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# GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior

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A B S T R A C T

Innovation is critical for organizational success, with employees' innovative work behavior (IWB) forming a key microfoundation of firm-level innovation. While prior research has identified various antecedents of IWB, the role of generative AI (GenAI) remains underexplored. We address this gap by investigating how employees' capabilities to use and evaluate GenAI influence their IWB. Building on the dynamic capabilities view, we further explore how employees' capabilities to sense technological shifts shape the development of these GenAI capabilities and ultimately foster IWB. We test our model using survey data from 439 business consultants in Germany, Austria, and Switzerland, analyzed via partial least squares structural equation modeling (PLS-SEM). Our results show that employees' sensing capabilities promote both GenAI capabilities and directly enhance IWB. While employees' capability to evaluate GenAI promotes IWB, GenAI usage capability does not. Moreover, we identify a significant mediation pathway: employees' sensing capabilities enhance GenAI usage capability, which in turn enables GenAI evaluation capability and thereby fosters IWB. This study contributes to the IWB literature by exploring relevant yet understudied antecedents: employees' sensing capabilities and their capabilities to use and evaluate GenAI. Moreover, it extends emerging research on GenAI in innovation management by adopting a differentiated capability perspective and uncovering the distinct roles and interplay of employees' GenAI usage and evaluation capabilities.

## 1. Introduction

Innovation is widely accepted as a crucial success factor for companies, as innovation is considered to be at the "heart of organizations' pursuit of long-term competitive advantage" (Roberts & Candi, 2024, p. 2). However, a recent Boston Consulting Group report reveals that 83 % of companies view innovation as a top three priority, but only 3 % are truly prepared to deliver on their innovation ambitions (Manly et al., 2024).

Against this backdrop, employees' innovative work behavior (IWB) has gained increasing attention among researchers and practitioners (Volery & Tarabashkina, 2021). IWB is conceptualized as a set of distinct yet interrelated behavioral activities of an employee—including idea exploration, generation, championing, and implementation—that collectively span all phases of the innovation process (De Jong & Den Hartog, 2010; Kör, Wakkee, & van der Sijde, 2021; Scott & Bruce, 1994). In other words, employees play a crucial role in driving organizational innovation (De Jong & Den Hartog, 2010; Mazzucchelli, Chierici, Abbate, & Fontana, 2019). Empirical studies found that employees' IWB is positively associated with organizational performance (Shanker, Bhanugopan, Van der Heijden, & Farrell, 2017) and firm-level innovation (Strobl, Matzler, Nketia, & Veider, 2020). This view aligns with the microfoundations perspective, which conceptualizes individual-level actions—such as IWB—as fundamental building blocks of organizational-level outcomes like innovation and performance (De Jong & Den Hartog, 2007; Felin, Foss, & Ployhart, 2015; Palmié, Rüegger, & Parida, 2023).

Emerging generative AI (GenAI) technologies (e.g., ChatGPT, Dall-E, and Gemini) offer promising opportunities to enhance employees' IWB. GenAI technologies represent a powerful subcategory of AI (Schryen, Marrone, & Yang, 2025) and an advancement beyond traditional AI (Roberts & Candi, 2024). Specifically, GenAI technologies incorporate the ability to generate novel and meaningful content, such as text, images, and audio, based on underlying training data (Feuerriegel, Hartmann, Janiesch, & Zschech, 2024), renewing the interest in utilizing AI technologies

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as a tool for innovation (Piller, Srour, & Marion, 2024).

Recent conceptual work emphasizes that GenAI is not intended to replace human creativity but to augment it (Bilgram et al., 2023). Previous studies show, for instance, that GenAI can promote employees' innovative behavior by augmenting work abilities (Yin, Jiang, & Niu, 2024), like solving problems in a novel and useful manner (Jia, Luo, Fang, & Liao, 2024). For example, GenAI already synthesizes vast libraries of annotated medical scans that accelerate radiologists' anomaly-detection models, and it generates studio-quality product photos with tailored captions so e-commerce merchandisers can list new items without costly photo shoots (Deloitte, 2024a). Moreover, individuals collaborating with GenAI show better creative performance than humans without GenAI support (Holzner, Maier, & Feuerriegel, 2025). In co-creative settings, GenAI can support employees in defining problems, envisioning solutions, and subsequently validating these solutions (Grange, Demazure, Ringeval, Bourdeau, & Martineau, 2025). Most studies examining GenAI and its influence on creative outcomes and innovation frame GenAI as a human–GenAI co-creation process (e.g., Boussioux, Lane, Zhang, Jacimovic, & Lakhani, 2024; Grange et al., 2025).

Understanding how GenAI affects individual-level IWB remains an underexplored area within this field, presenting a research gap we aim to address. Examining the influence of GenAI on employees' IWB is essential, as IWB represents a crucial success factor for companies (e.g., Shanker et al., 2017). Due to the complex and multifaceted nature of GenAI and building on a capabilities perspective, we incorporate two distinct GenAI constructs—GenAI usage capability and GenAI evaluation capability—following the AI literacy scale of Wang, Rau, and Yuan (2023). GenAI usage capability "refers to the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2023, p. 4). In contrast, GenAI evaluation capability "refers to the ability to analyze, select and critically evaluate (Gen) AI applications and their outcomes" (Wang et al., 2023, p. 4). This argumentation leads to our first research question (RQ):

**RQ1.** How do employees' capabilities to use and evaluate GenAI technologies shape their IWB?

Building on the dynamic capabilities view (Teece, 2007)—often used as a theoretical lens in innovation management (e.g., Akter et al., 2023; Ferreira, Coelho, & Moutinho, 2020; Held, Heubeck, & Meckl, 2025; Hock-Doepgen, Heaton, Clauss, & Block, 2025; Ritala, Aaltonen, Ruokonen, & Nemeh, 2024)—we further argue that individual-level IWB in the digital age requires more than the capabilities to use and evaluate GenAI. While the dynamic capabilities view typically encompasses three core activities—sensing opportunities and threats, seizing opportunities, and transforming resources (Teece, 2007)—this study focuses specifically on individual *sensing capabilities*, conceptualized as employees' ability to detect and interpret shifts in the technological landscape and the market environment (Harvey, 2025; Schoemaker, Heaton, & Teece, 2018). We focus on sensing capabilities as they are considered particularly relevant to navigating emerging technologies (Zabel, O'Brien, & Natzel, 2023). These sensing capabilities allow for early insights into market changes and technological advancements (Harvey, 2025; Teece, 2007) and might form a relevant antecedent to the effective development of employees' GenAI usage and evaluation capabilities, as well as IWB. Since employees likely first need to recognize the relevance and potential of GenAI, sensing capabilities provide the cognitive foundation upon which employees can build the required capabilities to leverage GenAI as a driver of IWB. Including employees' sensing capabilities is vital to investigating the antecedents of GenAI capabilities with the ultimate goal of leveraging IWB. We formulate our second and third RQs as follows:

**RQ2.** How do employees' sensing capabilities influence their capabilities to use and evaluate GenAI?

**RQ3.** How do employees' sensing capabilities influence their IWB?

Drawing on individual-level dynamic capabilities and recent innovation management literature on GenAI, we hypothesize that employees' sensing capabilities promote both the capability to use (H1) and the capability to evaluate GenAI (H2). Further, we hypothesize that employees' sensing capabilities promote their IWB (H3). Next, we suggest that employees' GenAI usage capability and GenAI evaluation capability enhance their IWB (H4 and H5). Finally, we hypothesize that employees' GenAI usage capability promotes their GenAI evaluation capability (H6).

We test our hypotheses using partial least squares structural equation modeling (PLS-SEM) on a large-scale empirical sample of 439 business consultants from a leading global consultancy in Germany, Austria, and Switzerland. We selected this sample because the participating consultants already integrate GenAI into their daily work processes and work in different industries, which means that they have to deal with a broad and ever-changing range of problems and issues, and, therefore, require IWB.

Furthermore, the consulting industry is particularly affected by emerging GenAI technologies. Recent industry evidence shows that leading consultancies are already redesigning their entire client-delivery workflows around GenAI: McKinsey's (2025) Global AI Survey reports that 21 % of professional-services firms have fundamentally reworked at least some workflows to deploy the technology. A Forbes article further showcases that GenAI is revolutionizing traditional consulting, as its tools deliver analytical and strategic-planning services with remarkable speed, efficiency, and cost-effectiveness (Minevich, 2024).

Our paper makes several valuable contributions to the literature. First, we contribute to IWB literature (e.g., De Jong & Den Hartog, 2010; Kör et al., 2021; Scott & Bruce, 1994; Volery & Tarabashkina, 2021). Our results demonstrate that employees' sensing capabilities promote their IWB. Employees' capability to use GenAI does not promote their IWB, but the capability to evaluate GenAI does. Therefore, our study complements previous studies regarding the antecedents of IWB (e.g., AlEssa & Durugbo, 2022; Anser, Yousaf, Khan, & Usman, 2021; Gelaidan, Al-Swidi, & Al-Hakimi, 2024; Yuan & Woodman, 2010) by integrating individual sensing capabilities and an emerging and disruptive technology: GenAI.

Second, we contribute to the emerging literature on GenAI in innovation management (e.g., Chiarello, Giordano, Spada, Barandoni, & Fantoni, 2024; Cillo & Rubera, 2025; Kanbach, Heiduk, Blueher, Schreiter, & Lahmann, 2024; Roberts & Candi, 2024). While prior studies have highlighted the transformative potential of GenAI for creativity and innovation, recent reviews emphasize that empirical research in this domain remains fragmented (Holzner et al., 2025). Addressing this observation, our study adopts a capability perspective that explores the *antecedents*, *mechanisms*, and *outcomes* of two distinct but interrelated GenAI capabilities in the innovation context: GenAI usage capability and GenAI evaluation capability. This approach complements existing empirical studies that typically conceptualize GenAI as a single, undifferentiated construct (e.g., Cimino, Felicetti, Corvello, Ndou, & Longo, 2024; Rana, Pillai, Sivathanu, & Malik, 2024; Singh, Chatterjee, & Mariani, 2024).

The remainder of this study provides the theoretical foundation (Chapter 2), derives the hypotheses (Chapter 3), details the methodology (Chapter 4), presents the empirical results (Chapter 5), and concludes with theoretical and practical implications, limitations, and suggestions for future research (Chapter 6).

## 2. Theoretical background

### 2.1. Innovative work behavior (IWB)

IWB is defined as "the intentional creation, introduction and application of new ideas within a work role, group or organization, in order to benefit role performance, the group, or the organization" (Janssen, 2000, p. 288). De Jong and Den Hartog (2010) further elaborate on IWB as a sequence of interrelated but distinct behavioral stages—idea exploration, idea generation, idea championing, and idea implementation—reflecting the whole span of the innovation process. In other words, IWB represents a multi-dimensional, overarching construct that captures all behaviors through which employees contribute to the innovation process (De Jong & Den Hartog, 2007). In simpler terms, in our study, we view IWB as the individual-level behavior of an employee. Importantly, this view distinguishes IWB from creativity, which typically focuses solely on generating novel ideas (Amabile, 1988; De Jong & Den Hartog, 2010). Therefore, we rely on the conceptualization by Kör et al. (2021), who position IWB as central to all organizational innovation efforts (see also Huhtala & Parzefall, 2007; Scott & Bruce, 1994). We view IWB as going beyond functional roles and argue that it is relevant for all company employees, not just for innovation departments.

