = .238$; Long $\beta = .423$; $\Delta\beta = -.185$; $p = .042$) and Resistance $\rightarrow$ Perceived Performance (Short $\beta = -.259$; Long $\beta = -.536$; $\Delta\beta = .278$; $p = .036$).

Short vs Medium MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Training ($p=.000$); therefore, we refrained from comparing parameters that involve this composite for these groups. Permutation MGA showed that there was one significant difference in the direct effect: Emotional Trust $\rightarrow$ Resistance (Short $\beta = -.479$; Medium $\beta = -.115$; $\Delta\beta = -.364$; $p = .029$). Permutation MGA found no significant group differences in total effects for the remaining focal links.

Medium vs Long Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA found no significant differences in the direct and total effects between the groups for the focal links.

Gen AI usage

Low vs High MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Effort Expectancy and Resistance ($p=.045$; $p = .020$); therefore, we refrained from comparing parameters that involve these composites for these groups. Permutation MGA showed group differences in the direct effects: Psychological Empowerment $\rightarrow$ Perceived Performance (Low $\beta = .955$; High $\beta = .656$; $\Delta\beta = .298$; $p = .040$), Social Influence $\rightarrow$ Adaptability (Low $\beta = .270$; High $\beta = -.089$; $\Delta\beta = .359$; $p = .019$), and Training $\rightarrow$ Perceived performance (Low $\beta = .423$; High $\beta = -.036$; $\Delta\beta = .459$; $p = .022$). There also are significant group differences in the total effects for: Social Influence $\rightarrow$ Perceived Performance (Low $\beta =$

.169; High $\beta = -.053$;), $\Delta\beta = .222$; $p = .027$), Social Influence $\rightarrow$ Psychological Empowerment (Low $\beta = .203$; High $\beta = -.049$;), $\Delta\beta = .252$; $p = .012$) and Training $\rightarrow$ Psychological Empowerment (Low $\beta = -.469$; High $\beta = .164$;), $\Delta\beta = -.633$; $p = .003$).

Low vs Medium Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed group differences for the following direct paths: Psychological Empowerment $\rightarrow$ Perceived Performance (Low $\beta = .955$; Medium $\beta = .557$; $\Delta\beta = .398$; $p = .002$), Resistance $\rightarrow$ Perceived performance (Low $\beta = .196$; Medium $\beta = -.157$;), $\Delta\beta = .352$; $p = .023$), Social Influence $\rightarrow$ Resistance (Low $\beta = -.229$; Medium $\beta = .040$; $\Delta\beta = -.269$; $p = .048$), and Trialability $\rightarrow$ Adaptability (Low $\beta = .210$; Medium $\beta = -.132$; $\Delta\beta = .342$; $p = .042$). There were no significant differences in the total effects between the groups for the focal links.

Medium vs High MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Adaptability, Effort Expectancy, Performance Expectancy, Social Influence ($p=.002$; $p = .000$; $p = .029$; $p = .025$); therefore, we refrained from comparing parameters that involve these composites for these groups. Permutation MGA found no significant differences in the direct and total effects between the groups for the other focal links.

Personal usage

Low vs High MICOM indicated configural invariance. Compositional invariance (Step-2) failed for Effort Expectancy and Performance Expectancy ($p=.011$; $p = .006$); therefore, we refrained from comparing parameters that involve these composites for these groups. Permutation MGA showed group difference for the direct effect AI anxiety $\rightarrow$ Adaptability (Low $\beta = .178$; High $\beta = .553$; $\Delta\beta = -.376$; $p = .025$).

Low vs Medium Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA found no significant differences in the direct effects between the groups. For the total effects permutation MGA found differences in Social Influence $\rightarrow$ Perceived Performance (Low $\beta = .1111$; Medium $\beta = -.003$; $\Delta\beta = .115$; $p = .046$) and Social Influence $\rightarrow$ Psychological Empowerment (Low $\beta = .123$; Medium $\beta = -.002$; $\Delta\beta = .124$; $p = .044$).

Medium vs High Configural and compositional invariance were supported, enabling meaningful comparison of path coefficients. Permutation MGA showed differences in the groups in direct effect Adaptability $\rightarrow$ Perceived performance (Medium $\beta = .075$; High $\beta = .423$; $\Delta\beta = -.376$; $p = .047$).

4.2 Qualitative results

The qualitative results were analyzed using Braun & Clarke's (2006) reflexive thematic analysis approach. Through coding and categorization, several overarching themes were developed to capture employees' experiences with Generative AI. The code structure can be found in Appendix D: Codes per theme.

4.2.1 Theme 1: Acceptance of Generative AI (what is its usefulness and fit?)

A recurring theme in the interviews about the implementation of Generative AI was how do employees think and feel about the usefulness of Generative AI, how easy is it to use and what factors affect acceptance focusing on potential social influence and facilitating conditions. This theme builds upon the UTAUT framework that is integrated in the conceptual model that forms the foundation of this research.

Subtheme 1.1 Performance expectancy

The participants evaluated Generative AI in terms of how useful it is or would be for their work. Acceptance is pragmatic, the majority sees Generative AI as useful, but certainly not everywhere. Many described tangible productivity gains especially in technical and routine tasks like coding or debugging, one participant explained: *“The productivity increase is ridiculous, especially in debugging code”* (Interview 9). Support in administrative tasks was also mentioned as a clear benefit: *“Especially for administrative tasks I notice that things become easier, it helps me draft emails and meeting notes much quicker, that is where I really notice time saving.”* (Interview 4). Applications where usefulness was often mentioned as limited or unreliable is in text-based tasks such as writing reports or summarizing: *“I think if I would write a report now or also an article, I wouldn’t use it, because I don’t see the quality improvement there.”* (Interview 3). Alongside these evaluations of the present situation, participants also talked about future performance expectations: *“I think it will help a lot, because the support with emails and reports will free up time for other work.”* (Interview 13) and *“I see the potential in our field, but it isn’t really there yet”* (Interview 11).

Subtheme 1.2 Effort expectancy

The consensus throughout the interviews was that Generative AI is seen as tooling that is easy to use, where participants find it intuitive to use: *“Yes, I find it quite intuitive. I don’t feel like I need to read a whole manual.”* (Interview 13) Due to the low effort required to engage with Generative AI many participants indicated that it was easy to experiment with, and they felt comfortable using the tooling, where comfort also grew with use: *“For coding, it feels comfortable and natural”* (Interview 2). However, several participants did mention that integration was not completely automatic and that it takes time to adapt, for example: *“I still often just use Google, even though I could have asked CoPilot or Chat, it’s the old habit I fall back on”* (Interview 13). The main challenge here seems overcoming old routines or lacking knowledge of when to use Generative AI: *“My limitation with CoPilot right now is that I just don’t know what all the possibilities are. If I knew more about that and understood it better, I might use it more quickly and easily.”* (Interview 8).

Subtheme 1.3 Social influence and norms

Contrasting views emerged during the interviews when participants spoke about social influence impacting their adoption to or acceptance of Generative AI. For some, colleagues played a central role in their motivation and confidence to experiment with the tooling: *“Sometimes in discussions with others I think, oh, that’s also a smart way to use it. So I think we are all still learning, what works well, what doesn’t work, and what problems may arise. That is, I think, the same as with anything when you use a new tool.”* (Interview 5). In their eyes social influence is an important factor in the acceptance of Generative AI: *“Yeah, because*

the more I notice the colleagues use it or the more talk about it, the more encouraged I feel about using it.” (Interview 9). Where one participant mentioned to be of social influence themselves: “I became a super user and show many things and on a low-key train colleagues; my secretarial team is hesitant, but showing quick wins helps to slightly win them over.” (Interview 4). In some cases, a lack of social influence was identified, in this group we see a split between, there is no social influence: and there is no social influence, but it would have an impact if it would be present: “Well, if I knew what it could do and how it could make my work easier, I would start using it more easily and more quickly. But from both the staff in my team and the project managers, I actually hear very little about them using it. So then I also wouldn’t immediately know how I should use it and what I could do with it.” (Interview 8). Besides the positive social influence towards acceptance of Generative AI, participants also experience the opposite, illustrated by the following quote “I do think the way others use it influences how I use it. I also think it has an impact because I’m still relatively new in the organization. I’ve been here for two years now, but you still need to build up a certain credibility for your knowledge. And that can’t come from using AI. In addition, in my experience, you also learn less by relying on machine learning. So, I try to use it as little as possible, only for coding and especially debugging Python code. And people are mostly just afraid of it, it’s mainly a case of being wary of the unknown.” (Interview 2). Others found themselves resistant to social influence regarding their either positive or negative perception of Generative AI, showed by the following two quotes: “I think, well, I don’t really pay much attention to what other people think or say. I do use it quite a lot, perhaps even more at the beginning, for example, when my team leader was still rather hesitant about it.” (Interview 5) and “But I just notice that I really don’t feel like trying it at all. At the same time, I do look with some admiration at people who, even with reluctance, still give it a try, just to see what it’s like. I don’t have to choose it, but I could at least try it. Yet I find that I simply don’t feel like trying it at all, partly because it’s being pushed on me so much.” (Interview 7).

Subtheme 1.4 Facilitating conditions and organizational support

Foundational to the implementation and acceptance of Generative AI are facilitating conditions. Something that was valued by most participants is the access to training substantiated by these quotes: “Super fun, they were very enthusiastic and there was a lot of energy in those trainings. That really made me want to get started with it.” (Interview 4) and “Yes, as soon as Copilot was rolled out, I quickly took that training, and it was really useful. You immediately got practical examples that I could apply the very next day.” (Interview 6). Though participants also pointed out several challenges and opportunities about said training, including its accessibility, the content being too basic or generic, lacking role-specific content and the lack of skills and/or knowledge of the trainers: “Yes, that’s right, of course a lot of training sessions have been offered, but they are often quite generic, and I find that they don’t really match what I need.” (Interview 2). Some participants mentioned that clear policies and smooth rollout processes created confidence in the organization being satisfied with the rollout, however there is divergence about this as others mention that the absence of this generated hesitation before. Uncertainty about the adoption within the organization is something that demotivates employees in fully adopting and adopting, as they question the following: “What I maybe miss a little bit is that I’m not sure what the long-term vision is. Is this really something that will become embedded in our way of working, or just a temporary experiment?” (Interview 12). People also disengage with the implementation due to tool limitations, many participants mentioned either not using Generative AI because of this: “... that I think, okay, never mind, I’ll just do it myself. So that’s where my impatience comes in, the gap between good prompting and what actually comes out, yes, there’s still something

there.” (Interview 14) or they mention using other tools than Co-Pilot that have not been approved by the organization as they find the quality of Co-Pilot’s output lacking: *“I have the impression that ChatGPT often performs better than Copilot, so I usually use it instead of Copilot.”* (Interview 5). Something that exists independently of this research but was mentioned as reinforcing are the signs of in-house development of LLMs, which several participants interpreted as reinforcing organizational legitimacy and institutional backing.

4.2.2 Theme 2: A spectrum of adoption and adaptation

The participants positioned themselves along a broad spectrum in how they engage and perceive Generative AI and its implementation. Ranging from enthusiastic early adopters, heavy users and visionaries who integrated Generative AI into daily work, to those expressing principled resistance and avoidance. This resistance is often grounded in ethical concerns, mistrust or the urge to hold onto established routines. In between is a large group of pragmatic or selective users, who engage with Generative AI for specific tasks where it clearly adds value, while (actively) not using it in other contexts. This shows that adoption and adaptation is not static, but shaped by different factors including peer influence, perceived risks and benefits, role-specific demands and generational or personal differences. This creates a broad and nuanced spectrum on which the participants can be placed, rather than a binary division between users and non-users.

Subtheme 2.1 Enthusiast and heavy users

Some participants described themselves as enthusiastic, early adopters and high-frequency users of Generative AI. *“En dat ja vanaf het moment dat het een beetje opkwam, ben ik er meteen ingedoken. Ik vond het gewoon heel interessant om er alles van te leren.”* (Interview 1) They talked about integrating the tools into their daily workflow, where they often experiment across tasks and find value in a lot of efficiency gains: *“It’s been mostly out of my own interest that I’ve been trying things out as soon as they became available.”* (Interview 3). Some call themselves “super-users”, standing at the front of the implementation promoting the use of Generative AI and guiding other colleagues in using the tooling: *“Of course, I was put forward as a super user, and that suits me because I often take the lead in these kinds of things.”* (Interview 4, Appendix). Some participants in this group even have a visionary view on the use of Generative AI: *“Yes, I’ll just say it like this. I always go a bit faster than the rest. So, I try to explore what is possible with AI. For our organization this means that I do feel called upon to provide direction here, in a kind of visionary role”* (Interview 1). These heavy users mention daily use and talk about a lot of different applications of Generative AI: *“But often, yes, I actually use it quite a lot in my work. In my high-end work, there are very few reasons for me not to use it, only if it’s really not allowed or not possible. Otherwise, I’ll use it.”* (Interview 5), heavy on the coding and debugging, brainstorming, translations, searching information and many others, these quotes are two examples of such daily applications: *“So I am not aware how everybody uses it, but I do have a few colleagues that use it on the daily to search for information or brainstorm”* (Interview 9) and *“Yeah, I would say I use it on a daily basis. I think most often I use it for translating as Dutch is not my mother tongue.”* (Interview 12).