The relevance of IWB stems from its demonstrated impact on a wide range of organizational outcomes. For instance, IWB has been linked to enhanced organizationaantel performance (Shanker et al., 2017) and firm-level innovation (Strobl et al., 2020). These findings align with the broader microfoundations perspective, which states that individual-level actions—such as IWB—shape organizational-level outcomes (Felin et al., 2015; Palmié et al., 2023). Reflecting its increasing strategic importance, scholarly interest in IWB has grown substantially over the past decade, illustrated through various recent literature reviews (e.g., AlEssa & Durugbo, 2022; Farrukh, Meng, Raza, & Wu, 2023).

Previous research has highlighted a broad set of individual and organizational (or contextual) factors that serve as antecedents of IWB (e.g., Yuan & Woodman, 2010). At the individual level, positive mood (Madrid, Patterson, Birdi, Leiva, & Kausel, 2014), cultural intelligence (Afsar, Al-Ghazali, Cheema, & Javed, 2021), or employee creativity (Volery & Tarabashkina, 2021) have been shown to enhance IWB.

Most research has focused on organizational antecedents of individual-level IWB as an outcome (Volery & Tarabashkina, 2021). These antecedents include servant leadership (Gelaidan et al., 2024), knowledge management infrastructure capabilities (Anser et al., 2021), team learning behaviors (Widmann & Mulder, 2018), or human resource management practices like feedback, autonomy, or training (Bos-Nehles, Renkema, & Janssen, 2017). Moreover, perceived organizational support for innovation (Scott & Bruce, 1994), organizational climate (Volery & Tarabashkina, 2021), and the quality of leader-member relationships (Janssen & van Yperen, 2004) represent relevant organizational antecedents of IWB.

In summary, IWB is a multifaceted construct vital in fostering organizational innovation and performance (e.g., Strobl et al., 2020; Shanker et al., 2017). To fully leverage its potential, it is essential to understand which factors drive IWB. Against this backdrop, GenAI represents a promising but underexplored individual-level antecedent of IWB. Realizing GenAI's potential, however, likely requires that employees can identify and interpret technological developments and market changes—an ability captured by the concept of employees' sensing capabilities. These sensing capabilities may provide the cognitive foundation for developing GenAI usage and evaluation capabilities, which in turn can enable IWB. The following section introduces GenAI and its potential for innovation management.

### 2.2. Generative AI and its potential for innovation management

The release of ChatGPT in November 2022 brought GenAI to the forefront of AI discussions (Gartner, 2023). This tool quickly gained traction, reaching 100 million monthly active users within two months—a record as the fastest-growing consumer application in history (Reuters, 2023). We adopt the definition of Feuerriegel et al. (2024, p. 111) and refer to GenAI as "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data."

GenAI goes further than traditional AI as it can generate new data based on training data (Roberts & Candi, 2024); therefore, GenAI can be classified as a powerful subcategory of AI (Schryen et al., 2025). Moreover, GenAI is based on generative modeling, differentiating it from discriminative modeling (often used for data-driven decision support) by employing a machine learning architecture, such as a deep neural network (Feuerriegel et al., 2024; Ng & Jordan, 2001).

Figure 1 illustrates the procedural differences between discriminative and GenAI models, as conceptualized by Banh and Strobel (2023). Accordingly, discriminative AI models rely on existing data to determine boundaries and make classifications or decisions. This process is linear, proceeding from data input to boundary determination, ultimately reaching a specific conclusion. In contrast, GenAI models operate through an iterative cycle involving prompt input, creation, and generation of new, meaningful content. Here, the process is inherently creative, allowing for continuous refinement through specifying and generating cycles, which enables the model to produce novel outputs rather than merely categorizing existing data (Banh & Strobel, 2023).

A key feature of GenAI is its adaptability through prompting. Rather than retraining the model for specific tasks, users can steer GenAI's outputs by providing tailored instructions—so-called *prompts*—that define the desired format, tone, or objective (Liu et al., 2023). This mechanism enables a flexible application of pre-trained models across various use cases. *Prompt engineering* focuses on the systematic design of prompts to enhance the quality of generated outputs (Liu & Chilton, 2022). As a result, the interaction between users and GenAI takes the form of a co-creation process in which prompt design plays a central role in shaping the relevance and quality of the generated output (Feuerriegel et al., 2024).

From an innovation management perspective, there seems to be no limit to the presumed added value of these GenAI technologies. At the organizational level, recent studies indicate that GenAI could influence business model innovation (Kanbach et al., 2024; Teng, Ye, & Martinez, 2025), enhance ideation processes (Eisenreich, Just, Gimenez-Jimenez, & Füller, 2024), change consumer behavior and corresponding marketing strategies (Cillo & Rubera, 2025), foster digital supply chain innovation (Wang & Zhang, 2025a), and improve exploratory and exploitative innovation (Singh et al., 2024).

These examples infer that GenAI represents a disruptive innovation for companies. Consequently, there has been a substantial increase in research interest for innovation management researchers, evident from the rapidly increasing number of publications in this area (e.g., Akter et al., 2023; Chen & Chan, 2024; Chiarello et al., 2024; Haefner, Parida, Gassmann, & Wincent, 2023; Mariani & Dwivedi, 2024; Sedkaoui & Benaichouba, 2024).

Due to the significance of GenAI in corporate innovation management, most of these studies focus on the impact of GenAI on innovation management at the organizational level. However, this focus on firm-level innovation omits that innovation is critically dependent on individuals and their actions (Felin et al., 2015; Palmié et al., 2023).

### 2.3. Employees' GenAI usage and evaluation capabilities

Most of the current research in innovation management literature regarding GenAI is in the form of literature reviews with a focus on future research directions (e.g., Akter et al., 2023; Haefner et al., 2023; Mariani, Machado, Magrelli, & Dwivedi, 2023; Roberts & Candi, 2024; Sedkaoui & Benaichouba, 2024). However, an increasing number of quantitative empirical studies have emerged on the subject (e.g., Cimino et al., 2024; Rana et al., 2024; Singh et al., 2024).

What is striking about these quantitative empirical studies is that they often choose a single construct to measure the GenAI component of their research model. Cimino et al. (2024) use a construct named "generative AI appropriation," which represents the process by which innovation managers adapt GenAI tools (such as ChatGPT) to their specific work requirements and integrate these tools into their

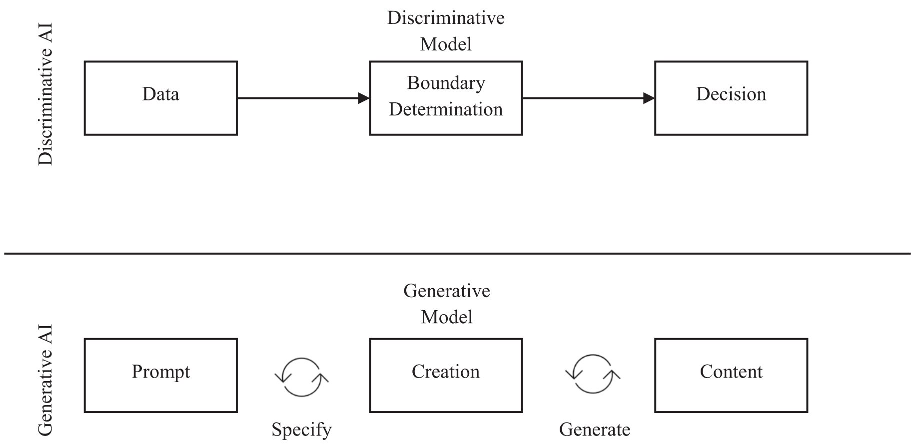


**Fig. 1.** Procedural differences of discriminative AI and generative AI.
Own illustration based on Banh and Strobel (2023, p. 5).

workflows. Rana et al. (2024) utilize the construct "use of Generative AI," defined as the deployment of GenAI technology by organizations for various business functions, where it is leveraged to enhance organizational effectiveness and performance. Singh et al. (2024) utilize a construct called "adoption of GenAI," defined as organizations' integration and utilization of GenAI technologies to enhance performance through innovative outputs and efficiency gains.

While these studies offer essential empirical findings regarding GenAI in innovation management, we build on them using two different GenAI constructs. Thus, our study aims to differentiate further and break down GenAI in the application toward individual-level IWB. Adapted from the AI literacy scale introduced by Wang et al. (2023), we distinguish between the foundational GenAI capabilities of *usage* and *evaluation*.

First, we consider employees' GenAI usage capability, which "refers to the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2023, p. 4). This construct centers on operational proficiency, enabling users to engage with GenAI tools without requiring in-depth reflection. Beyond mere tool application, GenAI usage involves flexible adaptation to various requirements and efficient integration of different GenAI tools into workflows. Thus, we propose that GenAI usage capability allows employees to leverage technical tools and quickly become familiar with their functions.

Second, we include the construct employees' GenAI evaluation capability, which "refers to the ability to analyze, select and critically evaluate (Gen) AI applications and their outcomes" (Wang et al., 2023, p. 4). This construct emphasizes that users need reflective capabilities beyond handling technology developed through consistent engagement with GenAI. Given the "black-box" nature of AI models (Mueller, Hoffman, Clancey, Emrey, & Klein, 2019), evaluative skills are essential for making informed decisions and critically scrutinizing the validity of generated content. For instance, critical thinking is pivotal when applying GenAI in complex decision-making contexts (Wang et al., 2023). Users who learn to identify both the strengths and limitations of GenAI outputs can tailor these results to the specific demands of their work context, optimizing outcomes accordingly.

In other words, GenAI usage capability is about applying the tools as they are in the absence of much critical thinking (Liu, Zhang, & Zhang, 2025). In contrast, GenAI evaluation capability involves a deeper understanding and the cognitive ability to assess the quality and relevance of the GenAI-generated outputs.

### *2.4. Dynamic capabilities lens and employees' sensing capabilities*

Dynamic capabilities refer to a "firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments" (Teece, Pisano, & Shuen, 1997, p. 516). The dynamic capabilities framework is widely used and recognized in management research (e.g., Eisenhardt & Martin, 2000; Schilke, Hu, & Helfat, 2018; Teece, 2007; Zollo & Winter, 2002) and explains how firms can achieve competitive advantage in dynamic environments characterized by innovation-driven competition (Teece, 2014).

Organizational capabilities can generally be distinguished into ordinary and dynamic capabilities (Winter, 2003). Ordinary capabilities encompass performing administrative, operational, and governance-related functions required to accomplish tasks (Teece, 2014). In contrast, dynamic capabilities are needed for strategic change and renewal (Agarwal & Helfat, 2009; Helfat et al., 2007) and enable companies to change the way they currently earn their living (Helfat & Winter, 2011). Dynamic capabilities include conducting acquisitions and new product development (Helfat & Winter, 2011) or business model design (Teece & Linden, 2017).

Dynamic capabilities are underpinned by three core activities: *sensing* opportunities and threats, *seizing* opportunities, and *transforming* resources (Teece, 2007). First, sensing capabilities refer to scanning the market, detecting shifts, and sensing market changes before the competition does, which is especially critical in turbulent environments (Schoemaker et al., 2018). After firms sense an opportunity, they must seize it through new products or services requiring investments in development and commercialization activity (Teece, 2007). A natural extension of sensing and seizing capabilities is the need to transform the organization in response to the realized opportunities. Specifically, transforming capabilities enable firms to continuously adapt by redesigning their internal structures and reshaping external relationships, ensuring they remain agile in dynamic environments (Day & Schoemaker, 2016).

GenAI is increasingly viewed through the lens of organizational capabilities (AL-Khatib & Ramayah, 2024; Shore, Tiwari, Tandon, & Foropon, 2024). However, due to the focus of dynamic capabilities theory on firm-level capabilities, this framework neglects the role of the individuals (i.e., managers and employees) and their capabilities behind the companies (Heubeck, 2023; Salvato & Vassolo, 2018). This criticism gave rise to the microfoundational research stream of dynamic capabilities (Adner & Helfat, 2003; Helfat & Martin, 2015; Heubeck, 2024). This research stream fundamentally states that competitive advantage at the firm level is created by the capabilities of individuals (Felin et al., 2015; Foss & Mazzelli, 2025).

Building on this micro-level logic, we shift the firm-level focus of existing research regarding GenAI to the individual level. In this vein, we argue that employees inherently use GenAI tools—for example, an individual user writes a ChatGPT prompt. Therefore, the GenAI capabilities of employees are critical for realizing and building firm-level

GenAI capabilities. Thus, this view enriches recent firm-level research, which views GenAI through the lens of organizational capabilities (AL-Khatib & Ramayah, 2024; Shore et al., 2024), by focalizing individual-level GenAI capabilities: employees' GenAI usage capability and GenAI evaluation capability.

We further investigate employees' sensing capabilities as antecedents of GenAI capabilities, as sensing capabilities are particularly relevant to navigating emerging technologies (Zabel et al., 2023). Sensing capabilities at the individual level encompass the ability of employees to detect and interpret shifts in the technological landscape, providing early insights into market changes and technological advances (Harvey, 2025; Teece, 2007). Thus, sensing capabilities are especially critical for digital transformation in general and new technologies in particular (Warner & Wäger, 2019). Given GenAI's potential for substantial technological and market disruptions, employees' capability to sense emerging opportunities and threats is critical in such an unpredictable environment. For example, employees can be involved in digital opportunity evaluation—a critical microfoundation of sensing capabilities—and assess the opportunities and risks of a new technology, leading to the decision whether to adopt it or not (Leso, Cortimiglia, Ghezzi, & Minatogawa, 2024). Cross-industrial sensing, especially monitoring digital initiatives and technology adoption of employees in other industries, is a promising way to identify emerging technological trends and technology usage (Ellström, Holtström, Berg, & Josefsson, 2022). Thus, because GenAI represents an emerging technology landscape that needs to be explored by individuals, we focus on employees' sensing capabilities as facilitators of GenAI capabilities.

## 3. Hypothesis development

In the following section, we develop our hypotheses, with Fig. 2 summarizing the research model.

According to Teece (2007), sensing capabilities involve scanning and monitoring technological developments and hypothesizing about the evolution of technologies, making them particularly relevant to navigating emerging technologies (Zabel et al., 2023). Specifically, employees' cognitive functions, such as perception and attention, help generate novel hypotheses and recognize trends (like GenAI) relevant to opportunities and threats, a process termed "generative sensing" (Dong, Garbuio, & Lovallo, 2016; Helfat & Martin, 2015). More concretely, this involves digital scouting and digital scenario planning as an essential foundation for quickly making sense of unexpected trends (Warner & Wäger, 2019). Once a technology is identified as potentially important, it must be further probed and tested practically to gain a deeper understanding (Schoemaker et al., 2018).

Individuals with strong sensing capabilities can, therefore, identify novel technologies (like GenAI) at an earlier stage and develop a richer understanding of their potential use cases and value. We suggest that strong employees' sensing capabilities increase their capability to use and evaluate GenAI. Their information advantage—due to strong sensing capabilities—might enable them not only to recognize relevant application areas but also to critically assess the quality and usefulness of GenAI outputs. For instance, an employee with strong sensing capabilities may actively monitor discussions and updates about GenAI tools and thereby learn that specific models produce hallucinated or biased results. Such insights can inform prompting strategies or encourage a more cautious interpretation of generated content, enhancing GenAI usage and evaluation capability. Therefore, we state the following two hypotheses:

**H1**. Employees' sensing capabilities enhance their GenAI usage capability.

**H2.** Employees' sensing capabilities enhance their GenAI evaluation capability.

We further argue that employees' sensing capabilities enhance their IWB. Accordingly, IWB begins with identifying opportunities or problems that arise (De Jong & Den Hartog, 2010). Moreover, dissatisfaction with the status quo due to environmental changes is a relevant antecedent of IWB (Yuan & Woodman, 2010). This starting point closely aligns with the conceptualization of sensing capabilities to detect environmental shifts and opportunities (Teece, 2007). Sensing capability is a cognitive process through which environmental changes are perceived (Lin, Su, & Higgins, 2016).

Previous studies found that sensing capabilities positively influence the performance of the initiation and implementation of innovation (Lin et al., 2016). One reason is that sensing capabilities are crucial to identifying a novel problem as a foundation for innovation (Birkinshaw, Hamel, & Mol, 2008; Lin et al., 2016). Furthermore, sensing capabilities improve product and process innovation (Alshanty & Emeagwali, 2019). One underlying mechanism here is that employees with stronger sensing capabilities can access and integrate a greater breadth of knowledge sources, which is associated with greater innovation success (Leiponen & Helfat, 2010).

Accordingly, we argue that employees' sensing capabilities provide a relevant antecedent of IWB, as they could enable employees to recognize change, formulate ideas, and initiate innovative action. Thus, we hypothesize:

**H3.** Employees' sensing capabilities enhance their IWB.

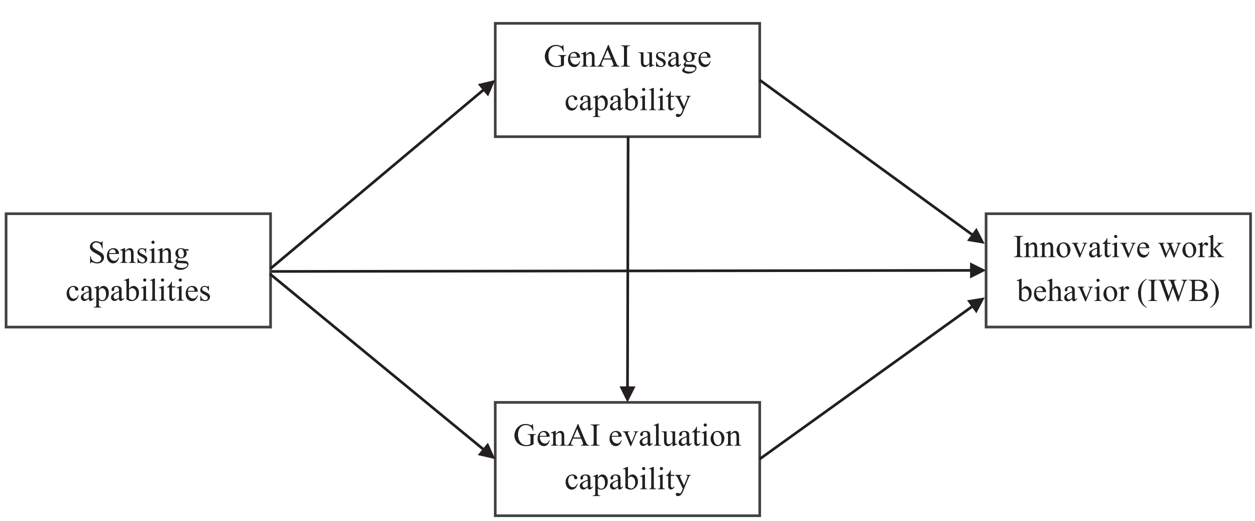


**Fig. 2.** Research model.

We further argue that employees' capabilities to use and evaluate GenAI promote their IWB. As GenAI-mediated innovation is increasingly conceptualized as a co-creative process (e.g., Grange et al., 2025), the quality and innovativeness of outcomes are not inherent to the technology itself but emerge through the co-creation with the user (Feuerriegel et al., 2024; Liu et al., 2023).

There are already plenty of suggested use cases of how GenAI can support IWB, including user journey mapping, idea generation, and prototyping (Bilgram & Laarmann, 2023), with GenAI augmenting employees' working abilities (Yin et al., 2024). Yet, these observed benefits are not automatic: users must be able to steer GenAI via prompt formulation and iterative specification to produce valuable results (Liu et al., 2023). As the prompting process is probabilistic and generative rather than deterministic, employees actively shape the generated output via a trial-and-error process and continuously specify their desired tasks as input prompts until their task is solved (Banh & Strobel, 2023).

Empirical studies further show that GenAI can support employees in defining problems, envisioning solutions, and testing these solutions (Grange et al., 2025). GenAI has also been found to influence individual-level creativity and innovation routines regarding speed, quality, and quantity for various tasks like creation planning or prototyping (Chu, Baxter, & Liu, 2025). Moreover, Zhang, Yu, and Ma (2025) found that integrating GenAI into everyday workflows enhances both incremental and radical innovation.

The interactive nature of GenAI also demands continuous evaluation of the generated content, especially given known limitations such as hallucination and bias (Feuerriegel et al., 2024). Users must critically assess which outputs are valid, implementable, and useful within their specific task context. This evaluative process is crucial for translating GenAI-generated outputs into concrete IWB.

Taken together, employees who possess strong capabilities to use and evaluate GenAI—by effectively utilizing and prompting the technology, steering its output, and critically evaluating its relevance—are better positioned to harness the technology's innovation potential. These capabilities enable employees to actively contribute to ideating and implementing novel solutions, thereby fostering IWB. Thus, we posit:

**H4.** Employees' GenAI usage capability enhances their IWB.

**H5.** Employees' GenAI evaluation capability enhances their IWB.

We further aim to investigate the nuanced mechanisms between both GenAI capabilities.

We argue that employees' GenAI usage capability is foundational for developing their GenAI evaluation capability. Following Wang et al. (2023), (Gen)AI usage capability refers to individuals' operational ability to interact with and apply (Gen)AI tools effectively to accomplish tasks. In contrast, (Gen)AI evaluation capability requires higher-order cognitive skills, including critically assessing (Gen)AI outputs and determining their appropriateness and reliability. Empirical validation of the AI literacy framework by Wang et al. (2023) demonstrates that these two capabilities are conceptually distinct yet interdependent, with operational competence being a prerequisite for reflective evaluation.

This interdependence is further supported by Liu et al. (2025), who position GenAI usage and GenAI evaluation both in the cognitive skill domain within their AI literacy framework. Furthermore, they propose a hierarchical differentiation between both GenAI capabilities, with GenAI usage needing medium-order thinking skills and GenAI evaluation needing higher-order thinking skills. That suggests that GenAI usage capability is the precondition for GenAI evaluation capability.

The already described technical nature of GenAI systems reinforces this suggested relationship. GenAI operates on a generative rather than deterministic logic, requiring users to iteratively specify and refine prompts to produce useful content (Banh & Strobel, 2023). This trial-and-error process involves using and testing what prompts lead to the best output. In other words, the GenAI usage capability will likely lead to better GenAI evaluation capability. Taken together, we posit:

**H6.** Employees' GenAI usage capability enhances their GenAI evaluation capability.

## 4. Method

### *4.1. Data collection and sample*

For the empirical validation of the research model, we surveyed business consultants located in Germany, Austria, and Switzerland from one of the leading consultancies worldwide. This internationally renowned consultancy operates globally in over 100 countries, with several 100,000 employees and a turnover of tens of billions of dollars per year.

We surveyed the strategy, consulting, and innovation units of this company. This sample is particularly suitable for our research, as these consultants already work with GenAI and integrate it into their work. Additionally, these consultants work across industries and have advised various projects and clients. Thus, these consultants must deal with ever-changing problems and client needs, which require them to incorporate IWB.