Subtheme 2.2 Principled resistance and avoidance

Where some participants positioned themselves as enthusiastic early adopters, on the other end of the spectrum, there are people who actively resist the use of Generative AI. Although

only a minority of participants voiced strong resistance, their perspective illustrates that them not adopting is not about lacking access, skills or knowledge, but active avoidance grounded in personal values, lack of trust and discomfort: *“I notice that I personally also have a kind of aversion to it and think, well, it will last my time. I’m not going to actively contribute to it.”* (Interview 7). A cluster of concerns is about the quality the data an LLM uses to learn from and generate output with, including risk of reinforcement bias, hallucinations and more. This is what one of the interviewees mentioned about their concern: *“But yes, with Generative AI I’ve had a kind of doomsday image from the very beginning. That system scours the entire internet, teaches itself everything from it, and then we all start generating texts with generative AI, which we put back on the internet. Then you get a machine that starts repeating itself. There’s already a lot of nonsense on the internet, and if the internet starts filling itself up, that doesn’t seem like a good idea to me.”* Another concern that was mentioned often, both by adopters as well as resisters was the diffusion of knowledge and the decrease of the human ability due to Generative AI: *“you still need to build credibility for your knowledge. And that can’t come from using AI. So I try to use it as little as possible.”* (Interview 2). Besides the concerns resistance also comes from skepticism: *“...there’s a lot of communication about it, but whether it really adds value, I doubt it.”* (Interview 7). Where some think that it is overhyped. These perspectives mark the resistant end of the spectrum of adoption, contrasting sharply with the enthusiasts in subtheme 2.1, while the majority of participants fell somewhere in between adopting GenAI pragmatically or selectively, covered in subtheme 2.3.

Subtheme 2.3 Selective or pragmatic use

The majority of the participants are not the enthusiastic early adopters or active resisters. They adopted a pragmatic, task-specific approach to Generative AI. They mostly frame it as ‘just another tool’: *“Personally, not really afraid to be replaced. Um. I see Generative AI as an accessory, not as a threat.”* (Interview 3). They think it is helpful in some contexts (coding, translation, brainstorming, drafting texts), but find it inappropriate or unnecessary to use it in others (e.g. writing reports, creative processes or tasks requiring credibility). Their engagement with Generative AI is guided by practical boundaries: open to using it where it clearly adds value or saves time, but they resist full reliance, most of the time this is either due to quality issues: *“I do try, but I am very critical of the output it generates, so I don’t actually use it to write a report, for example, or to write a project proposal, because I think there are still too many drawbacks to it for that.”* (Interview 13) or ethical concerns. For some this means that they only use it when permitted by organizational rules: *“Yeah, if I specifically use it for coding, then only when the project allows it. Otherwise I don’t bother.”* (Interview 12) or only for low-stake tasks. This group sees Generative AI as a tool supports their daily activities instead of taking over, *“Well, I don’t think you create impact just by saving more time — at least not for TNO. I mean, that’s not our task. The impact lies in our thinking capacity, I believe. And in what we add on top of GenAI. But anyway, that’s my opinion. So, time savings, yes, certainly more efficient. Can it replace certain processes? Certainly. Yes, so really as a tool, as support, so actually, the introduction of Copilot is more like getting a new software package or a new PC. I really see it as support.”* (Interview 13). The pragmatic use of Generative AI can look very different per user, some use it almost daily for selective tasks, where others use it only occasionally. As the spectrum of adoption, adaptation and application is very broad, the difference in use is shaped by a range of influencing factors, which are discussed in the next section.

Subtheme 2.4 Influencing factors of adoption and adaptation

Whether participants adopt to Generative AI and adapt their work practices to it or not is shaped by a range of individual, social and organizational factors. These influences help explain why some participants became early adopters, others resisted, and the majority adopted pragmatically. On the individual level there are several factors that influence if and how employees adopt to Generative AI. Demographics and generational aspects are brought up by participants as something they see making a difference in adoption, they mention things as older employees not being able to keep up: *“Yes, not older people who are in those guilds, right? The programmers’ guild that we have here. Yes yes, well, if they don’t keep up, then they’ll have a problem.”* (Interview 1) or older people that do not see its potential: *“Yes, generally the people in my department are quite old, I mean, the average age is I think 55+, so they see this as a kind of revolution that is, as it were, only temporary.”* (Interview 2). Another thing that also came up frequently in the interviews was role-based differences in adoption and acceptance, managers and consultants mention efficiency but limited impact: *“that the data analysis I now do manually, that the system will eventually get smart enough to recognize patterns and deviations. I can imagine that happening, but a big part of my added value is making the project team function. I don’t think a Generative AI will ever take that over.”* (Interview 8) and *“Well, I don’t think you create impact just by saving more time, at least not for our organization. The impact lies in our thinking capacity, I believe.”* (Interview 13). Where scientist and engineers reported that using Generative AI significantly increases their productivity: *“Yeah, I think it would. It would sometimes take me two days before, and now with GenAI it can be done in half a day.”* (Interview 5) and they also noted that the technology not only accelerates existing tasks but enables them to do things they previously could not, shown by these quotes: *“Sometimes with certain things, you think, well, I wouldn’t know how to approach this, so then you don’t do it or you say it will take too much time and whatever else. And now you actually do more things than you used to, that are possible.”* (Interview 11) and *“For me, I’d say there are one or two languages I’m pretty familiar with, where I don’t really need to rely on it. But even then, it can still speed up my work quite a lot. And then there are languages I don’t know at all, and even there, if I just write the comments, it will generate the code.”* (Interview 3). At the same time, participants also described differences in motivation and dependency. Enthusiasts adopt due to curiosity and self-interest, where others adapt because they feel social pressure and are afraid to fall behind: *“No, I think I noticed that I used it quite little in my private life, then I noticed in my surroundings that people were going to use it and I thought, oh, I have to go along with this a bit, I can’t not do this.”* (Interview 14). In contrast some participants expressed concerns about growing dependency, which for some works as a demotivator: *“On the other hand it also makes you lazy, so normally you would think I want to look up formulas and write them down and do an analysis or something, but now you can just say write me a code to do that. Then people are more likely to just click on the code, see the output, and think, well, that looks fine, it must be correct. Whereas if you had done it yourself from scratch, you would have run into issues that you would have learned from and that would have given you more confidence in the solution you ultimately generated.”* (Interview 2), or they mention feeling uncomfortable: *“...but then I think, yes, sometimes I feel uncomfortable about the fact that it now goes so easily, and then I wonder, was this really necessary, couldn’t I have done this myself? That’s more what I think, yes.”* (Interview 14). Other participants showed deeper anxiety or hesitation than just the fear of dependency: *“But I seriously worry a lot about the quality of those answers. So then I think, yes, this will go completely wrong.”* (Interview 7). Some participants noted anxiety not only for themselves but also among their colleagues: *“I notice that they are a bit anxious about the whole GenAI development, because they are very quick to worry that it will cost them their jobs. They think that soon they will be redundant if everything is handled through Gen AI, and they find that very scary.”* (Interview 4). In addition to these individual and role-based differences, participants also emphasized that the organizational context shaped their willingness to adopt. Poorly executed training could

undermine credibility: *“The trainers barely knew how to turn on a computer, which damaged credibility.” (Interview 2).* By contrast, clear guidelines and spaces for discussion were seen as supportive: *“I value organizational clarity and training, especially opportunities for discussion about dilemmas.” (Interview 14).* These organizational conditions did not determine adoption outright, but they influenced whether employees engaged with Generative AI confidently or cautiously.

4.2.3 Theme 3: Psychological empowerment (Feeling empowered or de-skilled?)

How employees' sense of psychological empowerment is affected by Generative AI is a central theme coming forward from the interviews: do they feel more autonomous, capable and feel like they have more impact, or do they experience loss of control and skills? The dynamic between employees' psychological empowerment and potential de-skilling is key to understanding the human impact of Generative AI, highlighting that implementation is more than a technical and organizational process, it also touches employees on an individual level.

Subtheme 3.1 Autonomy and control

Autonomy and control regarding the implementation and integration of Generative AI seems to be a double-edged sword. Participants mention empowerment by gaining freedom and sustained independence, but others feel pressured, constrained by organizational or social expectations and worry about losing control over their work. One of the participants links Generative AI directly to having more freedom: *“Yes, you know, I just have more time to do other things. Of course, I already have more than enough to do, but I now use my knowledge and experience in a different way, which gives me much more space for other things... many more things I can do within our organization, because our organization is of course also very flexible in what you are allowed to do. You know, this also makes the organization a bit more fluid.” (Interview 4).* Many participants emphasized their determination to keep control, where they frame actively protecting the autonomy and control they have over their work: *“But I feel that I am quite critical about it. I don't just run to Generative AI for all kinds of information; I don't do that. I believe it's your own responsibility what comes out of it. It's your choice whether to believe what that thing produces. And rather than just believing it, you should check it in some way and put it into perspective.” (Interview 13).* Something that affects autonomy for people is a forced rollout where one of the participants had a very clear view about *“No, I notice that ever since this came up a few years ago it just really provokes aversion in me. You buy a new computer and suddenly Copilot is on it, and you can't get rid of it. And I think: why are you interfering? You open PowerPoint, and the thing immediately starts suggesting everything? I can design my own slides, I enjoy that much more, I'm not going to let AI do it. On my phone too, suddenly WhatsApp has this irritating little button at the bottom, and you have to switch it off chat by chat. That's completely ridiculous, it's being forced on you, and that creates more resistance. I'd rather just be able to turn all those things off with one button across all my devices. Yes, I think about the rollout within the organization quite badly. It just gets rolled out as if it's self-evident. I mean, everyone just gets it on their computer. You don't have the option to turn it off. I notice that I just... I simply don't want it. And I would really appreciate it if that were respected, so that I am not forced.” (Interview 7).* Taken together, these factors show that autonomy regarding Generative AI is not solely about the freedom it creates, but also about the ability to resist unwanted integration. Some feel empowered to use the tooling in their own terms, where others push back against forced

implementation, showing that empowerment regarding Generative AI is both about choice and the capability it may increase.

Subtheme 3.2 Competence and confidence

This subtheme captures how Generative AI affects how competent employees feel: does it enhance their skills and confidence, or does it have the opposite effect where insecurity, dependency and fear of losing authenticity grows because of it? Some participants describe feeling more capable because Generative AI enables them to do things they could not do before, examples are using different programming languages, translating into different languages or helps them feel more structured, one of the participants noticed a noticeable increase in their skills: *“I think I can now apply my skills in more areas, so in that sense it has broadened my horizon.”* (Interview 2) however they also underscore the need for a baseline competence to evaluate the outputs of Generative AI, otherwise the sense of capability could be misleading: *“So you need to have a certain amount of knowledge yourself in fact-finding before you can take over the kinds of things a computer generates as being reliable.”* (Interview 2). Multiple participants emphasize their concern about skill-erosion, dependency and over-reliance on Generative AI. These concerns are not only present among resisters, but also among those who already use Generative AI: *“So I see as a big problem that data leaks away and that knowledge, so to speak, leaks away from people.”* (Interview 14, Appendix), where it is not only mentioned as an individuals’ issue, but some participants see it as a giant collective issue: *“So I see as a big problem that data leaks away and that knowledge, so to speak, leaks away from people.”* (interview 2). The trend from the interviews is that there are people that feel more competent due to using Generative AI, but regarding competence a lot of people are worried about human skills decreasing, especially for the younger generation who, in their eyes, will miss crucial learning opportunities because of the existence of Generative AI.

Subtheme 3.3 Meaning and values: alignment

Regarding the implementation of Generative AI making employees’ work more meaningful, there are two sides to the story. For some it unlocks potential, expands possibilities and aligns with values of innovation: *“Yeah, because it takes away a lot of the tasks that maybe are just time consuming as well. Like what I said with the modifying some documents with a lot of data. That's not something that I will learn anything from really. And usually it's just time consuming, so having it done by AI is quite convenient and in that sense, I really don't mind at all. So yeah, I can spend less time in these things and spend more time on a little bit more meaningful tasks.”* (interview 9) and others see this potential also for the future *“Does my work become more meaningful then? Perhaps eventually, if this goes well enough, I will need less time to manage a project, which ultimately increases the efficiency of the project. That would mean that together we could do more projects for the same money and so, in the end, society would get more value for its money. So in that sense, yes, more meaningful.”* (Interview 8). For others adoption and adaptation are shaped by different needs as not everyone values efficiency or automation equally, where some resist because it does not align with their perception of meaningful work. They mention that reliance on Generative AI undermines authenticity and integrity which dilutes their professional identity: *“But I can imagine that it undermines integrity, right? For example, if you were to have Generative AI write an entire report for you that you charged the company €50,000 for, then I would... I would have a problem with that. I would feel uncomfortable about it, also if colleagues were to do that.”* (Interview 13).

Subtheme 3.4 Impact: effectiveness

Do employees feel their work makes a greater difference because of using Generative AI, or in other words, are they making more impact because of it? Opinions are divided. Participants highlight that using Generative AI enhances productivity, or lets them take on things that they otherwise could not, enabling people to get more work done in a certain amount of time and also expand their scope: *“I’d never done web design before, but with Generative AI I managed to create a simple page with a textbox and button so we could actually demonstrate our work. Normally that would have taken a front-end colleague, but this way we could show impact to outsiders in a way they understood. It really helped me do something different and make more impact than I could have on my own.”* (Interview 6). However, there is skepticism about Generative AI helping to make more impact, where these two participants emphasize that being more productive does not account for feeling a meaningful difference in the impact they make: *“No, not really. Well, maybe impact sometimes, because you just get more done in less time. So if you assume that, say, I now get 10% more done in a week, and you assume that’s evenly distributed across how much impact I make, then I’m making about 10% more impact per week. But I don’t really feel that much has changed.”* where the second participant is even more critical about it: *“I don’t think you create impact just by saving more time, at least not for TNO. That’s not our task. The impact lies precisely in our thinking capacity, I believe, and in what we add on top of GenAI. But well, that’s my personal opinion. So time savings, certainly, more efficiency, certainly, that some processes can be replaced, certainly. But really only as a tool.”* (Interview 13). Others note little to no impact due to their limited use of Generative AI. Several participants do note the potential of Generative AI helping them to make more impact in the (near) future: *“Not yet, I would say, because I still need it. It still costs me quite some time to really work on my prompts and get to the results. Yeah, I think in the very short distant future I can, because a lot of routine tasks or tasks that require a lot of manual work, like filling in Excel sheets or recoding of variables I think is a really good example. And I think those kinds of things... and that’s not the stuff that really drives me or makes a lot of impact.”* (Interview 12). These different perspectives show that impact assessment is not only about objective productivity measures: can I get more work done in the same amount of time, but reflects how people feel about the nature of valuable work.