The region of Germany, Austria, and Switzerland offers a suitable context for our study as it is one of Europe's largest and most dynamic consulting markets. Germany alone generated almost 50 billion euros in consulting revenues in 2024 (BDU, 2024). Moreover, these three countries share a common business language and similar data protection regulations. Germany hosts the EU's largest pool of GenAI start-ups. It incorporates the second-highest share of AI-skilled workers among the OECD countries (McKinsey, 2023), making this region particularly fertile ground for examining how employees acquire GenAI usage and evaluation capabilities and translate them into IWB.

Surveying consultants in the context of digital transformation is also in line with similar established studies (e.g., Warner & Wäger, 2019). Consultants are critical in advising and implementing GenAI solutions across industries (Deloitte, 2024b). A recent report by the consultancy McKinsey (2024) highlights the significant adoption of AI among consulting firms, positioning them as leaders in deploying GenAI technologies. Accenture reported over three billion GenAI-driven bookings in recent years, showcasing consultants' extensive hands-on experience with this technology (Accenture, 2024). This substantial figure demonstrates that consultants are well-versed in the practical applications of GenAI, making them highly suitable for our research context.

We created the survey, including initial pre-tests between April and June 2024. The pre-tests were conducted with two professors, a doctoral student, and two target group consultants to ensure the survey was comprehensible. After the pre-tests and minor adjustments, the data collection phase finally occurred in July 2024. We contacted 1174 consultants via personalized mail containing a link to the online survey. In this way, we received 439 completed responses, which corresponds to a response rate of 37.4 %. This response rate can be classified as very good and exceeds comparable research settings (e.g., Cimino et al., 2024). Table 1 shows the sample characteristics and demographic data of the respondents. To summarize, we have a well-balanced sample encompassing diverse experience levels across all industries.

Before starting with the data analysis, we tested for common method bias and non-response bias. We assessed common method bias by conducting Harman's single-factor test and defined the widely used value of >50 % as acceptable (Harman, 1976; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Our data set showed a value of 25.39 %, which indicates that common method bias is not a concern in our study. Furthermore, we compared data obtained at the beginning (first 33 %) and at the end (final 33 %) of the collected responses to conduct a non-response bias test. To identify significant differences, we performed a sample *t*-test on our constructs. We could not find any significant differences between early and late respondents, demonstrating that non-response bias is not a concern in this study.

**Table 1**
Sample characteristics.

| Variable | | No. | % |
|---|---|---|---|
| Gender | Female | 184 | 41.9 |
| | Male | 253 | 57.6 |
| | Non-binary | 2 | 0.0 |
| Education (highest level) | High School Diploma | 17 | 3.8 |
| | Bachelor's Degree | 71 | 16.1 |
| | Master's Degree/ Diploma | 315 | 71.8 |
| | Doctorate | 34 | 7.7 |
| | Others | 2 | 0.0 |
| Work experience (in years) | Less than 1 | 16 | 0.4 |
| | 1–3 | 88 | 20.0 |
| | 3–5 | 71 | 16.2 |
| | 5–10 | 117 | 26.7 |
| | More than 10 | 147 | 33.5 |
| Company affiliation (in years) | Less than 1 | 100 | 22.8 |
| | 1–3 | 130 | 29.6 |
| | 3–5 | 62 | 14.1 |
| | 5–10 | 90 | 20.5 |
| | More than 10 | 57 | 13.0 |
| Career Level | Intern/Working Student | 40 | 9.1 |
| | Analyst | 87 | 19.8 |
| | Consultant | 108 | 24.6 |
| | Manager | 91 | 20.7 |
| | Senior Manager | 57 | 13.0 |
| | Principal | 27 | 6.2 |
| | Managing Director | 29 | 6.6 |
| Industry expertise (more than one answer possible) | Health and Public Sector | 175 | 39.9 |
| | Finance | 188 | 42.8 |
| | Communications and Media | 118 | 26.9 |
| | IT and Software | 137 | 31.2 |
| | Resources | 109 | 24.8 |
| | Consumer Goods | 165 | 37.6 |
| | Mobility and Automotive | 188 | 42.8 |

$N = 439$.

### 4.2. Variable measurements

All measurement items used in this study were extracted from well-researched and established scales (De Jong & Den Hartog, 2010; Harvey, 2025; Wang et al., 2023) and constructed using a 5-point Likert scale ranging from "Strongly Agree" to "Strongly Disagree." Details of the constructs and their measurement items are summarized in the Appendix.

To assess the construct of employees' *sensing capabilities*, we used the scale of Harvey (2025)—an adapted form of Ancona & Caldwell (1992)—emphasizing the microfoundations of sensing capabilities as part of dynamic capabilities. This scale captures the environmental scanning activities of employees (i.e., on the individual level), focusing on their ability to observe technological trends, competitor activities, and market ideas. The measurement scale consists of four items.

To measure the constructs of *GenAI usage capability* and *GenAI evaluation capability*, we extracted the scale of the AI literacy framework of Wang et al. (2023). We modified it slightly by exchanging the original terminology "AI" with "GenAI." GenAI usage capability is measured using three items, and GenAI evaluation capability is also measured using three items.

The construct of *IWB* was measured using the scale of De Jong and Den Hartog (2010), which is operationalized through four dimensions: idea exploration, idea generation, idea championing, and idea implementation. This scale consists of ten items that capture the full spectrum of employees' IWB, from exploring new ideas to successfully implementing innovative solutions in their work. Although these dimensions reflect different aspects of the innovation process, De Jong and Den Hartog (2010) found only weak differences between the four dimensions, leading to a one-construct solution.

### 4.3. Model evaluation

We used structural equation modeling (SEM) and the statistical software SmartPLS 4 for the data analysis. Thereby, we oriented ourselves to the guidelines of Hair, Hult, Ringle, and Sarstedt (2022) and applied the partial least squares (PLS) path modeling method. PLS-SEM fits our research model as it is particularly well-suited for an explanation-prediction perspective (Hair & Sarstedt, 2021; Sarstedt & Danks, 2022), providing better predictive capabilities than covariance-based approaches (CB-SEM) (Hair, Risher, Sarstedt, & Ringle, 2019).

Hair et al. (2019) highlight four key considerations when deciding whether PLS-SEM is appropriate: (1) data characteristics, (2) model characteristics, (3) model estimation, and (4) model evaluation. We systematically assessed our study against these four criteria and concluded that PLS-SEM is the most suitable technique. Compared with CB-SEM, which excels in confirmatory tests of compact theoretical models, PLS-SEM better serves our goal of jointly predicting and explaining the complex network of direct, indirect, and sequential effects in our research model (Hair et al., 2022). Moreover, PLS-SEM can estimate all relationships of all constructs in parallel (Becker, Cheah, Gholamzade, Ringle, & Sarstedt, 2023). Therefore, we chose this technique to assess the relationships between sensing capabilities, GenAI capabilities, and individual-level IWB.

## 5. Results

### 5.1. Measurement model

To calculate the measurement model, we used the standard PLS-SEM algorithm. The quality criteria assessments are shown in Tables 2 and 3, including indicator reliability, composite reliability, convergent validity, and discriminant validity.

To assess the indicator reliability, we defined outer factor loading values of $>0.50$ as acceptable. Although there is a general threshold value of $>0.708$, loadings between 0.40 and 0.70 are also acceptable, and it is not always necessary to exclude items with factor loadings $<0.708$ (Hair et al., 2022). For the constructs sensing capabilities, GenAI usage capability, and GenAI evaluation capability, all items exceeded the threshold value of 0.50. For the construct IWB, Item 1 (factor loading $= 0.396$) and Item 2 (factor loading $= 0.451$) were removed due to the low factor loading.

To assess internal consistency, we examined Cronbach's alpha and composite reliability. A Cronbach's alpha value of $>0.70$ was defined as acceptable due to the exploratory nature of our research (Hair, Black, Babin, & Anderson, 2014). In addition, a composite reliability value of $>0.70$ was defined as sufficient (Hair et al., 2022). All constructs met those criteria. Therefore, we can state that internal consistency and composite reliability are not a concern in this study.

To assess convergent validity, we considered the average variance extracted (AVE) and defined acceptable values as AVE $> 0.50$ (Fornell & Larcker, 1981). Furthermore, an AVE between 0.40 and 0.50 was also acceptable if Cronbach's alpha coefficient exceeded 0.60 (Fornell & Larcker, 1981). In Table 2, it is shown that the AVE for the constructs sensing capabilities, GenAI usage capability, and GenAI evaluation capability is clearly above the threshold value of 0.50. The AVE of 0.475 for the construct IWB is slightly below the threshold value 0.50. However, given that Cronbach's alpha value of 0.84 exceeds 0.60 and the composite reliability value is also more than sufficient (0.846), the marginally lower AVE value is unproblematic, and we can conclude that all of our constructs satisfy convergent validity (Fornell & Larcker,

**Table 2**
Measurement model evaluation.

| Construct and indicator | Factor loading | Composite reliability | AVE | Cronbach's α |
|---|---|---|---|---|
| **Sensing capabilities** | | 0.830 | 0.645 | 0.817 |
| Sensing capabilities 1 | 0.749 | | | |
| Sensing capabilities 2 | 0.848 | | | |
| Sensing capabilities 3 | 0.765 | | | |
| Sensing capabilities 4 | 0.847 | | | |
| **GenAI usage capability** | | 0.734 | 0.631 | 0.703 |
| GenAI usage capability 1 | 0.880 | | | |
| GenAI usage capability 2[R] | 0.678 | | | |
| GenAI usage capability 3 | 0.812 | | | |
| **GenAI evaluation capability** | | 0.734 | 0.642 | 0.718 |
| GenAI evaluation capability 1 | 0.705 | | | |
| GenAI evaluation capability 2 | 0.847 | | | |
| GenAI evaluation capability 3 | 0.843 | | | |
| **Innovative work behavior** | | 0.846 | 0.475 | 0.840 |
| Innovative work behavior 3 | 0.629 | | | |
| Innovative work behavior 4 | 0.590 | | | |
| Innovative work behavior 5 | 0.594 | | | |
| Innovative work behavior 6 | 0.748 | | | |
| Innovative work behavior 7 | 0.720 | | | |
| Innovative work behavior 8 | 0.767 | | | |
| Innovative work behavior 9 | 0.716 | | | |
| Innovative work behavior 10 | 0.725 | | | |

$N = 439$; R = inversed item.

**Table 3**
Heterotrait-monotrait ratio.

| | Constructs | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 1 | GenAI evaluation capability | | | | |
| 2 | GenAI usage capability | 0.731 | | | |
| 3 | IWB | 0.421 | 0.290 | | |
| 4 | Sensing capabilities | 0.292 | 0.256 | 0.493 | |

1981). Treating AVE values that are marginally below 0.50 as acceptable in exploratory research is consistent with pertinent research in high-impact journals (e.g., Kumar, Shankar, Hollebeek, Behl, & Lim, 2025; Lam, 2012; Tran & Thai, 2025).

To assess the discriminant validity of the constructs, we used the Heterotrait-Monotrait Ratio (HTMT) and defined a cut-off value of 0.85 (Henseler, Ringle, & Sarstedt, 2015). Table 3 shows that all average correlations were below that cut-off value, supporting discriminant validity.

### *5.2. Structural model*

The next step was to assess the structural model. We first examined the variance inflation factors (VIFs) to identify potential collinearity among the predictor constructs. As shown in Table 4, all VIF values remain below the critical threshold of 3, indicating that collinearity is not a concern in the structural model (Hair et al., 2019).

In the next step, we calculated the structural model utilizing the standard bootstrapping algorithm (5000 samples) and calculated $R^2$ values, path coefficients, and significance levels. We classified the significance levels as follows: extremely significant ($p < 0.001$), highly significant ($p < 0.01$), and significant ($p < 0.05$). Furthermore, we defined the sizes of the effects as strong ($\beta > 0.35$), moderate ($\beta > 0.15$), and weak ($\beta > 0.02$).

PLS path analysis of the research model showed that sensing capabilities explain 4.0 % (0.040) of the variance of GenAI usage capability. Sensing capabilities and GenAI usage capability explain 29.1 % (0.291) of the variance of GenAI evaluation capability together. Lastly, sensing capabilities, GenAI usage capability, and GenAI evaluation capability explain 23.7 % (0.237) of the variance in IWB. Table 5 shows an overview of the hypothesis test results of structural modeling.

Hypothesis 1 stated that employees' sensing capabilities promote their GenAI usage capability. Our empirical findings support this hypothesis, as sensing capabilities have an extremely significant, moderate positive effect on GenAI usage capability ($\beta = 0.201$, $p < 0.001$). Hypothesis 2 predicted that employees' sensing capabilities are positively related to their GenAI evaluation capability. The analysis shows that Hypothesis 2 can be accepted due to a highly significant, weak positive effect of sensing capabilities on GenAI evaluation capability ($\beta = 0.127$, $p = 0.003$). Hypothesis 3 stated that employees' sensing capabilities promote their IWB. This hypothesis can be accepted due to the extremely significant, strong positive effect of sensing capabilities on IWB ($\beta = 0.356$, $p < 0.001$). Hypothesis 4 proposed a positive influence of employees' GenAI usage capability on their IWB. Although the coefficient is positive, this hypothesis is rejected due to statistical insignificance ($\beta = 0.028$, $p = 0.566$). Hypothesis 5 predicted that employees' GenAI evaluation capability promotes their IWB. This hypothesis can be accepted due to an extremely significant, moderate positive effect of GenAI evaluation capability on IWB ($\beta = 0.242$, $p < 0.001$). Hypothesis 6 posited that employees' GenAI usage capability promotes their GenAI evaluation capability. The analysis supports this hypothesis due to the extremely significant and strong, positive effect of GenAI usage capability on GenAI evaluation capability ($\beta = 0.499$, $p < 0.001$). All direct effects are also illustrated in Fig. 3.

**Table 4**
Variance inflation factors.

| | VIF |
|---|---|
| GenAI evaluation capability → IWB | 1.411 |
| GenAI usage capability → GenAI evaluation capability | 1.042 |
| GenAI usage capability → IWB | 1.394 |
| Sensing capabilities → GenAI evaluation capability | 1.042 |
| Sensing capabilities → GenAI usage capability | 1.000 |
| Sensing capabilities → IWB | 1.065 |

**Table 5**
Hypothesis test results.

| Hypothesis | β | $p$ | t | Result |
|---|---|---|---|---|
| **H1.** Sensing capabilities → GenAI usage capability | 0.201 | < 0.001 | 4.192 | Supported |
| **H2.** Sensing capabilities → GenAI evaluation capability | 0.127 | 0.003 | 2.985 | Supported |
| **H3.** Sensing capabilities → IWB | 0.356 | < 0.001 | 7.668 | Supported |
| **H4.** GenAI usage capability → IWB | 0.028 | 0.566 | 0.574 | Not Supported |
| **H5.** GenAI evaluation capability → IWB | 0.242 | < 0.001 | 5.039 | Supported |
| **H6.** GenAI usage capability → GenAI evaluation capability | 0.499 | < 0.001 | 12.712 | Supported |

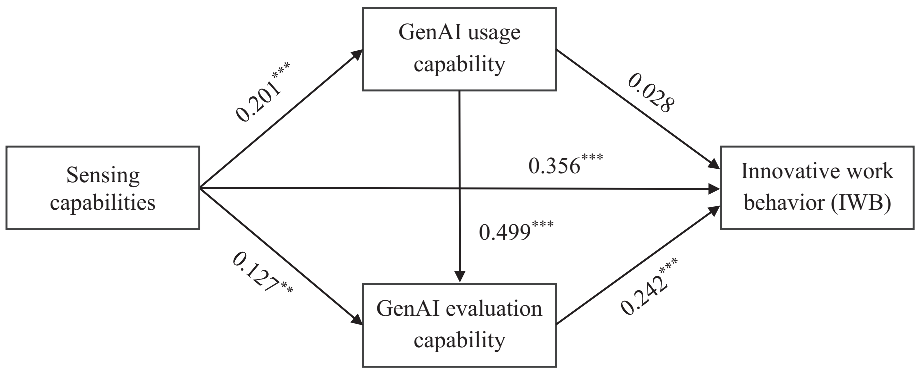


**Fig. 3.** Research model with path results (**$p < 0.01$, ***$p < 0.001$).

### 5.3. *Mediation effects*

The analysis also reveals several significant indirect effects within the model, which are also illustrated in Table 6. First, the path from *sensing capabilities → GenAI usage capability → GenAI evaluation capability* demonstrates an extremely significant indirect effect (β = 0.100, $p <$ 0.001). This finding indicates that GenAI usage capability is a significant mediator between sensing capabilities and GenAI evaluation capability.

Further, the indirect effect from *GenAI usage capability → GenAI evaluation capability → IWB* is also extremely significant and positive (β = 0.121, $p < 0.001$), highlighting the role of GenAI evaluation capability in mediating the relationship between GenAI usage capability and IWB.

However, the path from *sensing capabilities → GenAI usage capability → IWB* shows a non-significant indirect effect (β = 0.006, $p$ = 0.582). This nonfinding suggests that while sensing capabilities may influence GenAI usage capability, there is no statistically significant relationship between GenAI usage capability and IWB.

In contrast, the indirect effect of *sensing capabilities → GenAI evaluation capability → IWB* is positive and highly significant (β = 0.031, $p$ = 0.011). This finding implies that the capability to evaluate GenAI mediates the relationship between sensing capabilities and IWB.

Finally, the complete mediation path (*sensing capabilities → GenAI usage capability → GenAI evaluation capability → IWB*) is positive and significant (β = 0.024, $p$ = 0.005), indicating that this complete mediation chain has an indirect effect on IWB. Thus, the results demonstrate that employees' sensing capabilities drive IWB through improved GenAI usage capability and subsequent improved GenAI evaluation capability.

## 6. Discussion

Considering the widely accepted view that innovation is crucial for organizational success and the recently observed discrepancy between innovation prioritization and readiness (Manly et al., 2024), the questionof how organizations can promote their innovativeness arises. This study focuses on employees' IWB, a key microfoundation of organizational-level innovation (De Jong & Den Hartog, 2010; Scott & Bruce, 1994; Shanker et al., 2017).

Specifically, we investigate the antecedents of employees' IWB. We address a research gap regarding how GenAI technologies influence employees' IWB by examining two distinct capabilities—GenAI usage and evaluation capabilities—based on the AI literacy framework by Wang et al. (2023). Building on the dynamic capabilities view (Teece, 2007), we further introduce employees' sensing capabilities as foundational antecedents of both GenAI capabilities and IWB. We conducted a PLS-SEM analysis using a large-scale empirical sample of 439 business consultants to test our hypothesized research model.

The findings reveal that employees' sensing capabilities enhance both GenAI capabilities—usage and evaluation (H1 and H2)—and directly foster their IWB (H3). Further, we found that the employees' capability to use GenAI does not enhance their IWB (H4), but the capability to evaluate GenAI does (H5). Finally, we found that employees' capability to use GenAI enhances their capability to evaluate GenAI (H6).

The most unexpected result is our null finding for H4. This finding might indicate that operational proficiency in GenAI is, by itself,

**Table 6**
Indirect effects.

| Indirect effects | $\beta$ | $p$ | $t$ |
|---|---|---|---|
| Sensing capabilities → GenAI usage capability → GenAI evaluation capability | 0.100 | < 0.001 | 3.867 |
| GenAI usage capability → GenAI evaluation capability→ IWB | 0.121 | < 0.001 | 4.474 |
| Sensing capabilities → GenAI usage capability → IWB | 0.006 | 0.582 | 0.550 |
| Sensing capabilities → GenAI evaluation capability → IWB | 0.031 | 0.011 | 2.534 |
| Sensing capabilities → GenAI usage capability → GenAI evaluation capability → IWB | 0.024 | 0.005 | 2.827 |

insufficient to stimulate employees' IWB. Recent studies allow us to suggest why. Lee et al. (2025) report that when knowledge workers feel "confident" merely using GenAI, their critical-thinking effort drops and ideas converge on conventional solutions, an effect they refer to as mechanized convergence. Complementing this, large-scale experiments show that individuals with low (Gen)AI literacy are actually more receptive to (Gen)AI because they imbue the technology with an aura of "magic," which in turn suppresses reflective scrutiny (Tully, Longoni, & Appel, 2025). In other words, basic usage skills can lull employees into accepting the model's first plausible answer. In contrast, the evaluation dimension, which was conceived in the recent scale validation by Liu et al. (2025) as the peak of GenAI competence, provides users with the cognitive tools to recognize superficiality, iteratively provide new prompts, and integrate domain knowledge. Our data, therefore, suggest that without this higher-order evaluative layer, GenAI usage capability may plateau—or even restrain—true innovation.

In addition, our findings reveal significant indirect effects that highlight the pathways through which employees' sensing capabilities enhance IWB. Specifically, we demonstrated that employees' sensing capabilities positively influence both GenAI capabilities—usage and evaluation—with GenAI evaluation capability subsequently driving IWB. This indirect effect pathway highlights that sensing capabilities facilitate an employee's evaluative engagement with GenAI, thereby serving as an essential antecedentof leveraging GenAI's full potential in fostering IWB. Additionally, while employees' GenAI usage capability positively influences the GenAI evaluation capability, it does not directly lead to IWB. This nuanced result suggests that the capability to "simply" use and apply GenAI tools is insufficient to drive IWB; rather, the critical evaluation—as a higher-order thinking skill—of GenAI outputs contributes to IWB.

Moreover, the complete mediation chain (*sensing capabilities → GenAI usage capability→ GenAI evaluation capability → IWB*) demonstrates a statistically significant effect, underscoring the interconnected nature of these constructs. This pathway suggests the critical role of employees' capability to use and evaluate GenAI as mediators that convert sensing capabilities into individual-level IWB. However, the indirect effect associated with the complete mediation chain is comparatively small ($\beta = 0.024$). Although this coefficient attains statistical significance, its magnitude suggests a modest contribution to the explained variance in IWB, thereby limiting its independent managerial relevance. A comparison with the other indirect paths reinforces this interpretation: the *GenAI usage capability → GenAI evaluation capability → IWB* pathway is considerably stronger ($\beta = 0.121$), the *sensing capabilities → GenAI evaluation capability → IWB* link is also stronger ($\beta = 0.031$), and the direct *sensing capabilities → IWB* effect remains substantially greater ($\beta = 0.356$). Consequently, organizations should regard GenAI usage capability primarily as a preparatory stage that facilitates the development of GenAI evaluation capability, while prioritizing resource allocations toward enhancing employees' sensing capabilities and, above all, their capability to evaluate GenAI outputs, since these elements yield the most pronounced gains in IWB.