4.2.4 Theme 4: Performance, fast but not flawless

This theme addresses how employees evaluate a difference of their performance due to Generative AI. Many highlight that using Generative AI helps them to save time and accelerate their work and be a brainstorm partner for them. However, they also note limitations in quality, reliability and creativity.

Subtheme 4.1 Time savings/Speed

The largest gain that participants notice is in productivity. Using Generative AI helps them finish tasks faster, reduce time pressure and handle more work in less time. The magnitude and nature of these gains vary systematically across task types, revealing insights about the impact of Generative AI on different forms of work. For technical tasks, programming and data analysis showed the largest productivity improvements, where one of the participants observed the following: *“You could almost call it well, but then with a positive spin with coding, the speed up is pretty insane in my opinion. Um, I think if we could leverage that more, the generation of code is... It’s hard to put a number on that, but I feel like it can be 10 times as fast, especially if you are not as native in that language.”* (Interview 3). In knowledge tasks productivity gains more modest, but still provides important productivity gains, participants

mention increased speed in searching for information, summarizing long texts or drafting content and really value the gains for administrative or repetitive tasks: *“Yes, especially the speed, right? The quick literature search or just quickly looking something up, like, how does it work?”* (interview 13). This suggests that the impact of Generative AI on knowledge work is more about task delegation than another example is this: *“Um, yeah, because it takes away a lot of the tasks that maybe are just time consuming as well. Like what I said with the modifying some documents with a lot of data. That's not something that I will learn anything from really. And usually it's just time consuming, so having it done by AI is quite convenient and in that sense, I really don't mind at all. So yeah, I can spend less time in these things and spend more time on a little bit more meaningful tasks.”* (interview 9). There are nuances and limits to the increased productivity. Using Generative AI is not always seen as efficient, where some participants note that learning to use Generative AI or refining prompts cost them time rather than saving it: *“Not yet, I would say, because I still need it. It still costs me quite some time to really work on my prompts and get to the results. So I think only if I have similar tasks more and more often it will actually help me.”* (interview 12). This suggests that the productivity benefits of Generative AI follow an adoption curve where initial time investment is needed before users see real efficiency gains. Others mention an efficiency threshold for smaller tasks or when they have to spend a lot of time checking the output Generated by the LLM: *“when I think OK double checking the results that AI give me cost me as much as writing it on my own or doing it on my own in the 1st place then then I'm not using it.”* (interview 12). In sum, the main bottlenecks to productivity are both user-related (the time to learn and refine prompts) and tool related (errors and the need for verification).

Subtheme 4.2 Quality, trust and verification

While participants valued Generative AI for speeding up tasks, they repeatedly emphasized that the outputs required constant verification. A consistent pattern across the interviews was that the outputs of Generative AI were seen as useful, but not fully trustworthy, making critical checks and user responsibility unavoidable. One of the participants explained: *“Yeah absolutely... I think this the fact checking thing is a huge issue, an eye opener for me was with mathematical derivations, when I hand checked them, I saw that it was not right... you really have to be a bit careful with trusting the information. The unease and awareness that this is not 100% true... is continuously there, It's just not something that holds me back to the level that I wouldn't do it anymore. But I think that raises my carefulness to a specific level.”* (Interview 3), another participant also experienced the inconsistency and questionable factual grounding: *“The fear I have is about the quality of the output. Yes, in that training they also mentioned it, you sit at the table with 10 people, you type the same prompt 10 times, and you get 10 different answers, also about facts, like amounts or costs or how long something should take. Copilot, of course, only draws on a small part, at least, that's how I understood it, a small portion of the web. It bases its truth on that, and that is the truth of Copilot at that moment. So it's not the kind of factual correctness that you need.”* (Interview 13). Regarding perceived quality improvement of their own work due to Generative AI the vast majority sees little to no improvement. Participants described that while the tools could generate text or summaries, these outputs often failed to meet the standards required in their work: *“I don't think any thought about this has ever popped into my mind... I think the quality of results is more or less identical, quite untouched”* (Interview 3). The general tendency is that speed and quantity are where the improvements lie, but quality improvements are not present: *“I think that you gain speed and you gain quantity, but not in quality. So you get much more information in a short time and you can use much more information.”* (Interview 13). However, there are people that described more mixed experiences and see improvements in quality in some cases, as interviewee 10 highlights: *“Sometimes yes, sometimes no. For certain tasks I do see that the quality is better. For other tasks I think that if I had just done it*

myself, it might have been better. So sometimes yes, sometimes no. I think at this moment many things are still experimental, and because I also don't yet have full knowledge myself, I'm still a bit on a learning curve. I think it will get better in the future, but right now sometimes I see that the results are better when done by AI, and sometimes not". Even when participants acknowledged occasional improvements, they emphasized that the responsibility for the final product is that of the user rather than that of the tool, one of them explained: *"It is of course also about learning how to work with it. I think it's just a tool that can help you with certain things, but you don't lose people's responsibility for the final product. And I think that's also sometimes the point, you shouldn't just copy-paste the result from A to B. That's how I see it."* (Interview 5). This positions Generative AI more as an assistant prone to error rather than a source of dependable quality.

Subtheme 4.3 Creativity and ideation

Beyond efficiency and quality improvements participants also reflected on the role of Generative AI in the creativity within their work and ideation. Some were enthusiastic and described how they used Generative AI as a sparring partner or brainstorming aid. They mention using Generative AI as a way to generate ideas, help getting unstuck and broaden perspectives, where one participant mentioned: *"Yeah, if I specifically use it for that, if so, if I really use it as A. brainstorming partner or with coming up with ideas, then yes. But usually, I think I use it in a way that I very clearly formulate a task that it's supposed to do and it's doing it. So it really depends if yes I willingly use it. To give me creative ideas, give me alternatives. Brainstorm with me. So yeah, it's to a limited point?"* (Interview 12). Multiple participants framed the use of Generative AI as if it were a colleague to share and test ideas with *"...it can also be useful when you just need to spar a bit. That's not something you would call a colleague for, but for that I sometimes find it super useful"* (Interview 5). At the same time, participants were clear that the creative value of Generative AI had its limits. They often distinguished between its literal output, often considered of low quality and using it to get their own thinking process started: *"Yes, but what actually comes out is worthless in terms of literal content, as output. But indeed, if it is used as a brainstorming tool to get you thinking, then it still has added value."* (Interview 6), where someone else also mentioned that they used Generative AI in early phases to get ideas, but that they would not directly adopt its suggestions: *"I never use the information that comes from Generative AI as it is, so to speak. I do use it for the early phases, for getting some ideas, a bit of brainstorming, but I never, let's say, copy-paste everything that's in there."* (Interview 10). The role of Generative AI in the creativity aspect of people's work varied across participants. Where some see added value, others mention concerns about decreasing human creativity when relying on a LLM: *"...and then I think, couldn't I have come up with this myself? That I almost start to have some doubts about my own creativity or thinking ability."* (Interview 14) Where others do not share that concern as they see themselves as the true creative source: *"...actually I have that less, because one of my own skills is out-of-the-box thinking, transdisciplinary. So I look at how in one discipline they use this, in another they use that, and then I see if I can apply it here as well"* (Interview 2). Several participants also emphasized that GenAI does not generate genuinely new ideas but rather repackages existing patterns. As one noted: *"...there is no new physics being generated by AI recognizing patterns, because no new formula comes out of it"* (Interview 7). This perspective reflected view of others who stressed that true out-of-the-box thinking remained a human skill, with GenAI serving at best as a trigger or sparring partner. The current limitations participants saw also made them think about the future role Generative AI can play, where they mention Generative AI as their personal assistant or actual additional colleague: *"...then you really have an extra colleague, so to speak. One that is free and never complains, so that seems to me an added value"* (Interview 13). Overall, participants framed GenAI less as a source of original creativity, and more as a sparring partner useful for sparking ideas and broadening horizons but requiring human judgement and originality to shape the results.

4.2.5 Theme 5: Organizational enablers and barriers

Organizational conditions also played a decisive role in how the implementation of Generative AI impacted employees. Participants emphasized that adoption was strongly shaped by facilitating conditions, including training offerings, tool availability and the policies governing their use. These organizational enablers and barriers were often experienced differently throughout the sample.

Subtheme 5.1 Training and capacity building

Training and capability development were widely recognized as legitimate and valuable for the implementation of Generative AI. While several participants valued the existence and quality of trainings, others were more critical of the content, highlighting gaps or questioning the relevance for those already confident in using the technology. Several participants spoke positively about the training opportunities that were offered: *“They have good trainings, which probably weren’t cheap, but I’m very happy they invested that and didn’t make it a very boring meeting. So that makes it easy for me to recommend all my colleagues: go there, go there, you learn something”* (Interview 12). Others did not necessarily see direct value for themselves but still emphasized the importance of training for the organization: *“The trainings themselves? Yes, I think for certain groups of employees it is certainly good to have those very basic trainings. If you don’t like experimenting with new things yourself, then I think it’s good to have it explained. And I also see that many colleagues, also some older colleagues, really benefited from following such a training once.”* (interview 5). At the same time, others were more critical, pointing out barriers or gaps in the training(s) offered. For frontrunners or people who moved beyond the basics of Generative AI, the existing program was seen as irrelevant: *“Yeah, I thought the training was poor. Look, if you just about know where the power button on the computer is, if you can just manage that, and you know how to open Word and go to tno.nl in the browser, then I think it’s a really good training. If that’s where your computer skills end, sure. But for the average person, yeah... a bit mediocre.”* (interview 2, appendix ...), this is also the reason some did not attend: *“I didn’t do the training. When I saw it was just the basic course, I thought that’s a waste of my time. I get really frustrated if I sit in a training and only hear things I already know.”* (Interview 5). The criticisms regarding the training often centered around the diversity of needs. Participants highlighted that a single, generic program could not meet the needs of both beginners and advanced users: *“Yes, that’s right, of course there are a lot of beginners in the organization in that respect, people who have never done anything with LLMs before. I also understand that if you want to roll something out across TNO, you have to make sure it works reasonably well for almost everyone, whether you are a beginner or more advanced. But you could also think: we offer different options, so the beginners can choose what they want, and the advanced people choose what they want. I think maybe it should be looked at in smaller groups instead of making one thing for everyone, because then it will never be good enough for anyone.”* (Interview 2), suggesting that training should be differentiated by skill level and role. Across the different perspectives, there was consensus about training being essential for successful implementation, even participants who found little direct value for themselves noted that it was important that everyone in the organization received some form of training, to ensure a shared baseline of knowledge and responsible use: *“Yes, I’m not entirely sure. But I actually think that everyone needs some degree of training, so that you at least know what you are doing and don’t just throw anything into it.”* (Interview 6), and this thought was reinforced by others: *“I did feel it was important that everyone was trained. Otherwise you get big differences in how people handle it.”* (Interview 10).

Subtheme 5.2 Tool access and vendor lock-in

Access to Generative AI tools was rolled out quickly across the organization and everyone could directly apply for a license, with Microsoft Co-Pilot becoming widely available. However, multiple participants expressed frustration with being restricted to Microsoft Co-Pilot, which they experienced as a form of vendor-lock in. Co-pilot was often compared unfavorably to other tools and indicated that a lack of choice limited their work. Where the trade-off between basic accessibility and limitations on advanced use was mentioned: *“Yes, and it’s quite a lot, it’s made rather difficult for you. Look, if you just want to do the basic things, like if you just want a Copilot license to summarize your texts or something, that’s fine. But as soon as you have more complex use cases, you immediately end up in a discussion about whether this is allowed under the policy.”* (Interview 5). This against acknowledges different needs within the organization, where CoPilot is found not to meet them: *“Yeah, definitely. I mean, everyone used to make fun about the Internet Explorer, and I kind of have the idea that Copilot is the Internet Explorer of the LLMs. So I think, yeah, especially for researching, for looking up specific studies or like everything on the science-written part, Perplexity would be my preferred option, and for coding ChatGPT is much better than Copilot.”* (Interview 12). Besides their concern being limited to Co-Pilot in their own work, it was noted by different participants that they are afraid about the tool choice affecting the organizations’ competitiveness and innovation possibilities: *“Ah, that it is finally focused on Copilot, and in my view that is actually a huge limitation when I see what ChatGPT can do better. And then, yes, I actually don’t think we can afford this. Because you will fall behind compared to a company that is allowed to use a good tool, or rather, a better one.”* (Interview 11). While access to Copilot was rolled out quickly and widely, participants experienced the lack of choice as a barrier rather than an enabler. They felt that vendor lock-in limited their work-effectiveness and when the official tool did not fit their needs, employees turned to other, sometimes unauthorized, alternatives.

Subtheme 5.3 Policy, governance and safety of use

Organizational policies and governance were repeatedly mentioned as factors that shaped how employees engaged with Generative AI. Participants recognized the need for policies, but their experiences were different. Some valued strict and clear guidelines as offering safety and direction, where others found the same policies too restrictive or unclear. They mentioned governance to be too bureaucratic or inconsistent with the organizations’ innovative identity. The following three quotes illustrate this ambivalence coming from the interviews:

1. Clear rules: *“And then at a certain point it suddenly became very clear: okay, you are allowed to use Copilot, and this is how you are allowed to use it. It was really introduced all at once, but I found that very nice and pleasant because it simply gave clear guidelines, while at the same time also taking into account the company’s interests, like: okay, how are we going to deal with this?”* (interview 14)
2. Unclear policy: *“As of now, yeah, I mean for sure a lot of tasks. I think it hasn’t penetrated that deeply for me also because I feel like I’m still lacking an overview of what tools are out there which are allowed within TNO.”* (interview 3)
3. Policies too restrictive: *“Well yes, but then you come to how long it takes before these things actually become available here for the regular employee, that is really a bit disappointing, because what I want should be easily possible. You know, it would take me two hours to build something in Python that I can now just do on OpenAI. But that’s not allowed, and internally the tooling is also not made available to be able to do something with it. Whereas I know that at Fraunhofer, for example, it would be*

possible without any problems because they chose a different approach there.” (interview 5)

Besides the rules themselves, participants commented on how the policies and implementation was communicated. Key-points that were mentioned are the long silence at the start of the implementation, the reliance on the communication via Intranet and that a lack of formal introduction made participants feel uncertain. Contradicting in the answers of the participants was how they thought about the style of governance, where some felt that things were too bureaucratic and moved too slowly: *“...why does it all have to be so heavy, why does it all have to take so long? Why do we make it so complicated for ourselves? We always turn it into a mega process.” (Interview 5)* others found that the organization moved too fast without a clear long-term vision: *“...what I maybe miss a little bit is that I’m not seeing the bigger vision on how TNO sees the use of GenAI within TNO like over five years... At the moment it feels a bit we are using it because everyone does and because of the AI Act, you need to train your people, so we are training them now. So it feels more pragmatic at the moment. But I’m missing a bit the bigger vision and the why are we doing this and what are the consequences?” (Interview 12).* The following quote illustrates how some participants found the too bureaucratic and slow approach not aligning with the identity of the organization: *“For a long time we were very silent about it, so I thought: hey, our slogan is ‘innovation for life,’ but what are we actually doing with AI? I even got questions from people: am I allowed to use it or not?” (Interview 14),* linking the way the organization implements Generative AI too its credibility, another participant also found this conflicting, emphasizing this view: *“So I find it very strange that with GenAI we have this feeling that there needs to be such a strict regime around it. While at the same time we really want to encourage it and become more efficient. So I find it very contradictory, it feels like the program tries to convey in its communication, “oh, we love innovation, and we’re going to improve our processes,” while in the way it is actually set up you can see that it is very restrictive.” (Interview 5).* Despite the criticisms, there were participants that did see the governance as supportive once communication picked up, others proposed improvements such as an Generative AI integrity office.

4.2.6 Theme 6: Ethical and societal concerns

Because of the nature of Generative AI, its implementation not only comes with organizational aspects, but also raised broader ethical and societal concerns among the participants. Reflections regarding these concerns often went beyond immediate work-related situations, pointing to risks about bias, transparency, environmental costs, and geopolitics.

Subtheme 6.1 Bias and transparency

One of the most frequent concerns mentioned throughout the interviews were that of bias and lack of transparency. The risks that participants foreshadowed position bias and transparency as more than just technical issues. Concerns about bias reflected both technical and societal fears. Participants explained that they feared that systematic stereotypes and inequalities would be reinforced in the outputs because the LLMs are trained on large, not curated datasets. This fear was not only about visible errors, but also about hidden biases: *“I think I have concerns about biases that I don’t see immediately, that they may be systematically in there” (Interview 3),* where another participant mentioned a similar

example: *“It’s still a bit of a black box where it actually comes from. So I don’t really know whether the data I get from it is biased. But I have had a few times where I thought, hey, this is quite stereotypical”* (Interview 2). Several participants also mentioned concerns about cultural bias and specifically western dominance: *“Let’s say if the majority of training data comes from Western countries, you will always get the Western answer, which is definitely not always the right answer.”* (Interview 3). Another key concern participants mentioned multiple times is the interactive nature of bias, where they described how LLMs may act as people pleasers and mirror user assumptions, which leads to creating echo chambers and reinforcing existing beliefs a user has instead of challenging them: *“I have concerns with the fact that I feel like a lot of them, at least the large language models, are people pleasers.”* (Interview 3) with this other participant illustrating the same: *“And the question is whether it tells you what you want to hear. That seems to me the danger, that you end up in a kind of funnel, because of course it learns from earlier prompts and then uses that again for new outputs. So the danger is that you get a kind of tunnel vision, and that it no longer really thinks out of the box. Of course, it’s always very nice when it only gives positive confirmation, but that’s also immediately the danger. It’s very pleasant if someone confirms what you already think, but that’s exactly not what I want. Yes, of course it feels nice when someone says you’re doing well and shares your view, but that’s precisely the danger.”* (Interview 13). Alongside concerns about bias, participants repeatedly emphasized the lack of transparency in how Generative AI produces its outputs. Several described the models as a black box, highlighting that it is unclear how specific answers are generated: *“...because it’s still a black box, you don’t know where it comes from”* (Interview 6). This concern goes beyond doubt about the reliability of the results, but complicates their professional use, where accountability and credibility are essential. As a mitigation strategy some participants emphasized the importance of explicit disclosure, creating transparency whenever content is generated with AI. *“I think you should always disclose when something has been generated by AI”* (Interview 2).

Subtheme 6.2 Environmental costs

While most concerns from participants were focused on practical or organizational issues, there were participants that raised the question of the environmental footprint of Generative AI. Concerns centered around energy use and sustainability; however the views were mixed, with some taking a worried stance on one side: *“Another dilemma, I once heard that at the moment AI puts a huge burden on all the servers with all the energy costs that come with it, which makes me wonder whether people are aware of this and whether, as humanity, we should even want to pour so much energy into it, because after all we only have one world.”* (interview 8). Others admitted knowing not much about it: *“Well I do think about it yes, but I find it difficult because I don’t have enough knowledge about the environmental aspects”* (interview 14). A final group dismissed the issue altogether, either seeing it as a minor concern *“Other issues, I don’t really see any energy problems if I have to be honest.”* or taking a short-term perspective *“In that respect I may be a bit simple about it, I think to myself: yes, I work now, I learn now, and I do everything now. Well, what happens in 100 years? To be honest, I couldn’t care less.”* (interview 4). Overall, environmental concerns were less frequently mentioned than other risks, but they illustrate an emerging awareness of the tension between technological innovation and sustainability goals.

Subtheme 6.3 Geopolitics

Participants also reflected on the geopolitical implications of Generative AI. Topics regarding geopolitics that were touched are global inequalities, risks of harmful use and the

concentration of power in big tech companies. Participants worried about the separation of groups due to the concentration of benefits that Generative AI brings in especially the west. They feared that other regions or minorities would fall behind: *“about many smaller groups they simply know nothing. And I find that unethical. Because then, once again, it is always the majority groups who get an extra tool. My mother also speaks Dutch, like every Groninger nowadays, but 200 years ago that was different. And of course there are many languages in the world, with just a few hundred thousand speakers, and people there may not feel comfortable in a larger language. So in that way, those people won’t have access to these kinds of tools. I really do find that unethical. It is not good. It is once again a tool that serves the majority.”* (Interview 6). In addition to the concentration of benefits they also worry about the Western dominance of training data: *“From now on, for example, we in the Netherlands, many people here already use it. But it is still very Western. Most of the data is from European people, or from people in the West. But we don’t have that much data from, for example, the Global South or from people who simply don’t have access to computers and such. So yes, I see that as becoming more and more the case with the data, because it is from a specific part of the world. But you mean socially? Yes, socially. That is why I think that if there is no real thought given to what data is added and how it is balanced, then I do see a danger for the future.”* (interview 10). The potential harmful applications of Generative AI were also mentioned, these concerns entailed misuse in misinformation, deepfakes and warfare contexts: *“If I am afraid of anything, it is harmful applications, like deepfakes, or if it is used in warfare.”* (Interview 1). This shows that participants also situate the risks of Generative AI at a societal and global level. Finally, they also reflected on the concentration of power in the hands of a few big tech companies, which is illustrated by the following quote: *“So I do see a long-term danger of AI, that you end up in a kind of whirlpool that feeds itself. That’s also the case, of course, you all go in a certain direction together and become influenceable. Naturally, if big tech companies can just put millions of things into it, then your output will be influenced. That’s what happens, of course. So yes, it also becomes politically charged and misused for propaganda and such. I also have friends in the IT world who are really critical; they say: I’m done with it, I’m just going to stop, because with this we are feeding a kind of monster that will eventually turn against us.”* (interview 13). Where they also touch on tool choice being linked to strategic dependency: *“So you also limit yourself in your learning as a company by the tooling you choose, while other comparable institutes, think of Fraunhofer, are much further ahead. They have simply chosen a completely different setup to make GenAI available within their work processes, which gives them much more flexibility and also better models available, and they are not so dependent on Microsoft.”* (interview 5).

5 Discussion

This study investigated how employees experience the introduction in their organization, focusing on how their perceptions and responses to the technology influence their psychological empowerment and job performance. Using a mixed-methods approach (survey of 363 employees and 14 follow-up interviews), the research found that employees who actively adapted to Generative AI felt significantly more empowered in their work (experiencing greater autonomy, competence, meaning, and impact) which in turn translated to higher perceived performance. In essence, engaging with Generative AI tended to be a psychologically beneficial process: adaptation was associated with positive empowerment and performance outcomes, whereas resistance to the technology corresponded with lower empowerment and performance.

These findings provide an integrative human-centred perspective on Generative AI implementation, showing that the technology's value is shaped not by its technical capabilities alone, but by how employees respond to it emotionally and integrate it into their work. To understand these mechanisms the following section elaborates on the key themes that explain what the impact of the implementation of Generative AI is on employees and how organizational conditions shape this.

5.1 Beyond ease of use: Revisiting technology acceptance in the Generative AI context

Performance expectancy versus effort expectancy

Our findings suggest that traditional technology acceptance predictors require reinterpretation when applied to Generative AI in post-adoption contexts. Whereas prior models like UTAUT and TAM emphasized ease of use alongside usefulness as central drivers of technology acceptance, and recent studies on Generative AI adoption similarly show that performance expectancy and effort expectancy significantly influence intention to use (Kim, Blazquez, & Oh, 2024; Budhathoki, Zitar, Njaya, & Timsina, 2024; Chen, et al., 2025). However, our results show that in the context of Generative AI, these factors do not operate symmetrically, when employees are already interacting with embedded, intuitive Generative AI tools. Given the widespread embedding in systems and integration of Generative AI tools across workflows engagement can occur passively, therefore, our behavioral outcomes reflect a wide spectrum of active and passive use and integration, rather than binary adoption decisions. Consistent with classic acceptance models, performance expectancy (the belief that Generative AI will improve job outcomes) emerged as a strong driver of proactive engagement. Quantitatively, higher perceived usefulness of Generative AI significantly increased employees' willingness to adjust their work practices to integrate Generative AI and simultaneously reduced resistant behaviors. Qualitative findings reinforced this pattern: many of the participants described how tools like ChatGPT or Copilot saved time on routine tasks and enabled new capabilities, confirming substantial performance gains in their work. These results show that performance expectancy generalizes beyond the adoption stage and remains a central driver of meaningful integration in post-adoptive contexts. Conversely, effort expectancy (perceived ease of use of the technology) had no significant impact on

either adaptive or resistant behaviors in our model. This finding diverges from both UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and prior studies on Generative AI adoption (Kim, Blazquez, & Oh, 2024; Budhathoki, Zirar, Njoya, & Timsina, 2024; Chen, et al., 2025). The divergence can be explained by a shift from adoption to post-adoption adaptation. Prior studies evaluate intention to use, whereas our study investigates how employees integrate Generative AI after it has already been introduced in their workflows. In this context, effort expectancy appears to have become a baseline expectation rather than a meaningful differentiator. Interviewees consistently described Generative AI tools as intuitive and requiring little learning effort, even if they were not willing to adapt their work practices to it. This results in very limited variance in effort expectancy across respondents and thus effort expectancy appears to lose explanatory power and functions as a hygiene factor, necessary for basic engagement, but insufficient to predict deeper behavioral adjustments. This mechanism aligns with research on post-adoptive system use, which suggests that once a technology becomes routinized and embedded, continued engagement and adaptation is shaped primarily by perceived usefulness, experiential evaluations and coping responses, rather than effort expectancy (Jaspersen, Carter, & Zmud, 2005; Burton-Jones & Gallivan, 2007). Within this context of highly intuitive, natural-language interfaces and highly educated, digitally proficient workforce, usability becomes a non-issue that does not meaningfully distinguish employees who actually embrace Generative AI and those who remain resistant.