### 6.1. Theoretical contributions

Grounded in a concise capability architecture, we link individual-level sensing capabilities, drawn from the dynamic capabilities framework, with GenAI usage and evaluation capabilities, derived from the AI-literacy literature, to explain how employees transform emerging digital tools into IWB. Our study makes several valuable contributions to the literature.

First, we contribute to IWB literature (e.g., De Jong & Den Hartog, 2010; Kör et al., 2021; Scott & Bruce, 1994; Volery & Tarabashkina, 2021). Our results demonstrate that employees' sensing capabilities promote IWB. The capability of employees to use GenAI does not facilitate their individual-level IWB, but the GenAI evaluation capability does. Therefore, our study complements previous studies regarding the antecedents of IWB, including servant leadership (Gelaidan et al., 2024), positive mood (Madrid et al., 2014), cultural intelligence (Afsar et al., 2021), or employee creativity (Volery & Tarabashkina, 2021).

While prior research has predominantly focused on organizational antecedents of IWB (Volery & Tarabashkina, 2021), our study applies a dynamic, cognitively grounded capability perspective, addressing so far highly understudied antecedents: employees' sensing capabilities and their capabilities to use and evaluate GenAI. By distinguishing between different GenAI-related capabilities and highlighting the foundational role of sensing capabilities, we provide a more nuanced understanding of how employees translate technological potential into IWB. Thus, we answer recent calls for empirically studying individual-level dynamic capabilities in the context of GenAI (Heubeck & Held, 2025).

Second, we contribute to the emerging literature on GenAI and its creative potential in the broader innovation management context (e.g., Chiarello et al., 2024; Cillo & Rubera, 2025; Kanbach et al., 2024; Roberts & Candi, 2024; Sedkaoui & Benaichouba, 2024; Singh et al., 2024). While prior studies have highlighted the transformative potential of GenAI for creativity and innovation, recent reviews emphasize that empirical research in this domain remains fragmented (Holzner et al., 2025).

Against this backdrop, our study adopts a capability perspective that explores the *antecedents*, *mechanisms*, and *outcomes* of two distinct but interrelated GenAI capabilities of employees in the innovation context: GenAI usage capability and GenAI evaluation capability. In line with previous studies, we frame GenAI and its potential benefits as a result of a human–GenAI co-creation process (e.g., Boussioux et al., 2024; Grange et al., 2025). Our study and its capability perspective complement previous studies by highlighting the central role of human capabilities in realizing the creative potential of GenAI technologies. We examine how employees' sensing capabilities serve as cognitive antecedents that enable the development of these GenAI capabilities and how, in turn, these capabilities shape IWB. We also explore the mechanisms between GenAI usage and evaluation capabilities.

This approach complements existing studies that typically conceptualize GenAI as a single, undifferentiated construct (e.g., Cimino et al., 2024; Rana et al., 2024; Singh et al., 2024). Finally, our study extends a growing body of research applying the dynamic capabilities lens to GenAI (e.g., AL-Khatib & Ramayah, 2024; Shore et al., 2024) by offering a fine-grained microfoundational view of how individual-level capabilities can be developed and mobilized to unlock GenAI's innovative potential in everyday work.

### 6.2. Practical contributions

Our study contains essential practical implications for companies and managers aiming to enhance the IWB of their employees by leveraging employees' sensing capabilities and GenAI capabilities. While we emphasize throughout our study that our findings should be interpreted in context, given that the data were collected in Germany, Austria, and Switzerland, we argue that the following practical implications are nonetheless transferable to other countries with a similar level of technological maturity.

Our study showed that employees' sensing capabilities (i.e., the ability to scan the environment and collect and filter new information) enhance IWB (i.e., make employees more innovative). In addition, employees' sensing capabilities facilitate employees' GenAI usage and evaluation capabilities of GenAI. Therefore, companies should devote considerable resources to increasing their employees' sensing capabilities. Concrete measures include, for example, regularly sending employees to conferences, seminars, and trade shows (Khan, Daddi, & Iraldo, 2020), where they can observe new trends, exchange knowledge, and build professional networks. Another instrument is the effective monitoring of competitor activities like changes in product offerings or prices (Helfat & Raubitschek, 2018). Complementing these initiatives, firms could establish weekly "tech-radar" sessions in which crossfunctional teams review recent patent filings, start-up funding rounds, and specialist blogs, assessing their relevance for ongoing projects; an AI-powered monitoring platform that curates weak signals into personalized newsfeeds would further embed trend sensing into employees' daily routines.

Furthermore, our study showed that employees' GenAI usage capability does not affect their IWB, while employees' capability to evaluate GenAI outputs critically enhances their IWB. Against the backdrop that GenAI is often framed through a human-GenAI co-creation process (e.g., Boussioux et al., 2024; Grange et al., 2025), this perspective implies that the output of GenAI is dependent on the capabilities of the employee interacting with the technology. Thus, companies should focus primarily on increasing employees' evaluation skills concerning GenAI outcomes to leverage GenAI effectively. Effective ways of achieving this are creating suitable training formats and upskilling initiatives, highlighting the strengths and weaknesses of GenAI to understand its underlying functioning (Pinski, Adam, & Benlian, 2023). For example, firms could offer scenario-based micro-workshops in which employees diagnose hallucinations and bias in GenAI outputs and discuss the ethical trade-offs of deploying such content in client work. In parallel, organizations might develop a living "prompt-engineering handbook" that pairs effective prompt templates with evaluation checklists, ensuring that users move beyond basic tool operation toward rigorous, critical appraisal of GenAI suggestions.

Finally, our study shows that GenAI is generally a complex and multi-layered construct. We demonstrate this by differentiating between employees' GenAI usage capability and GenAI evaluation capability. Through this nuanced approach, we create an awareness for managers and companies to consider that the realized potential of GenAI is not certain and that the "simple" capability to apply and use the technology is not sufficient. The value of GenAI for individual-level IWB is unlocked through employees' capability to critically evaluate the output, highlighting the crucial role that humans still play.

### *6.3. Limitations and future research*

As with any other study, this study has several limitations that open avenues for future research. First, the cross-sectional nature of our data limits the ability to make strong causal inferences. Although we developed our hypotheses based on robust theoretical foundations and tested them using PLS-SEM, future studies could employ longitudinal designs or experimental methods.

Second, our data are based on self-reported measures, which may be subject to social desirability and common method bias. Although we conducted Harman's single-factor test and took procedural precautions to mitigate such biases, self-report data cannot fully capture the richness and behavioral nuance of how employees interact with GenAI in real-world contexts. Future research could triangulate survey data with behavioral or usage data (e.g., log files from GenAI systems) or adopt mixed-method designs to enrich the findings.

Third, while consultants represent an ideal population for studying GenAI in high-paced, dynamic, and innovative settings, the generalizability of our findings to other industries or occupational groups may be limited. Consultants typically operate in project-based structures with high digital affinity, which may not reflect the broader workforce. These contextual levers amplify both the development of GenAI capabilities and the translation of those capabilities into IWB. The pattern may diverge in domains with stricter regulatory oversight or lower digital intensity. In healthcare, for instance, stringent data-protection rules could reduce GenAI usage capability yet increase the salience of GenAI evaluation capability as clinicians must scrutinize GenAI outputs for liability reasons. In public administration, limited autonomy and bureaucratic procedures might dampen the entire capability–IWB chain, whereas in education, moderate autonomy but high ethical scrutiny could shift emphasis toward GenAI evaluation skills. As Deloitte's (2024a) cross-industry scan of innovative GenAI use cases underscores, the innovation potential of GenAI varies strongly across industries. Future studies could replicate our model in other professional contexts (e.g., manufacturing, public sector, or healthcare) to test the boundary conditions of our findings.

Fourth, because our sample comes from Germany, Austria, and Switzerland—countries embedded in a strong European regulatory framework such as general data protection regulations—employees' GenAI perceptions are likely filtered through strict data-privacy and ethical-evaluation requirements. Future research could investigate how varying levels of AI regulation impact the relationship between GenAI capabilities and innovation, a topic of growing importance for international business (e.g., Wang & Zhang, 2025b).

Fifth, although we differentiated GenAI capabilities into usage and evaluation dimensions based on a validated scale, GenAI remains an evolving phenomenon with diverse application contexts. Future research should explore additional facets of GenAI-related competencies—such as prompt engineering proficiency, ethical awareness, or collaboration fluency in human-AI teams—and examine their interplay with innovation-related outcomes.

Finally, our study focuses on individual-level sensing capabilities as antecedents of GenAI capabilities and IWB. In line with the original scale of Harvey (2025) and broader dynamic capabilities literature (e.g., Teece, 2007), we conceptualize these sensing capabilities as broad and general higher-order capabilities. Future research could extend that view and examine how GenAI can support individuals with their sensing capabilities (e.g., digital AI-supported dashboards to recognize new technological trends).

## Declaration of GenAI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeepL (https://www.deepl.com/de/translator) and ChatGPT (https://chat.openai.com) to improve readability and linguistic formulation of some of the sentences. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## CRediT authorship contribution statement

**Patrick Held:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Tim Heubeck:** Writing – review & editing, Supervision.

## Consent to participate

Consent was obtained from all individual participants included in the study.

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## Declaration of competing interest

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

The second author is an Editorial Board Member for this journal and was not involved in the editorial review or the decision to publish this article.

## Appendix

Measurement scales.

| Construct | Item |
|---|---|
| Sensing capabilities | S1: I look for what competing firms are doing.<br>S2: I scan the environment for market ideas/expertise.<br>S3: I collect technical information/ideas from individuals outside my firm.<br>S4: I scan the environment for technical ideas/expertise. |
| GenAI usage capability | U1: I can skillfully use GenAI applications to help me with my daily work.<br>U2: It is usually hard for me to learn to use a new GenAI application.$^{R}$<br>U3: I can use GenAI applications to improve my work efficiency. |
| GenAI evaluation capability | E1: I can evaluate the capabilities and limitations of a GenAI application after using it for a while.<br>E2: I can choose a proper solution from various solutions provided by GenAI.<br>E3: I can choose the most appropriate GenAI application from a variety for a particular task. |
| Innovative work behavior | I1: I pay attention to issues that are not part of my daily work.*<br>I2: I wonder how things can be improved.*<br>I3: I search out new working methods, techniques or instruments.<br>I4: I generate original solutions for problems.<br>I5: I find new approaches to execute tasks.<br>I6: I make important organizational members enthusiastic for innovative ideas.<br>I7: I attempt to convince people to support an innovative idea.<br>I8: I systematically introduce innovative ideas into work practices.<br>I9: I contribute to the implementation of new ideas.<br>I10: I put effort in the development of new things. |

R=inversed scale; * = Removed due to low factor loading.

## Data availability

The authors cannot share the collected data due to confidentiality reasons.

## References

Accenture. (2024). Accenture and NVIDIA lead enterprises into era of AI. https://newsroom.accenture.com/news/2024/accenture-and-nvidia-lead-enterprises-into-era-of-ai (last accessed 19 June 2025).