Social influence and organizational support

Our study also examined UTAUT's social and facilitating factors, finding partial effects and providing a more nuanced view of its social and structural predictors in the context of post-adoptive Generative AI use. As expected, collegial and managerial encouragement (social influence) and availability of support and infrastructure (facilitating conditions) modestly encouraged employees' experimentation with and integration of Generative AI. Both factors showed small but significant positive relationships with employees' adaptive use of Generative AI, aligning with UTAUT theory and recent studies that highlight that peer enthusiasm and leadership endorsement as stimulus for Generative AI uptake. In the interviews, some participants described how seeing colleagues find "smart ways to use it" motivated them to experiment more with the tools themselves, reflecting a peer effect on adaptation. Others valued organizational signals like clear policies and managerial support that using Generative AI and in this specific case Co-pilot was encouraged. Taken together, these insights suggest that social influence and structural support play a meaningful, though modest role in encouraging employees to explore and integrate Generative AI into their workflows. Interestingly, neither social influence or facilitating conditions significantly reduced resistance. This suggest that structural support and managerial and peer encouragement may not be sufficient to overcome deeper emotional or cognitive barriers to Generative AI use. The interview data suggests that resistance was often rooted in personal values, trust concerns, or AI-related anxiety, factors to which social influence or facilitating conditions may need to be tailored more specifically to be effective. This aligns with recent calls in the literature to account for more emotional and identity-based reactions in technology implementation (Glikson & Woolley, 2020). Training participation, treated separately from general facilitating conditions in our model, exhibited a similarly nuanced pattern. While it did not significantly enhance adaptive behavior, it was associated with reduced resistance. This suggests that employees inclined to adapt already feel confident using the technology, perhaps because of its intuitive nature, and therefore derive less added value from the introductory training available during the study period. This interpretation was supported in the interviews: several participants noted they chose not to attend the training because they already knew how to use the tool and felt it was unnecessary for them. While

some of them did express interest in more tailored or advanced training in the future, the introductory format offered was seen as too basic to support deeper integration of Generative AI in their workflows. Taken together, these findings suggest that UTAUT's social and structural predictors retain partial explanatory power in post-adoptive contexts, shaping employees' willingness to experiment, but failing to address the deeper psychological barriers underlying resistance. This highlights an important limitation in the applicability of acceptance theory: while social encouragement and organizational support can facilitate initial engagement, sustained adaptation in Generative AI contexts ultimately depends on addressing affective and identity-related concerns that lie outside of the traditional UTAUT scope.

Trust in Generative AI: cognitive versus emotional

Building on our theoretical framework, where trust is conceptualized as comprising both cognitive and emotional dimensions, components (McAllister, 1995; Mayer, Davis, & Schoorman, 1995), our findings highlight trust as a central and multi-faceted determinant of Generative AI acceptance. Prior research has shown that higher trust in automation and AI systems enhances user adoption and sustained use (Lee & See, 2004; Glikson & Woolley, 2020). Surprisingly, only emotional trust proved significant in our results predicting adaptation and resistance: employees who felt that the tool was non-threatening, had their best interests in mind, or fit well with their values were far more likely to integrate it into daily workflows, and far less likely to resist its use. By contrast, cognitive trust, the purely rational belief that Generative AI produces correct and dependable outputs, showed no significant effect on either adaptation or resistance. This suggests that even if employees acknowledge the tool's capabilities, that alone does not guarantee that they will embrace it. The qualitative data helps to explain this pattern. Many participants stressed the importance of verifying the outputs of any Generative AI tool and not "just believing or accepting it", reflecting an underlying scepticism or cautious cognitive trust in check for many users. Emotional trust, however, was apparent in the way participants described feeling "comfortable" and even reassured when using Generative AI for certain tasks once they gained experience using it. For instance, one engineer noted that after some practice, using Generative AI for coding "feels comfortable and natural", indicating an affective ease with the tool that grew over time. It appears that if employees perceive Generative AI as a partner that feels natural to collaborate with and will not replace or harm them, they engage with it constructively. These findings suggest a critical addition to technology acceptance models and future acceptance theory should explicitly incorporate trust as a dual-faceted construct, acknowledging that feeling "safe" with a technology is as essential as believing in its technical capabilities.

Trialability, the opportunity to experiment

Trialability, the degree to which people feel they can experiment with a technology before full commitment, is a well-known driver of adoption: being able to "try out" an innovation in a low-risk setting builds familiarity and confidence, which encourages uptake (Rogers, 2003). Based on this logic, we expected trialability to promote adaptation and reduce resistance in the context of Generative AI. However, quantitatively we found no significant direct effect on either adaptive use or resistance. This result is surprising in the light of adoption literature, but becomes more interpretable when considered within this post-adoption context. Diffusion theory and related acceptance models conceptualize trialability as an adoption-stage mechanism, relevant when users are deciding whether to try a new technology (Rogers, 2003; Jasperson, Carter, & Zmud, 2005). In our study, many employees were already interacting with Generative AI systems. As a result "trying-out" the technology was not a discrete event but an ongoing feature of daily work. Employees were not waiting for a formal trial environment to test the technology; the implementation itself functioned as a live, evolving

context in which people could experiment as the tools became available. This reduces the extent to which trialability would independently explain adaptation because opportunities to “try-out” Generative AI were naturally embedded in day-to-day work or easily accessible outside formal channels. The qualitative data support this interpretation. Many participants had already experimented with Generative AI tools informally, often through personal use or self-directed experimentation prompted by curiosity. In this sense trialability was not a scarce resource but an inherent feature of Generative AI adaptation: once the tools were introduced into the workflow, employees could and did test them organically, even without formal support. Because experimentation was readily accessible, trialability did not function as a differentiating factor in explaining behavioral responses. These findings do not imply that trialability is irrelevant. Rather, they suggest that trialability operates as a baseline condition in post-adoptive Generative AI contexts. Any organization implementing Generative AI must ensure employees have room to experiment and learn without fear of consequences, but simply providing that opportunity doesn’t automatically translate into higher adaptation or reduced resistance, unless it addresses the user’s underlying uncertainties. In future models, trialability may function more effectively as an amplifier or moderator, for example amplifying the positive effect of performance expectancy by letting users see the usefulness of the tool for themselves, rather than as a direct predictor. This reinforces the importance of distinguishing between adoption and adaptation processes, and highlight that constructs that could be central in early-stage uptake may lose explanatory power once technologies become integrated into daily work. With trialability being the perfect example: during the initial introduction trialability can be crucial, but once Generative AI is embedded and broadly known other factors override the need for formal trials and the intuitive nature of the tool may ask for more specified introductions of how to best adapt work practices rather than an introduction alone.

AI anxiety: Fear and apprehension as barriers

A central emotional barrier emerging from our study is AI anxiety, defined as the apprehension, tension, or fear employees experience about working with Generative AI and its implications for their roles. Existing research shows that technology-induced stress can trigger avoidance, strain and resistance (Ragu-Nathan, Tarafadar, Ragu-Nathan, & Tu, 2008), and appraisal-coping models similarly argue that when technologies are appraised as threats, individuals respond with defensive coping behaviors (Beaudry & Pinsonneault, 2005). Quantitatively, AI anxiety significantly increased resistance to Generative AI, supporting the idea that threat-related emotions inhibit engagement and reinforce defensive coping. Interestingly, however, AI anxiety did not significantly reduce adaptation, suggesting that anxious employees may still interact with Generative AI when required or when perceiving clear instrumental benefits, but do so cautiously and with limited willingness to integrate it more deeply into their workflows. Anxiety therefore constrains proactive engagement without fully preventing basic use. The qualitative findings expand this interpretation and reveal that employees’ anxieties were more complex and multifaceted than the two dimensions captured in our survey (job insecurity and learning anxiety). Interviewees described fears that extended beyond the scale items, including loss of craftsmanship or professional identity, which was reflected in worries that relying on Generative AI would erode expertise or undermine the meaningful, valued parts of their work, this includes but is not limited to dependence anxiety, where users fear becoming over reliant on Generative AI and losing confidence in their own abilities. Others expressed anxiety about loss of control over work outputs, where they talked about the unpredictability of Generative AI and the risks of “things going completely wrong” if outputs were to be accepted without careful validation and oversight. This included employees fearing they would be held accountable for AI mistakes,

biased outputs, or incorrect information generated in critical contexts. These dimensions did not appear in the quantitative measurement but were repeatedly voiced in the interviews, suggesting that AI anxiety in practice is richer and more multidimensional than current scales capture. These findings highlight a conceptual gap: existing operationalizations of AI anxiety may underestimate the emotional complexities of real-world Generative AI implementation. These challenges are amplified by the rapidly evolving nature of Generative AI which causes employees' anxieties to evolve over time, making it difficult for any fixed measurement instrument to fully capture the breadth and depth of these emotional responses.

5.2 Dual pathways of user response: Adaptation vs Resistance to Generative AI

Employee responses to the implementation did not follow a simple “accept or reject” pattern. Instead, we observed a spectrum of engagement, from enthusiastic adaptation to pronounced resistance. In our study adaptation and resistance emerged as distinct but concurrent pathways, each shaped by different psychological and contextual factors. Quantitatively, adaptation was driven primarily by positive motivators such as performance expectancy, social influence, and facilitating conditions. This indicates that employees were more likely to integrate Generative AI in their work practices when they saw clear benefits, received encouragement, and felt supported. Resistance, however, was shaped predominantly by negative affective appraisals, particularly AI-specific anxieties, which significantly increased defensive or avoidance-oriented responses, even when employees acknowledged potential benefits of Generative AI. The qualitative results further expand this interpretation. Employees exhibited a spectrum of behavioral strategies, ranging from enthusiastic “super-users” to cautious experimenters and deliberate resisters. Many occupied a middle position as “selective users”, applying Generative AI for low-risk or efficiency-oriented tasks, while avoiding its application in areas involving judgement, creativity, or accountability. Notably, several employees simultaneously adapted in one part of their workflow and resisted in another, illustrating that adaptation and resistance are not mutually exclusive but can co-exist within the same individual. These responses reflect the nature of Generative AI as an embedded technology: as tools such as Copilot become integrated into core software, employees cannot entirely avoid contact with them, leading to hybrid forms of use. A key nuance that emerged is the role of verification behavior. While in traditional information systems contexts frequent checking of system outputs is interpreted as a form of resistance or distrust, in the context of Generative AI this behavior often reflects responsible and competent use. Given the probabilistic nature and occasionally unpredictable nature of Generative AI tools, verification is not necessarily a sign of reluctance but an inherent aspect of appropriate engagement. This observation extends prior adaptation literature by showing that behaviors historically treated as resistant coping may, for Generative AI, represent rational and safety-oriented use. The coexistence of enthusiasm and apprehension among users highlight the ambivalent nature of Generative AI integration. The interviews highlight why this dual pathway emerges. As Generative AI carries both promise and uncertainty, prompting what some employees described as a “double-edged” experience. While they recognized opportunities for efficiency and support, they also expressed concerns about unpredictability, accuracy, and loss of control over work processes. These mixed emotions aligns with coping theory, which distinguishes between opportunity-focused and threat-focused responses (Beaudry & Pinsonneault, 2005), and contrasts with traditional acceptance models such as UTAUT, which often conceptualize resistance and adoption as opposite ends of a single continuum. Our findings provide empirical support for coping theory's dual pathway perspective and demonstrate that both pathways can be activated simultaneously for the same individual. Together, these results suggest that Generative AI challenges linear models

of technology acceptance. Instead of moving progressively toward full adoption and integration, employees may engage in complex patterns of use that combine adaptation and selective resistance. This indicates that contemporary technology acceptance frameworks may need to be expanded to account for context-specific user responses in which positive and negative evaluations coexist, resulting in hybrid engagement that falls outside classic acceptance boundaries.

led some to restrict their use to specific contexts of double-check outputs extensively, behaviors consistent with resistant coping despite formal adoption. Importantly, however, our findings suggest that verification cannot straightforwardly be interpreted as resistance in the context of Generative AI.

5.3 From Adaptation to Empowerment and performance: psychological and performance outcomes of Generative AI use

One of the most striking findings in this study is that employees' engagement with Generative AI does not only reshape how they work, but also how they feel at work. Our quantitative model reveals a clear pattern: employees who actively adapted to Generative AI reported significantly higher empowerment. Adaptation increased all four dimensions of empowerment, autonomy, competence, meaning and impact, suggesting that as employees adapted to using Generative AI to reshape their way of working they experienced greater ownership over their work, competence increase, and a sense that their contributions made a more meaningful difference. Consequently, employees who resisted integration of Generative AI did not benefit from the empowerment-enhancing experiences associated with using the tool. The qualitative evidence reinforces this pattern. Employees who embraced Generative AI described feeling "freed up", more capable, and more in control of their work. Some noted that Generative AI gives them more space for other things, or helped them improve the quality of their outputs or overcome skill-gaps and helps them perform tasks they previously could not do. In contrast, employees who resisted often expressed disempowerment, feeling that Generative AI threatened their control, undermined their skills or was imposed in ways that reduced their autonomy. Several participants worried that over-reliance on Generative AI could erode their expertise or professional identity, and one participant described the automatic activation of Co-Pilot as taking away the autonomy they need to do their job properly, invading their workspace.

Moving from empowerment to performance, our structural model demonstrates that the performance benefits of Generative AI flow primarily through psychological empowerment rather than direct usage. Adaptation had a modest direct effect on perceived performance, but a much stronger indirect effect via empowerment, indicating that the real value of Generative AI emerges when employees feel more empowered in their work. Consistent with empowerment theory (Spreitzer, 1995) and with empirical evidence showing that empowered employees perform better (Seibert, Wang, & Courtright, 2011). Psychological empowerment emerged as the strongest predictor of employees' perceived performance in the model. Resistance showed a similar pattern, its direct negative effect on performance was modest, but its indirect effect via diminished empowerment was much larger. Together these results show that psychological empowerment is the central mechanism through which employees' behavioral responses to Generative AI translate into perceived performance outcomes. The qualitative findings reinforce and contextualize this pattern as employees who

felt empowered through the use of Generative AI commonly perceived performance gains, being more effective, creative or more focused on higher-value tasks. They often attributed productivity gains to the increased competence or autonomy they experienced when using Generative AI. Conversely, those who felt disempowered described their performance as suffering, for example because of distrusting its outputs or feeling overwhelmed by the changes the tool introduced. This alignment between these described experiences and the quantitative model underscore empowerment as the critical factor shaping how employees interpret the performance implications of Generative AI.

Together, these findings demonstrate that adaptation to Generative AI is not merely a behavioral response, but a consequential process that reshapes employees' sense of empowerment. By identifying psychological empowerment as the primary mechanism through which Generative AI use influences performance, this study extends empowerment theory to the context of AI-enabled work and challenges assumptions that technology use directly improves performance. Moreover, the results highlight disempowerment as a key pathway through which resistance undermines performance, offering a psychological explanation for the performance costs of resistant coping. In doing so, this study contributes to emerging Generative AI research by showing that the benefits of Generative AI depend less on the technology itself and more on the empowerment employees experience as they integrate it into their work.

5.4 Contextual qualitative insights: quality, trust and ethical concerns as cross-cutting influences on the success of Generative AI implementation

This section presents qualitative insights that extend beyond the constructs measured in the quantitative model. The data reveal that employees' engagement is shaped by a range of ongoing concerns about quality, trustworthiness, ethical alignment and the need for clear organizational expectations, direction and longer-term vision for Generative AI. A dominant theme was that while Generative AI improved speed and efficiency, employees viewed its outputs as "fast but not flawless". They consistently emphasized the need to verify the outputs Generative AI produced due to inaccuracies, inconsistencies, or fabricated hallucinated information. This reflects a view of Generative AI as a useful collaborator that nonetheless requires continuous human judgement. Even enthusiastic adapters described verification as an unavoidable part of responsible use of Generative AI, suggesting that the cognitive burden of checking outputs is an integral aspect of AI-enabled work. These concerns extend beyond traditional adoption constructs such as usefulness or ease of use. Employees also raised issues of trust and ethics, including algorithmic bias, lack of transparency about training data or decision logic, and uncertainty about the organization's chosen Generative AI model. Several participants expressed discomfort using tools whose inner workings they did not understand or whose outputs they feared might reinforce stereotypes. These ethical concerns shaped not only whether employees used Generative AI but also how and in which contexts they considered it appropriate. In some cases, perceived misalignment with professional values or doubts about the organization's selected tool fueled selective or even complete resistance.

These insights extend current technology acceptance and Generative AI research in several ways. First, they highlight that with content generating AI, perceived output quality and the

required verification effort are central to user experience yet absent from traditional acceptance theories. As such, the assumption that usefulness straightforwardly leads to performance gains gets challenged when employees must invest additional cognitive work to validate outputs. Second, the emergence of ethical and value-based hesitation among AI-enthusiastic employees suggest that trust in AI is multifaceted encompassing both performance trust and ethical trust. Finally these themes link technology acceptance to the growing literature on responsible AI, indicating that successful implementation requires attending not only to efficiency, but also to trustworthiness, transparency and value alignment. These qualitative insights extend our understanding of the factors shaping Generative AI integration and point to new theoretical directions, including constructs such as AI transparency, perceived bias risk, and verification burden as potential determinants of sustained Generative AI use.

5.5 Managerial implications

Beyond its theoretical contributions, this study offers actionable insights for organizations implementing Generative AI. The findings reveal that successful implementation depends not on the technology itself, but on how organizations create conditions for employee empowerment, adaptation and responsible use. The following sections translate our key findings into practical recommendations.

Fostering employee empowerment through experimentation and learning

Our findings show that Generative AI is not only a technological change, but a psychological one. Employees who adapted to Generative AI experienced substantial increases in psychological empowerment, which in turn drove perceived performance. These results indicate that the success of Generative AI implementation depends not on use alone, but on whether employees feel autonomous, competent, impactful and able to shape how the technology integrates in their work.

To create these conditions, organizations should approach the implementation of Generative AI as an empowerment challenge, rather than a technology deployment task. This requires moving from introducing a tool to building an environment in which employees can experiment, influence and grow with it. Four strategic actions follow directly from the evidence:

1. Give employees influence over how Generative AI is integrated into their work, instead of mandating uniform use. Participation and local adaptation strengthen autonomy and ownership.
2. Build empowerment-oriented learning environments, shifting from one-off training to ongoing, hands-on exploration. Employees benefit most when they can learn by doing, try, fail, iterate and see progress over time.
3. Create legitimate time and space for experimentation, signalling that exploration of Generative AI is valued, preventing it from being deprioritized amid daily tasks. This includes protected practice time and pilot environments.
4. Develop peer-led learning structures such as communities of practice, Generative AI “champions”, and space for informal knowledge exchange. Our qualitative findings suggest that social learning accelerates adaptation more effectively than top-down instruction.

Transforming resistance into constructive dialogue

Employee resistance to Generative AI is not simply a refusal to the technology. Quantitatively, resistance was negatively associated with empowerment and performance, while interviews revealed that that reluctance frequently emerged from feelings of lost control, uncertainty about value, or concerns about identity and ethics. Rather than interpreting resistance as opposition to be eliminated, organizations should treat it as information about unmet requirements for safe and meaningful implementation. Resistance can therefore be framed as threat-focused coping (Beaudry & Pinsonneault, 2005). When employees perceive Generative AI as a risk to a skill, privacy, competence, or fairness, defensive responses such as avoidance, or minimal compliance are rational. Implementation success depends not on suppressing these reactions, but on opening opportunities for dialogue and co-ownership. Three practical implications would be:

1. Create safe channels for employees to express reservation without judgement or career consequences. This could be regular dialogue sessions, Q&A hours or anonymous feedback channels, which would encourage honest reporting of issues before they escalate into disengagement.
2. Address the roots of the resistance rather than the surface behavior. If reluctance stems from skill gaps, offer coaching. If it stems from identity threat, emphasize augmentation, not replacement and if it comes from ethical or trust concerns, increase transparency and clarify measures taken for responsible use.
3. Shift from universal adoption to role-sensitive integration. Employees in the study did not want generic demonstrations, they wanted to know “how can this tool work for me in my specific role”. Co-developing workflows with teams creates relevance, reduces ambiguity and preserves expertise and craftsmanship rather than eroding it.

When organizations respond to resistance with empathy and participatory design, resistance becomes a source of insight rather than friction. Constructive resistance generates learning: it surfaces risks, may shape better workflows and helps to build trust in both the technology and implementation process. This way, resistance is not a threat to Generative AI implementation, it provides a more inclusive and sustainable integration approach.

Developing a clear organizational vision for Generative AI

Managers play a central role in translating organizational vision for Generative AI into everyday practice. Employees in this study emphasized that they want to see that Generative AI is not adopted merely because “everyone is doing it”, but because it serves a clear strategic purpose. When rationale is vague, engagement weakens, but when vision and value are transparent, willingness to experiment and integrate increases.

Leaders should therefore define and communicate a compelling “dot on the horizon”, as one of the participants formulated. They should convey a long-term purpose for Generative AI that aligns with organizational goals and societal contribution. Effective implementation requires both strategic clarity and local autonomy. This means not only explaining why Generative AI matters, but also enabling teams to determine how it can meaningfully support their work.

Key actions for leadership include:

1. Communicating a clear reason for the implementation and how it strengthens the organization’s mission.

2. Setting realistic expectations, avoiding both overhyping and oversimplification
3. Demonstrating commitment through visible usage and ongoing dialogue
4. Empowering teams to adapt Generative AI to their specific tasks, processes and expertise.

When employees understand both the purpose and practical application of Generative AI, implementation becomes much more credible, grounded and sustainable.

Implementing data governance and responsible use frameworks

A final implication for implementation concerns the role of organizational governance in enabling responsible Generative AI use. Across interviews, employees consistently expressed uncertainty about what happens to their input data, how outputs are stored and shared, and where the boundaries of appropriate use lie. Even employees who were technically enthusiastic reported hesitation due to unclear guidance on privacy, risk, and accountability. In this sense the ambiguity became a barrier, people were not resisting the technology itself, but the risk of using it wrong. To support confident and ethical adoption, organizations must establish transparent data governance frameworks. These should clearly outline what kinds of tasks are suitable for Generative AI, what specific Generative AI tool works best for what task, how sensitive information should be handled and who bears responsibility for decisions supported or generated by AI.

Effective governance should include:

1. Clear, accessible AI-use policies specifying applications and data handling rules
2. Transparent communication about how data is processed, stored and protected
3. Visible accountability mechanisms and ethical review processes
4. Framing governance as an enabler of innovation rather than a compliance barrier

When employees understand the safeguards in place and feel secure in their responsibilities, they are more willing to use Generative AI confidently and creatively. Robust governance therefore functions not only as risk mitigation, but as a foundation for empowerment, trust, and sustained, responsible integration for Generative AI.

Tailoring implementation across roles and organizational levels

A final implications concerns how implementation should be deployed across the organization. The findings show that Generative AI adoption and adaptation is not uniform: employees vary in skill level, trust and identity alignment. Some become enthusiasts, others experiment cautiously, and some resist. A single rollout strategy would not meet these diverse needs. To translate the earlier recommendations into practice, implementation should be tiered across organizational levels

- Senior leadership: Set vision, governance and long term direction.
- Middle management: Converts vision into practical workflows and role-specific guidance
- Teams and individuals: localize use, experiment and shape task level integration

This layered approach acknowledges that Generative AI implementation is not only a technical upgrade, but a distributed organizational change process. Instead of striving for

uniform adoption, organizations should strive for contextual adoption: Also adapting Generative AI to the work, not only forcing the work to adapt to the technology.

Specific implications for TNO

Based on the findings of this study, five priority actions are recommended for TNO to strengthen their Generative AI implementation and maximize employee empowerment and performance. These recommendations translate the study's insights into concrete steps to foster responsible, empowering and sustainable integration of Generative Ai across the organization.

1. Create protected experimentation time and peer led-learning communities rather than relying solely on formal training
2. Translate resistance into dialogue through safe feedback channels that address root causes
3. Communicate clear strategic vision explaining why Generative AI matters for TNO's mission, not just that it is being implemented
4. Establish transparent governance, clarifying appropriate use, data handling and accountability as empowerment enabler
5. Adopt tiered, role-sensitive rollout with co-developed workflows instead of universal mandates

5.6 Limitations

This study is not without limitations. The survey and interviews were cross-sectional, which limits causal inference. Although the hypothesized relationships were theoretically grounded, longitudinal data would be needed to confirm the temporal dynamics between adaptation, empowerment and perceived performance. Second, all data were self-reported, which may introduce common method bias and social desirability effects. Third, the research was conducted within a single organization (TNO), which was characterized by a highly educated and skilled workforce, limiting the generalizability of the findings to other organizational contexts. This organization formally rolled out Microsoft Copilot; however, employees also reported using other Generative AI tools. This single-site, mixed-tool context limits external validity and introduces heterogeneity in tool experience. Different systems offer varying capabilities, interfaces, and governance, which may influence appraisals of trust, anxiety, and trialability and potentially attenuate observed effects.

Fourth, the multi-group analyses should be interpreted with caution due to unequal subgroup sizes and partial measurement invariance across groups. Fifth, despite statistical evidence of discriminant validity, conceptual overlap may exist among certain variables due to their behavioral interconnections. Interview participation was voluntary, raising the possibility of self-selection bias. Data were collected during an early, largely voluntary stage of implementation with evolving policies; perceptions and behaviors may change as GenAI becomes routinized and governance matures. The qualitative phase was coded by the researcher alone, which introduces the possibility of researcher bias and prevents formal inter-coder reliability assessment.

Together, these limitations do not diminish the value of the findings, but they define the boundaries within which the conclusions should be interpreted and highlight opportunities for future research.

5.7 Future research

Given that Generative AI implementation is still in its early, rapidly evolving stage, future studies should use longitudinal methods to capture adaptation dynamics over time. Tracking the same employees (or teams) across multiple time points would reveal how empowerment, resistance and performance evolve as Generative AI tools mature and policies stabilize. Longitudinal data would show whether initially empowering effects of GenAI persist, grow, or fade as usage becomes routine.

Second, while this study focused on individual perceptions, Generative AI's impact likely extends to collective outcomes. Future work could compare teams or units that embrace Generative AI to those that resist it, examining differences in productivity, collaboration, innovation, and error rates. For example, do teams that proactively integrate GenAI tools complete projects faster, generate more novel ideas, or collaborate more smoothly than teams that avoid AI? One recent longitudinal field study found that GenAI adoption boosted individual productivity but did not by itself resolve core teamwork challenge. This suggests important open questions: how do team processes and organizational support systems moderate these effects, and what metrics (e.g. project success, innovation output, quality) best capture GenAI's value at the group level?

Third, there would be strong value in intervention-based research on how management actions shape adaptation. Prior integrative reviews highlight the need to study specific organizational practices (such as AI accessibility, human-in-the-loop oversight, and transparent governance) that help employees align with and accept AI. Researchers could implement and evaluate targeted interventions – for instance, randomized training programs, revised incentive structures, or new AI-use policies – to test their effects on employee anxiety, resistance, and empowerment. Such experimental or quasi-experimental designs would offer causal evidence about which managerial levers (e.g. enhanced training, clear ethical guidelines, role-appropriate incentives) most effectively reduce resistance and foster positive outcomes.

Finally, several nuanced factors emerged as underdeveloped areas. Employee adaptation to GenAI may vary widely across roles and tasks: for example, front-line knowledge workers might focus on efficiency gains while managers or specialists may worry more about oversight and decision-quality. Theoretical models even predict that improved GenAI reliability could shift organizational structure (e.g. requiring more managerial oversight to validate outputs). Ethical and identity concerns also appear critical. Participants in this and other studies voiced worries about data privacy, fairness, and the erosion of professional expertise. Indeed, research on GenAI suggests that its innovation and performance benefits depend on how organizations manage ethical dilemmas. Future studies should therefore examine how moral judgments, professional identity, or regulatory context influence GenAI use. For instance, scholars could analyze whether certain groups (by function, seniority, or domain) use GenAI selectively (e.g. for ideation but not final review) and how this affects team innovation. Systematically studying these variables, potentially through case comparisons or mixed methods, would extend the present work by uncovering the boundary conditions of GenAI adaptation.

In sum, future research should move beyond adoption intention toward dynamic, multi-level, and intervention-based examinations of how Generative AI reshapes work, identity, and performance over time.