Adner, R., & Helfat, C. E. (2003). Corporate effects and dynamic managerial capabilities. *Strategic Management Journal, 24*(10), 1011–1025. https://doi.org/10.1002/smj.331

Afsar, B., Al-Ghazali, B. M., Cheema, S., & Javed, F. (2021). Cultural intelligence and innovative work behavior: The role of work engagement and interpersonal trust. *European Journal of Innovation Management, 24*(4), 1082–1109. https://doi.org/10.1108/EJIM-01-2020-0008

Agarwal, R., & Helfat, C. E. (2009). Strategic renewal of organizations. *Organization Science, 20*(2), 281–293. https://doi.org/10.1287/orsc.1090.0423

Akter, S., Hossain, M. A., Sajib, S., Sultana, S., Rahman, M., Vrontis, D., & McCarthy, G. (2023). A framework for AI-powered service innovation capability: Review and agenda for future research. *Technovation, 125*, Article 102768. https://doi.org/10.1016/j.technovation.2023.102768

AlEssa, H. S., & Durugbo, C. M. (2022). Systematic review of innovative work behavior concepts and contributions. *Management Review Quarterly, 72*(4), 1171–1208. https://doi.org/10.1007/s11301-021-00224-x

AL-Khatib, A. W., & Ramayah, T. (2024). Artificial intelligence-based dynamic capabilities and circular supply chain: Analyzing the potential indirect effect of frugal innovation in retailing firms. *Business Strategy and the Environment, 34*(1), 830–848. https://doi.org/10.1002/bse.4018

Alshanty, A. M., & Emeagwali, O. L. (2019). Market-sensing capability, knowledge creation and innovation: The moderating role of entrepreneurial-orientation. *Journal of Innovation & Knowledge, 4*(3), 171–178. https://doi.org/10.1016/j.jik.2019.02.002

Amabile, T. M. (1988). In B. M. Staw, & L. L. Cummings (Eds.), *Research in organizational behavior, (Vol. 10*, pp. 123–167). Greenwich, CT: JAI Press.

Ancona, D. G., & Caldwell, D. F. (1992). Bridging the boundary: External activity and performance in organizational teams. *Administrative Science Quarterly, 37*(4), 634–665. https://doi.org/10.2307/2393475

Anser, M. K., Yousaf, Z., Khan, A., & Usman, M. (2021). Towards innovative work behavior through knowledge management infrastructure capabilities: Mediating role of functional flexibility and knowledge sharing. *European Journal of Innovation Management, 24*(2), 461–480. https://doi.org/10.1108/EJIM-09-2019-0250

Banh, L., & Strobel, G. (2023). Generative artificial intelligence. *Electronic Markets, 33*(63). https://doi.org/10.1007/s12525-023-00680-1

BDU. (2024). *Facts & Figures zum Consultingmarkt*. https://www.bdu.de/media/355573/facts-figures-vorjahr.pdf, 2024 (last accessed 2 August 2025).

Becker, J.-M., Cheah, J.-H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management, 35*(1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474

Bilgram, V., & Laarmann, F. (2023). Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods. *IEEE Engineering Management Review, 51*(2), 18–25. https://doi.org/10.1109/EMR.2023.3272799

Birkinshaw, J., Hamel, G., & Mol, M. J. (2008). Management innovation. *Academy of management Review, 33*(4), 825–845. https://doi.org/10.5465/amr.2008.34421969

Bos-Nehles, A., Renkema, M., & Janssen, M. (2017). HRM and innovative work behaviour: A systematic literature review. *Personnel Review, 46*(7), 1228–1253. https://doi.org/10.1108/PR-09-2016-0257

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science, 35*(5), 1589–1607. https://doi.org/10.1287/orsc.2023.18430

Chen, Z., & Chan, J. (2024). Large language model in creative work: The role of collaboration modality and user expertise. *Management Science, 70*(12), 9101–9117. https://doi.org/10.1287/mnsc.2023.03014

Chiarello, F., Giordano, V., Spada, I., Barandoni, S., & Fantoni, G. (2024). Future applications of generative large language models: A data-driven case study on ChatGPT. *Technovation, 133*, Article 103002. https://doi.org/10.1016/j.technovation.2024.103002

Chu, W., Baxter, D., & Liu, Y. (2025). Exploring the impacts of generative AI on artistic innovation routines. *Technovation, 143*, Article 103209. https://doi.org/10.1016/j.technovation.2025.103209

Cillo, P., & Rubera, G. (2025). Generative AI in innovation and marketing processes: A roadmap of research opportunities. *Journal of the Academy of Marketing Science, 53*, 684–701. https://doi.org/10.1007/s11747-024-01044-7

Cimino, A., Felicetti, A. M., Corvello, V., Ndou, V., & Longo, F. (2024). Generative artificial intelligence (AI) tools in innovation management: A study on the appropriation of ChatGPT by innovation managers. *Management Decision*. https://doi.org/10.1108/MD-10-2023-1968

Day, G. S., & Schoemaker, P. J. (2016). Adapting to fast-changing markets and technologies. *California Management Review, 58*(4), 59–77. https://doi.org/10.1525/cmr.2016.58.4.59

De Jong, J., & Den Hartog, D. (2007). How leaders influence employees' innovative behaviour. *European Journal of Innovation Management, 10*(1), 41–64. https://doi.org/10.1108/14601060710720546

De Jong, J., & Den Hartog, D. (2010). Measuring innovative work behaviour. *Creativity and Innovation Management, 19*(1), 23–36. https://doi.org/10.1111/j.1467-8691.2010.00547.x

Deloitte. (2024a). Generative AI and the future of work. https://www.deloitte.com/global/en/services/consulting/research/generative-ai-and-the-future-of-work.html (last accessed 31 July 2025).

Deloitte. (2024b). Now decides next: Moving from potential to performance. https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-generative-ai-in-enterprise.html (last accessed 19 June 2025).

Dong, A., Garbuio, M., & Lovallo, D. (2016). Generative sensing: A design perspective on the microfoundations of sensing capabilities. *California Management Review, 58*(4), 97–117. https://doi.org/10.1525/cmr.2016.58.4.97

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*, 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E

Eisenreich, A., Just, J., Gimenez-Jimenez, D., & Füller, J. (2024). Revolution or inflated expectations? Exploring the impact of generative AI on ideation in a practical sustainability context. *Technovation, 138*, Article 103123. https://doi.org/10.1016/j.technovation.2024.103123

Ellström, D., Holtström, J., Berg, E., & Josefsson, C. (2022). Dynamic capabilities for digital transformation. *Journal of Strategy and Management, 15*(2), 272–286. https://doi.org/10.1108/JSMA-04-2021-0089

Farrukh, M., Meng, F., Raza, A., & Wu, Y. (2023). Innovative work behaviour: The what, where, who, how and when. *Personnel Review, 52*(1), 74–98. https://doi.org/10.1108/PR-11-2020-0854

Felin, T., Foss, N. J., & Ployhart, R. E. (2015). The microfoundations movement in strategy and organization theory. *The Academy of Management Annals, 9*(1), 575–632. https://doi.org/10.1080/19416520.2015.1007651

Ferreira, J., Coelho, A., & Moutinho, L. (2020). Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation. *Technovation, 92-93*, Article 102061. https://doi.org/10.1016/j.technovation.2018.11.004

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering, 66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39. https://doi.org/10.2307/3151312

Foss, N. J., & Mazzelli, A. (2025). Bringing managers and management back into strategy: Interfaces and dynamic managerial capabilities. *Journal of Business Research, 186*, Article 114947. https://doi.org/10.1016/j.jbusres.2024.114947

Gartner. (2023). What's new in artificial intelligence from the 2023 Gartner Hype Cycle: Innovations in and around generative AI dominate and have transformative impact. https://www.gartner.com/en/articles/what-s-new-in-artificial-intelligence-from-the-2023-gartner-hype-cycle.

Gelaidan, H. M., Al-Swidi, A. K., & Al-Hakimi, M. A. (2024). Servant and authentic leadership as drivers of innovative work behaviour: The moderating role of creative self-efficacy. *European Journal of Innovation Management, 27*(6), 1938–1966. https://doi.org/10.1108/EJIM-07-2022-0382

Grange, C., Demazure, T., Ringeval, M., Bourdeau, S., & Martineau, C. (2025). The human-GenAI value loop in human-centered innovation: Beyond the magical narrative. *Information Systems Journal*, 1–23. https://doi.org/10.1111/isj.12602

Haefner, N., Parida, V., Gassmann, O., & Wincent, J. (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change, 197*, Article 122878. https://doi.org/10.1016/j.techfore.2023.122878

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis ($7^{th}$)*.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., & Sarstedt, M. (2021). Explanation plus prediction—The logical focus of project management research. *Project Management Journal, 52*(4), 319–322. https://doi.org/10.1177/8756972821999945

Harman, H. H. (1976). *Modern factor analysis, $3^{rd}$*. University of Chicago press.

Harvey, J.-F. (2025). Microfoundations of sensing capabilities: From managerial cognition to team behavior. *Strategic Organization, 23*(2), 167–194. https://doi.org/10.1177/14761270221142959

Held, P., Heubeck, T., & Meckl, R. (2025). Boosting SMEs' digital transformation: The role of dynamic capabilities in cultivating digital leadership and digital culture. *Review of Managerial Science, 1–29*. https://doi.org/10.1007/s11846-025-00919-5

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D. J., & Winter, S. G. (2007). *Dynamic capabilities: Understanding strategic change in organizations*. Oxford: Blackwell Publishing.

Helfat, C. E., & Martin, J. A. (2015). Dynamic managerial capabilities. *Journal of Management, 41*(5), 1281–1312. https://doi.org/10.1177/0149206314561301

Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy, 47* (8), 1391–1399. https://doi.org/10.1016/j.respol.2018.01.019

Helfat, C. E., & Winter, S. G. (2011). Untangling dynamic and operational capabilities: Strategy for the (n)ever-changing world. *Strategic Management Journal, 32*(11), 1243–1250. https://doi.org/10.1002/smj.955

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Heubeck, T. (2023). Managerial capabilities as facilitators of digital transformation? Dynamic managerial capabilities as antecedents to digital business model transformation and firm performance. *Digital Business, 3*(1), Article 100053. https://doi.org/10.1016/j.digbus.2023.100053

Heubeck, T. (2024). Looking back to look forward: A systematic review of and research agenda for dynamic managerial capabilities. *Management Review Quarterly, 74*(4), 2243–2287. https://doi.org/10.1007/s11301-023-00359-z

Heubeck, T., & Held, P. (2025). Management capabilities in the age of generative artificial intelligence (GenAI): A conceptual framework and future research directions. In J. Liebowitz (Ed.), *Achieving digital transformation through analytics and AI* (pp. 131–153). World Scientific. https://doi.org/10.1142/13939.

Hock-Doepgen, M., Heaton, S., Clauss, T., & Block, J. (2025). Identifying microfoundations of dynamic managerial capabilities for business model innovation. *Strategic Management Journal, 46*(2), 470–501. https://doi.org/10.1002/smj.3663

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and creativity: A systematic literature review and Meta-analysis. *arXiv*. https://doi.org/10.48550/arXiv.2505.17241. preprint arXiv:2505.17241.