6 Conclusion

The rapid integration of Generative AI into organizational workflows represents one of the most significant technological transformations in recent history. While strategic discussions have centred on efficiency gains and competitive advantage, the human experience of this transformation has remain underexplored. This study has addressed a critical gap by investigating how employees experience and respond to Generative AI, and how these experiences shape their psychological empowerment and perceived individual performance. Guided by an integrated framework combining the Unified Theory of Acceptance and Use of Technology (UTAUT), user adaptation theory, and psychological empowerment theory, this research employed a sequential mixed-methods design. Quantitative data from 363 employees and qualitative insights from 14 follow-up interviews revealed that the implementation of Generative AI is not merely a technical upgrade, but a deeply psychological process that reshapes how employees experience empowerment and performance in their work.

Employees' experiences with Generative AI implementation are characterized by a spectrum of engagement ranging from enthusiastic adaptation to principled resistance. This study demonstrates that these responses are not simply binary choices between acceptance and rejection, but rather complex coping strategies that are shaped by cognitive appraisals, emotional reactions, and organizational context. The central finding is that adaptation to Generative AI functions as a psychologically empowering process. Employees who actively adapted their work practices to integrate Generative AI experienced significantly greater psychological empowerment across all dimensions, which in turn enhanced perceived individual performance. This study reveals that psychological empowerment serves as the primary mechanism through which Generative AI use translates into performance benefits. When employees feel that Generative AI enhances their control, capability, and contribution at work, they perceive themselves as more productive, effective and creative. These experiences are shaped by multiple interacting factors. Performance expectancy emerged as the strongest predictor of adaptation, while emotional trust and AI-anxiety played critical affective roles. Surprisingly, effort expectancy, cognitive trust and trialability showed no significant effects, suggesting that in post-adoption contexts with intuitive interfaces, these traditional acceptance factors become baseline expectations rather than differentiators. Employees experience Generative AI implementation not as a neutral tool adoption but as a transformation that either empowers or disempowers them, depending on how they engage with it, how organizations support them, and how well the technology aligns with their values and work identity. The findings highlight that empowering outcomes do not emerge automatically from Generative AI implementation, but from the conditions organizations create around it. Employees value freedom to experiment, space to adapt tools to their work and the feeling that they can shape rather than merely follow technological change. Equally important is clear leadership direction, a shared organizational horizon that explains why Generative AI is introduced, what future the organization envisions, and how employees play a role within it. Organizations should combine bottom-up experimentation with top-down vision, supported by transparency, psychological safety, and the necessary resources that enable learning rather than enforcement of use.

The implementation of Generative AI represents far more than a technological upgrade. It is a fundamental restructuring process of how work is experienced, valued and performed. This study has shown that successful implementation depends not on the sophistication of the technology, but on psychological conditions that allow employees to integrate it in empowering ways. Organizations that approach Generative AI as merely a tool will likely struggle. As Generative AI continues to evolve and spread throughout organizations, the central challenge remains profoundly human: creating conditions where employees feel empowered rather than displaced, augmented rather than replaced and more capable of meaningful contribution rather than less. The findings of this study suggest that when organizations get this human dimension right, Generative AI becomes not a threat to employee wellbeing, but could become a pathway to it.

7 References

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Appendix

Appendix A: Interview guide

Question 1: Can you briefly introduce yourself? What is your role within TNO and what are your daily activities?

Question 2: When you look at your work in general, what makes you choose to use Generative AI in some cases and not/avoid it in others?

- Can you give an example?
- What factors influence your choice?

Question 2b: Tell me about how others around you use or talk about GenAI.

- How has that influenced the way you use it?

Question 3: Can you describe a recent task where you used GenAI, or could have used it but didn't? How did you approach it, and what was the result?

Question 4: Where has Generative AI clearly improved your work, and where has it made little to no difference?

- *Have you seen or heard examples where GenAI helped others in their work? What do you think about that?*

Question 5: How natural or comfortable does it feel to use Generative AI?

- What makes it feel that way?

Question 6: Have you ever felt uneasy or anxious about using GenAI, what caused that?

- What happened then?
- Where does that feeling come from?
- What would help to reduce it?
- Are there also ethical or societal concerns that play a role for you in using GenAI?

Question 7: Have you received support, training, or other help for using Generative AI? (Possible examples?) How did this help, or not?

Question 8a: Since Generative AI has been available, have you noticed any change in how you experience your work? *Do you think your work would change if you used GenAI more often? In what way?*

- More or less freedom? (autonomy)
- More or less confidence/self-assurance? (competence)
- More or less meaningful? (meaning)
- More or less influence? (impact)

Question 8b: How has Generative AI changed your work results? What has stood out the most to you?

- Faster?
- Better quality?
- More creative, thinking differently about things?

Question 9: If Generative AI were to disappear tomorrow, what would change in your work, both positively and negatively?

Question 10: How have you experienced the implementation of Generative AI here at TNO?

Question 11: How could Generative AI help you even better in your work in the future?

Question 12: Is there anything you would like to add? Do you have ideas or suggestions for how Generative AI could be better used here?

Appendix B: f square scores

	f-square
Adaptability -> Perceived performance	0.037
Adaptability -> Psychological empowerment	0.231
AI Anxiety -> Adaptability	0.000
AI Anxiety -> Resistance	0.113
Cognitive Trust -> Adaptability	0.013
Cognitive Trust -> Resistance	0.008
Effort Expectancy -> Adaptability	0.003
Effort Expectancy -> Resistance	0.010
Emotional trust -> Adaptability	0.063
Emotional trust -> Resistance	0.099
Facilitating conditions -> Adaptability	0.014
Facilitating conditions -> Resistance	0.000
Performance Expectancy -> Adaptability	0.133
Performance Expectancy -> Resistance	0.216
Psychological empowerment -> Perceived performance	0.688
Resistance -> Perceived performance	0.026
Resistance -> Psychological empowerment	0.191
Social Influence -> Adaptability	0.016
Social Influence -> Resistance	0.000
Trialability -> Adaptability	0.012
Trialability -> Resistance	0.009

Appendix C: Micom results

Gender Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.997	0.968	0.878	0.817
Adaptability	0.997	0.996	0.989	0.471
Cognitive Trust	0.997	0.994	0.981	0.485
Effort Expectancy	1.000	0.999	0.998	0.458
Emotional trust	0.999	0.999	0.998	0.330
Facilitating conditions	0.992	0.990	0.970	0.428
Perceived performance	1.000	0.992	0.975	0.959
Performance Expectancy	1.000	1.000	0.999	0.360
Psychological empowerment	0.991	0.988	0.969	0.499
Resistance	0.999	0.998	0.993	0.794
Social Influence	0.985	0.984	0.953	0.378
Training	1.000	1.000	1.000	0.528
Triability	1.000	0.995	0.981	0.992

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.242	0.000	-0.220	0.220	0.030
Adaptability	-0.183	0.002	-0.226	0.223	0.116
Cognitive Trust	-0.028	-0.001	-0.218	0.222	0.868
Effort Expectancy	-0.135	0.000	-0.216	0.229	0.242
Emotional trust	-0.089	0.001	-0.221	0.228	0.438
Facilitating conditions	-0.115	0.001	-0.221	0.222	0.313
Perceived performance	-0.011	0.000	-0.221	0.221	0.924
Performance Expectancy	-0.092	0.000	-0.216	0.218	0.412
Psychological empowerment	-0.175	0.001	-0.215	0.223	0.186
Resistance	-0.015	0.000	-0.222	0.215	0.893
Social Influence	0.038	-0.002	-0.217	0.219	0.730
Training	0.156	0.000	-0.102	0.104	0.002
Triability	-0.101	0.003	-0.218	0.222	0.372

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.147	-0.007	-0.357	0.325	0.393
Adaptability	-0.139	-0.008	-0.303	0.278	0.348
Cognitive Trust	-0.028	-0.011	-0.322	0.283	0.871
Effort Expectancy	-0.043	-0.014	-0.363	0.316	0.806
Emotional trust	-0.046	-0.012	-0.311	0.267	0.764
Facilitating conditions	-0.001	-0.009	-0.325	0.295	0.995
Perceived performance	-0.407	-0.016	-0.455	0.387	0.063
Performance Expectancy	-0.332	-0.012	-0.408	0.368	0.097
Psychological empowerment	-0.240	-0.011	-0.310	0.280	0.180
Resistance	-0.297	-0.009	-0.335	0.310	0.068
Social Influence	-0.091	-0.008	-0.346	0.318	0.607
Training	0.206	-0.006	-0.184	0.146	0.019
Triability	-0.426	-0.012	-0.389	0.338	0.021

Under 35 vs 35-44

Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.863	0.942	0.770	0.089
Adaptability	0.996	0.994	0.982	0.523
Cognitive Trust	0.987	0.993	0.978	0.143
Effort Expectancy	1.000	0.998	0.993	0.964
Emotional trust	1.000	0.998	0.995	0.782
Facilitating conditions	0.999	0.971	0.905	0.961
Perceived performance	0.963	0.984	0.955	0.088
Performance Expectancy	0.999	0.999	0.998	0.062
Psychological empowerment	0.978	0.978	0.944	0.421
Resistance	0.997	0.996	0.987	0.538
Social Influence	0.942	0.951	0.868	0.235
Training	1.000	1.000	1.000	0.144
Triability	0.993	0.978	0.929	0.586

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	-0.192	0.000	-0.273	0.278	0.169
Adaptability	0.282	-0.002	-0.281	0.264	0.044
Cognitive Trust	-0.043	-0.004	-0.282	0.265	0.737
Effort Expectancy	0.568	-0.003	-0.281	0.273	0.000
Emotional trust	0.421	-0.004	-0.280	0.270	0.004
Facilitating conditions	0.507	-0.002	-0.276	0.282	0.000
Perceived performance	0.399	-0.005	-0.286	0.283	0.003
Performance Expectancy	0.430	-0.002	-0.276	0.283	0.002
Psychological empowerment	0.313	-0.003	-0.275	0.279	0.009
Resistance	-0.381	0.004	-0.275	0.279	0.007
Social Influence	-0.213	0.002	-0.273	0.287	0.133
Training	-0.019	0.001	-0.120	0.123	0.863
Triability	0.181	-0.004	-0.280	0.279	0.196

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	-0.059	0.010	-0.431	0.467	0.810
Adaptability	-0.036	0.008	-0.370	0.404	0.858
Cognitive Trust	0.181	0.006	-0.377	0.406	0.374
Effort Expectancy	-0.546	0.012	-0.461	0.500	0.023
Emotional trust	-0.329	0.010	-0.360	0.395	0.087
Facilitating conditions	-0.096	0.013	-0.417	0.448	0.651
Perceived performance	-0.325	0.014	-0.405	0.357	0.236
Performance Expectancy	-0.426	0.016	-0.455	0.515	0.087
Psychological empowerment	-0.472	0.008	-0.367	0.397	0.015
Resistance	-0.141	0.012	-0.389	0.430	0.515
Social Influence	0.050	0.008	-0.434	0.459	0.822
Training	-0.050	0.011	-0.299	0.387	0.842
Triability	-0.715	0.014	-0.441	0.464	0.002

Under 35 vs 45-54

Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.735	0.924	0.713	0.075
Adaptability	0.998	0.995	0.984	0.650
Cognitive Trust	0.584	0.994	0.981	0.073
Effort Expectancy	0.999	0.999	0.996	0.669
Emotional trust	1.000	0.998	0.994	0.984
Facilitating conditions	0.989	0.972	0.919	0.652
Perceived performance	0.971	0.985	0.957	0.134
Performance Expectancy	0.999	0.999	0.998	0.185
Psychological empowerment	0.972	0.979	0.948	0.264
Resistance	0.999	0.996	0.987	0.831
Social Influence	0.961	0.957	0.877	0.354
Training	1.000	1.000	1.000	0.105
Triability	0.999	0.976	0.922	0.920

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	-0.263	-0.002	-0.282	0.281	0.067
Adaptability	0.210	0.001	-0.271	0.278	0.141
Cognitive Trust	0.594	0.001	-0.278	0.288	0.702
Effort Expectancy	0.783	-0.001	-0.273	0.278	0.000
Emotional trust	0.475	0.000	-0.268	0.277	0.001
Facilitating conditions	0.650	-0.002	-0.283	0.278	0.000
Perceived performance	0.325	0.000	-0.280	0.279	0.022
Performance Expectancy	0.388	0.000	-0.272	0.277	0.006
Psychological empowerment	0.326	0.001	-0.275	0.280	0.022
Resistance	-0.246	-0.003	-0.284	0.271	0.082
Social Influence	-0.146	-0.003	-0.290	0.281	0.316
Training	-0.154	0.000	-0.133	0.133	0.020
Triability	0.349	0.000	-0.282	0.281	0.017

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	-0.021	0.011	-0.407	0.440	0.923
Adaptability	-0.124	0.010	-0.360	0.392	0.531
Cognitive Trust	0.115	0.014	-0.369	0.411	0.582
Effort Expectancy	-0.776	0.018	-0.444	0.510	0.001
Emotional trust	-0.324	0.015	-0.376	0.418	0.111
Facilitating conditions	-0.294	0.019	-0.389	0.451	0.178
Perceived performance	-0.502	0.017	-0.522	0.588	0.074
Performance Expectancy	-0.476	0.014	-0.482	0.541	0.069
Psychological empowerment	-0.358	0.013	-0.368	0.418	0.077
Resistance	-0.246	0.009	-0.378	0.410	0.214
Social Influence	-0.105	0.014	-0.417	0.443	0.635
Training	-0.267	0.009	-0.235	0.305	0.043
Triability	-0.550	0.013	-0.464	0.501	0.027

Under 35 vs 55+

Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.979	0.986	0.958	0.164
Adaptability	0.999	0.996	0.990	0.767
Cognitive Trust	0.999	0.988	0.966	0.022
Effort Expectancy	0.999	0.998	0.995	0.544
Emotional trust	1.000	0.998	0.994	0.780
Facilitating conditions	0.990	0.984	0.951	0.470
Perceived performance	0.944	0.983	0.949	0.037
Performance Expectancy	1.000	0.999	0.998	0.611
Psychological empowerment	0.966	0.972	0.929	0.306
Resistance	0.998	0.996	0.987	0.716
Social Influence	0.943	0.973	0.930	0.077
Training	1.000	1.000	1.000	0.115
Triability	1.000	0.973	0.909	0.957

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	-0.259	-0.002	-0.293	0.284	0.079
Adaptability	0.333	0.003	-0.283	0.287	0.021
Cognitive Trust	-0.110	0.000	-0.276	0.296	0.461
Effort Expectancy	0.691	0.004	-0.289	0.286	0.000
Emotional trust	0.310	0.003	-0.281	0.280	0.028
Facilitating conditions	0.561	0.004	-0.283	0.300	0.000
Perceived performance	0.423	0.001	-0.288	0.287	0.008
Performance Expectancy	0.288	0.003	-0.284	0.292	0.049
Psychological empowerment	0.328	0.002	-0.281	0.287	0.023
Resistance	-0.108	-0.002	-0.294	0.277	0.466
Social Influence	-0.164	0.002	-0.292	0.290	0.276
Training	-0.245	-0.001	-0.137	0.144	0.001
Triability	-0.101	0.003	-0.284	0.306	0.511

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	-0.166	0.011	-0.359	0.398	0.380
Adaptability	-0.009	0.012	-0.374	0.427	0.964
Cognitive Trust	0.463	0.016	-0.397	0.451	0.031
Effort Expectancy	-0.407	0.013	-0.420	0.475	0.077
Emotional trust	-0.217	0.012	-0.397	0.428	0.399
Facilitating conditions	-0.179	0.010	-0.417	0.454	0.436
Perceived performance	-0.051	0.024	-0.561	0.671	0.879
Performance Expectancy	-0.269	0.019	-0.536	0.593	0.361
Psychological empowerment	-0.214	0.017	-0.378	0.435	0.316
Resistance	-0.240	0.012	-0.397	0.447	0.260
Social Influence	-0.205	0.014	-0.420	0.457	0.383
Training	-0.312	0.008	-0.191	0.282	0.014
Triability	-0.590	0.012	-0.407	0.465	0.010

Age 35-44 vs 45-54

Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.969	0.840	0.999	0.717
Adaptability	0.999	0.992	0.975	0.907
Cognitive Trust	0.998	0.990	0.965	0.718
Effort Expectancy	0.999	0.999	0.997	0.249
Emotional trust	1.000	0.999	0.998	0.599
Facilitating conditions	0.985	0.961	0.888	0.718
Perceived performance	0.999	0.988	0.962	0.940
Performance Expectancy	1.000	1.000	0.999	0.804
Psychological empowerment	0.982	0.983	0.957	0.386
Resistance	0.997	0.996	0.987	0.476
Social Influence	0.993	0.966	0.898	0.870
Training	1.000	1.000	1.000	0.102
Triability	0.996	0.997	0.989	0.277

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.066	-0.002	-0.322	0.318	0.694
Adaptability	0.078	0.002	-0.314	0.315	0.638
Cognitive Trust	-0.116	0.001	-0.318	0.312	0.472
Effort Expectancy	-0.250	0.002	-0.314	0.314	0.117
Emotional trust	-0.050	0.003	-0.306	0.317	0.765
Facilitating conditions	-0.186	0.001	-0.306	0.317	0.243
Perceived performance	0.030	0.002	-0.316	0.318	0.856
Performance Expectancy	0.039	0.002	-0.316	0.317	0.810
Psychological empowerment	-0.030	0.003	-0.310	0.324	0.853
Resistance	-0.126	0.000	-0.325	0.316	0.451
Social Influence	-0.011	-0.001	-0.310	0.320	0.941
Training	0.135	0.001	-0.153	0.161	0.085
Triability	-0.129	0.002	-0.306	0.314	0.416

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.052	0.006	-0.574	0.568	0.853
Adaptability	0.089	0.003	-0.407	0.412	0.679
Cognitive Trust	0.042	-0.002	-0.389	0.381	0.828
Effort Expectancy	0.232	0.001	-0.459	0.465	0.330
Emotional trust	-0.006	0.001	-0.403	0.400	0.979
Facilitating conditions	0.226	0.002	-0.411	0.413	0.292
Perceived performance	0.159	0.001	-0.524	0.537	0.582
Performance Expectancy	0.043	-0.001	-0.497	0.495	0.864
Psychological empowerment	-0.114	0.002	-0.400	0.413	0.598
Resistance	0.110	0.002	-0.461	0.466	0.654
Social Influence	0.114	-0.002	-0.461	0.461	0.632
Training	0.217	0.001	-0.249	0.262	0.075
Triability	-0.183	0.002	-0.483	0.488	0.466

Age 35-44 vs 55+

Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.953	0.955	0.827	0.273
Adaptability	0.997	0.993	0.980	0.705
Cognitive Trust	0.985	0.976	0.915	0.416
Effort Expectancy	0.999	0.999	0.997	0.264
Emotional trust	1.000	0.999	0.998	0.688
Facilitating conditions	0.979	0.980	0.939	0.334
Perceived performance	0.974	0.985	0.955	0.182
Performance Expectancy	0.999	1.000	0.999	0.179
Psychological empowerment	0.985	0.977	0.943	0.595
Resistance	0.997	0.996	0.987	0.412
Social Influence	0.999	0.981	0.945	0.989
Training	1.000	1.000	1.000	0.239
Triability	0.994	0.996	0.986	0.232

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.113	-0.002	-0.328	0.324	0.509
Adaptability	-0.040	0.003	-0.315	0.330	0.816
Cognitive Trust	0.048	0.003	-0.324	0.319	0.759
Effort Expectancy	-0.103	0.001	-0.316	0.319	0.543
Emotional trust	0.122	0.005	-0.313	0.326	0.469
Facilitating conditions	-0.060	0.002	-0.325	0.326	0.719
Perceived performance	-0.016	0.003	-0.326	0.321	0.927
Performance Expectancy	0.144	0.002	-0.327	0.330	0.389
Psychological empowerment	0.017	0.002	-0.321	0.329	0.920
Resistance	-0.266	-0.003	-0.328	0.328	0.112
Social Influence	0.004	0.004	-0.318	0.326	0.980
Training	0.226	0.001	-0.156	0.171	0.006
Triability	0.276	0.004	-0.327	0.335	0.105

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.218	-0.003	-0.508	0.491	0.387
Adaptability	-0.029	-0.005	-0.444	0.424	0.898
Cognitive Trust	-0.260	-0.009	-0.427	0.423	0.226
Effort Expectancy	-0.135	-0.001	-0.458	0.448	0.568
Emotional trust	-0.104	0.005	-0.400	0.400	0.616
Facilitating conditions	0.121	-0.001	-0.415	0.403	0.552
Perceived performance	-0.223	-0.013	-0.628	0.598	0.474
Performance Expectancy	-0.159	-0.009	-0.567	0.548	0.582
Psychological empowerment	-0.256	-0.008	-0.429	0.421	0.238
Resistance	0.102	-0.008	-0.516	0.468	0.681
Social Influence	0.221	-0.005	-0.479	0.474	0.380
Training	0.262	-0.001	-0.189	0.196	0.010
Triability	-0.159	-0.006	-0.471	0.478	0.510

Age 45-54 vs 55+

Step 2

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
AI Anxiety	0.883	0.959	0.847	0.076
Adaptability	0.997	0.994	0.983	0.603
Cognitive Trust	0.984	0.979	0.923	0.373
Effort Expectancy	1.000	1.000	0.999	0.513
Emotional trust	1.000	0.999	0.998	0.730
Facilitating conditions	0.987	0.986	0.962	0.425
Perceived performance	0.984	0.988	0.964	0.274
Performance Expectancy	1.000	0.999	0.998	0.484
Psychological empowerment	0.984	0.979	0.945	0.522
Resistance	0.999	0.996	0.987	0.802
Social Influence	0.992	0.981	0.940	0.692
Training	1.000	1.000	1.000	0.348
Triability	1.000	0.994	0.978	0.884

Step 3a

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.032	0.002	-0.329	0.318	0.850
Adaptability	-0.127	-0.002	-0.328	0.317	0.434
Cognitive Trust	0.171	-0.001	-0.316	0.328	0.311
Effort Expectancy	0.155	-0.005	-0.327	0.307	0.357
Emotional trust	0.172	0.000	-0.318	0.319	0.301
Facilitating conditions	0.118	-0.002	-0.322	0.319	0.480
Perceived performance	-0.009	-0.002	-0.322	0.324	0.959
Performance Expectancy	0.105	-0.002	-0.323	0.327	0.530
Psychological empowerment	0.050	-0.002	-0.315	0.323	0.771
Resistance	-0.131	0.001	-0.322	0.327	0.431
Social Influence	0.010	0.001	-0.321	0.325	0.966
Training	0.091	-0.002	-0.156	0.146	0.299
Triability	0.401	0.001	-0.328	0.333	0.016

Step 3b

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
AI Anxiety	0.142	-0.001	-0.465	0.456	0.555
Adaptability	-0.131	-0.007	-0.439	0.416	0.539
Cognitive Trust	-0.314	-0.004	-0.412	0.402	0.130
Effort Expectancy	-0.368	-0.003	-0.468	0.437	0.112
Emotional trust	-0.103	-0.005	-0.414	0.423	0.640
Facilitating conditions	-0.122	-0.006	-0.410	0.409	0.567
Perceived performance	-0.325	-0.009	-0.657	0.614	0.306
Performance expectancy	-0.207	-0.008	-0.600	0.593	0.505
Psychological empowerment	-0.134	-0.008	-0.431	0.409	0.535
Resistance	0.002	-0.003	-0.472	0.458	0.993
Social Influence	0.114	-0.003	-0.456	0.454	0.630
Training	0.045	-0.002	-0.084	0.071	0.299
Triability	0.029	-0.002	-0.533	0.508	0.907

Appendix D: Codes per theme

1.1 codes

Performance
Expectancy
Productivity
Applications of
Generative AI

Benefits
Advantages

1.2 codes

Ease of use
Usability
Effort expectancy
Comfort
Habit/Established
habits
Adaptation

1.3 codes

Social influence
UTAUT
Low social influence
Resistance to social
influence

1.4 codes

Facilitating conditions
Training
Organizational policy
Tool limitation
Organizational barriers
Satisfaction with rollout
Tool limitation
Uncertainty about
adoption
Development GenAI

2.1 codes

Adoption
Early
adopter/Frontrunner
Comfort with GenAI
Habit formation
Adaptation

Adoption out of self-interest
Applications of Generative AI
Visionary

2.2 codes
AI Anxiety
Concerns
Established old habits
Active non-AI use
Skepticism and critique
Adoption out of self-interest

2.3 codes
Boundary of use
Active non-application of Generative AI
NOT FINISHED

2.4 codes
Adoption: individual differences
AI anxiety
Adoption: task dependency, role based differences
Adoption: out of self interest
Adoption: Transparency, disclosure of AI use
Adoption: Crisis as a accelerator
Adaptation
Acknowledgement of different needs
Adoption: limited dependency
Generational differences

3.1 codes
Autonomy
Control
Only doesn't use if not allowed
Autonomy: wants to be in control
Collective discussions about application?
Autonomy without GenAI
Forced roll out
Transparency, disclosure of AI use

3.2 codes

Concern: dependency on GenAI
Decreasing human ability: skills. Critical thinking
Competence
Feeling less competent
Increasing insecurity due to GenAI
Loss of Authenticity
AI anxiety

3.3 codes
Integrity
Meaning
Loss of authenticity
Acknowledgement of potential

3.4 codes
Impact
Limited impact of GenAI
Lack of impact due to tool choice
Acknowledgement of potential
No change in work due to limited use
Applications of GenAI

3.5 codes
Job displacement
Lack of trust in the output
Discomfort with GenAI
AI anxiety

4.1 code
Perceived performance: Productivity
Coding/debugging
Searching information
Summarizing inputs
Efficiency threshold (no time saved)
Time-consuming to learn to use Generative AI
Writing texts

4.2 code
User responsibility for the output
Quality improvements
Low cognitive trust
Cognitive trust
Critical about its output
No quality improvement
Lack of trust in output
Factual inaccuracy

Code 4.3
Creativity
No creativity improvement
Decreasing human ability: creativity
Future vision: potential for brainstorming
Applications of Generative AI:

Code 5.1
Training
Training barriers
Not supplying for frontrunners
Need for training
Specific trainings for specific roles
Acknowledgement of diversity of needs
Training criticism
Important that everyone is trained
Peer learning

Code 5.2
Vendor Lock-In
Tool comparison
Tool limitation: copilot
Tool limitation
Tool choice affects competitiveness
Over integration (copilot)

Code 5.3
Organizational policy: clear rules
Uncertainty about adoption within organisation
Organizational gap: unclear time/resource expectations
Organisational critique: jumping too fast into it
Organizational barriers: delay/silence
Integrity office
Organizational communication: intranet
Organizational barrier: only com via intranet
Organizational barrier; identity tension
Organizational barrier unclear policy
Technical expertise missing from the program
Too bureaucratic, therefore inefficient

Organizational adoption gap
Facilitating conditions
Lack of long term vision

6.1 Code
Bias
Risk of bias reinforcement
Trust, systematic bias
Transparency, disclosure of AI use
Black box
Risk of echochamber

Code 6.2
Environmental concerns
No environmental concerns
Limited knowledge about environmental concerns

Code 6.2
Separation of groups: Western benefit
Fear of harmful applications
Manipulation by big tech