Huhtala, H., & Parzefall, M.-R. (2007). A review of employee well-being and innovativeness: An opportunity for a mutual benefit. *Creativity and Innovation Management, 16*(3), 299–306. https://doi.org/10.1111/j.1467-8691.2007.00442.x

Janssen, O. (2000). Job demands, perceptions of effort-reward fairness and innovative work behaviour. *Journal of Occupational and Organizational Psychology, 73*(3), 287–302. https://doi.org/10.1348/096317900167038

Janssen, O., & van Yperen, N. W. (2004). Employees' goal orientations, the quality of leader-member exchange, and the outcomes of job performance and job satisfaction. *Academy of Management Journal, 47*(3), 368–384. https://doi.org/10.5465/20159587

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal, 67*(1), 5–32. https://doi.org/10.5465/amj.2022.0426

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: Generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science, 18*(4), 1189–1220. https://doi.org/10.1007/s11846-023-00696-z

Khan, O., Daddi, T., & Iraldo, F. (2020). Microfoundations of dynamic capabilities: Insights from circular economy business cases. *Business Strategy and the Environment, 29*(3), 1479–1493. https://doi.org/10.1002/bse.2447

Kör, B., Wakkee, I., & van der Sijde, P. (2021). How to promote managers' innovative behavior at work: Individual factors and perceptions. *Technovation, 99*, Article 102127. https://doi.org/10.1016/j.technovation.2020.102127

Kumar, A., Shankar, A., Hollebeek, L. D., Behl, A., & Lim, W. M. (2025). Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption. *Journal of Business Research, 189*, Article 115160. https://doi.org/10.1016/j.jbusres.2024.115160

Lam, L. W. (2012). Impact of competitiveness on salespeople's commitment and performance. *Journal of Business Research, 65*(9), 1328–1334. https://doi.org/10.1016/j.jbusres.2011.10.026

Lee, H. P., Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025, April). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. *Proceedings of the 2025 CHI conference on human factors in computing systems* (pp. 1–22).

Leiponen, A., & Helfat, C. E. (2010). Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal, 31*(2), 224–236. https://doi.org/10.1002/smj.807

Leso, B. H., Cortimiglia, M. N., Ghezzi, A., & Minatogawa, V. (2024). Exploring digital transformation capability via a blended perspective of dynamic capabilities and digital maturity: A pattern matching approach. *Review of Managerial Science, 18*(4), 1149–1187. https://doi.org/10.1007/s11846-023-00692-3

Lin, H.-F., Su, J.-Q., & Higgins, A. (2016). How dynamic capabilities affect adoption of management innovations. *Journal of Business Research, 69*(2), 862–876. https://doi.org/10.1016/j.jbusres.2015.07.004

Liu, M., Zhang, L. J., & Zhang, D. (2025). Enhancing student GAI literacy in digital multimodal composing through development and validation of a scale. *Computers in Human Behavior, 166*, Article 108569. https://doi.org/10.1016/j.chb.2025.108569

Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys, 55*(9), 1–35. https://doi.org/10.1145/3560815

Liu, V., & Chilton, L. B. (2022, April). Design guidelines for prompt engineering text-to-image generative models. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1–23). https://doi.org/10.1145/3491102.3501825

Madrid, H. P., Patterson, M. G., Birdi, K. S., Leiva, P. I., & Kausel, E. E. (2014). The role of weekly high-activated positive mood, context, and personality in innovative work behavior: A multilevel and interactional model. *Journal of Organizational Behavior, 35*(2), 234–256. https://doi.org/10.1002/job.1867

Manly, J., Ringel, M., MacDougall, A., Harnoss, J., Wolke-Perten, J., Backler, W., … Viner, B. (2024). *Most innovative companies 2024: Innovation systems need a reboot*. Boston Consulting Group. https://www.bcg.com/publications/2024/innovation-systems-need-a-reboot (last accessed 10 June 2025).

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research, 175*, Article 114542. https://doi.org/10.1016/j.jbusres.2024.114542

Mariani, M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation, 122*, Article 102623. https://doi.org/10.1016/j.technovation.2022.102623

Mazzucchelli, A., Chierici, R., Abbate, T., & Fontana, S. (2019). Exploring the microfoundations of innovation capabilities. Evidence from a cross-border R&D partnership. *Technological Forecasting and Social Change, 146*, 242–252. https://doi.org/10.1016/j.techfore.2019.06.003

McKinsey. (2023). Effects of GenAI on the German labor market. https://www.mckinsey.de/news/presse/wie-genai-die-arbeitswelt-in-deutschland-veraendert (last accessed 2 August 2025).

McKinsey. (2024). The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (last accessed 19 June 2025).

McKinsey. (2025). The state of AI: How organizations are rewiring to capture value. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (last accessed 31 July 2025).

Minevich, M. (2024). GenAI revolution is reshaping the future of traditional consulting. https://www.forbes.com/sites/markminevich/2024/04/26/gen-ai-revolution-is-reshaping-the-future-of-traditional-consulting/.

Mueller, S. T., Hoffman, R. R., Clancey, W., Emrey, A., & Klein, G. (2019). *Explanation in human-AI systems: A literature meta-review, synopsis of key ideas and publications, and bibliography for explainable AI*. https://doi.org/10.48550/arXiv.1902.01876

Ng, A., & Jordan, M. (2001). In *On discriminative vs. generative classifiers: A comparison of logistic regression and naive Bayes* (pp. 841–848). Cambridge, MA: MIT Press.

Palmié, M., Rüegger, S., & Parida, V. (2023). Microfoundations in the strategic management of technology and innovation: Definitions, systematic literature review, integrative framework, and research agenda. *Journal of Business Research, 154*, Article 113351. https://doi.org/10.1016/j.jbusres.2022.113351

Piller, F. T., Srour, M., & Marion, T. J. (2024). Generative AI, innovation, and trust. *The Journal of Applied Behavioral Science, 60*(4), 613–622. https://doi.org/10.1177/00218863241285033

Pinski, M., Adam, M., & Benlian, A. (2023). AI knowledge: Improving AI delegation through human enablement. In *Proceedings of the 2023 CHI conference on human factors in computing systems* (pp. 1–17). ACM. https://doi.org/10.1145/3544548.3580794.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rana, N. P., Pillai, R., Sivathanu, B., & Malik, N. (2024). Assessing the nexus of generative AI adoption, ethical considerations and organizational performance. *Technovation, 135*, Article 103064. https://doi.org/10.1016/j.technovation.2024.103064

Reuters. (2023). ChatGPT sets record for fastest-growing user base - analyst note. https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/ (last accessed 19 June 2025).

Ritala, P., Aaltonen, P., Ruokonen, M., & Nemeh, A. (2024). Developing industrial AI capabilities: An organisational learning perspective. *Technovation, 138*, Article 103120. https://doi.org/10.1016/j.technovation.2024.103120

Roberts, D. L., & Candi, M. (2024). Artificial intelligence and innovation management: Charting the evolving landscape. *Technovation, 136*, Article 103081. https://doi.org/10.1016/j.technovation.2024.103081

Salvato, C., & Vassolo, R. (2018). The sources of dynamism in dynamic capabilities. *Strategic Management Journal, 39*(6), 1728–1752. https://doi.org/10.1002/smj.2703

Sarstedt, M., & Danks, N. P. (2022). Prediction in HRM research–A gap between rhetoric and reality. *Human Resource Management Journal, 32*(2), 485–513. https://doi.org/10.1111/1748-8583.12400

Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *The Academy of Management Annals, 12*(1), 390–439. https://doi.org/10.5465/annals.2016.0014

Schoemaker, P. J. H., Heaton, S., & Teece, D. (2018). Innovation, dynamic capabilities, and leadership. *California Management Review, 61*(1), 15–42. https://doi.org/10.1177/0008125618790246

Schryen, G., Marrone, M., & Yang, J. (2025). Exploring the scope of generative AI in literature review development. *Electronic Markets, 35*(13). https://doi.org/10.1007/s12525-025-00754-2

Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior: A path model of individual innovation in the workplace. *Academy of Management Journal, 37*(3), 580–607. https://doi.org/10.2307/256701

Sedkaoui, S., & Benaichouba, R. (2024). Generative AI as a transformative force for innovation: A review of opportunities, applications and challenges. *European Journal of Innovation Management*, 1–25. https://doi.org/10.1108/EJIM-02-2024-0129

Shanker, R., Bhanugopan, R., Van der Heijden, B. I., & Farrell, M. (2017). Organizational climate for innovation and organizational performance: The mediating effect of innovative work behavior. *Journal of Vocational Behavior, 100*, 67–77. https://doi.org/10.1016/j.jvb.2017.02.004

Shore, A., Tiwari, M., Tandon, P., & Foropon, C. (2024). Building entrepreneurial resilience during crisis using generative AI: An empirical study on SMEs. *Technovation, 135*, Article 103063. https://doi.org/10.1016/j.technovation.2024.103063

Singh, K., Chatterjee, S., & Mariani, M. (2024). Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. *Technovation, 133*, Article 103021. https://doi.org/10.1016/j.technovation.2024.103021

Strobl, A., Matzler, K., Nketia, B. A., & Veider, V. (2020). Individual innovation behavior and firm-level exploration and exploitation: How family firms make the most of their managers. *Review of Managerial Science, 14*(4), 809–844. https://doi.org/10.1007/s11846-018-0309-9

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives, 28*(4), 328–352. https://doi.org/10.5465/amp.2013.0116

Teece, D. J., & Linden, G. (2017). Business models, value capture, and the digital enterprise. *Journal of Organization Design, 6*(1). https://doi.org/10.1186/s41469-017-0018-x

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Teng, D., Ye, C., & Martinez, V. (2025). Gen-AI'S effects on new value propositions in business model innovation: Evidence from information technology industry. *Technovation, 143*, Article 103191. https://doi.org/10.1016/j.technovation.2025.103191

Tran, M.-L., & Thai, H.-C. V. (2025). Future-ready strategies: Dynamic managerial capabilities, digitalization, and green product innovation in building firm resilience. *Business Ethics, the Environment & Responsibility*, 1–24. https://doi.org/10.1111/beer.70007

Tully, S. M., Longoni, C., & Appel, G. (2025). Lower artificial intelligence literacy predicts greater AI receptivity. *Journal of Marketing, 89*(5), 1–20. https://doi.org/10.1177/00222429251314491

Volery, T., & Tarabashkina, L. (2021). The impact of organisational support, employee creativity and work centrality on innovative work behaviour. *Journal of Business Research, 129*, 295–303. https://doi.org/10.1016/j.jbusres.2021.02.049

Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology, 42*(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wang, S., & Zhang, H. (2025a). Generative artificial intelligence and internationalization green innovation: Roles of supply chain innovations and AI regulation for SMEs. *Technology in Society, 82*, Article 102898. https://doi.org/10.1016/j.techsoc.2025.102898

Wang, S., & Zhang, H. (2025b). Promoting sustainable development goals through generative artificial intelligence in the digital supply chain: Insights from Chinese tourism SMEs. *Sustainable Development, 33*(1), 1231–1248. https://doi.org/10.1002/sd.3152

Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning, 52*(3), 326–349. https://doi.org/10.1016/j.lrp.2018.12.001

Widmann, A., & Mulder, R. H. (2018). Team learning behaviours and innovative work behaviour in work teams. *European Journal of Innovation Management, 21*(3), 501–520. https://doi.org/10.1108/EJIM-12-2017-0194

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal, 24*(10), 991–995. https://doi.org/10.1002/smj.318

Yin, M., Jiang, S., & Niu, X. (2024). Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. *Computers in Human Behavior, 150*, Article 107987. https://doi.org/10.1016/j.chb.2023.107987

Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal, 53*(2), 323–342. https://doi.org/10.5465/AMJ.2010.49388995

Zabel, C., O'Brien, D., & Natzel, J. (2023). Sensing the metaverse: The microfoundations of complementor firms' dynamic sensing capabilities in emerging-technology ecosystems. *Technological Forecasting and Social Change, 192*, Article 122562. https://doi.org/10.1016/j.techfore.2023.122562

Zhang, X., Yu, P., & Ma, L. (2025). How and when generative AI use affects employee incremental and radical creativity: An empirical study in China. *European Journal of Innovation Management*. https://doi.org/10.1108/EJIM-04-2024-0466

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science, 13*(3), 339–351. https://doi.org/10.1287/orsc.13.3.339.2780