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Sensing the Future: A Qualitative Synthesis of How Employees' Technological Sensing Capabilities Shape GenAI Capabilities and Innovative Work Behavior

Mia Christy Patricia[1]*, Novrizal[2]

[1] Management, STIE Kasih Bangsa, email novrizal@stiekasihbangsa.ac.id
[2] Management, STIE Kasih Bangsa, email mia@stiekasihbangsa.ac.id

* Corresponding Author : Mia Christy Patricia

Abstract: This qualitative literature review synthesizes interdisciplinary research on how employees' technological sensing capabilities shape generative artificial intelligence (GenAI) capabilities and innovative work behavior. Drawing on dynamic capabilities theory, microfoundations of sensing, and human–AI interaction literature, the review integrates findings from management, information systems, and innovation studies. The synthesis reveals that technological sensing—employees' ability to identify, interpret, and anticipate emerging technologies—does not directly translate into innovation, but operates through the development of distinct GenAI capabilities. In particular, GenAI evaluation capability consistently emerges as a stronger driver of innovative work behavior than GenAI usage capability alone, as it enables critical judgment, contextualization, and creative recombination of AI-generated outputs. The review further highlights contextual moderators such as leadership support, task complexity, and organizational climate. Overall, the study advances theory by positioning individual sensing as a microfoundation of AI-enabled innovation and offers implications for organizations seeking to leverage GenAI beyond efficiency gains.

Keywords: Technological Sensing Capabilities; Generative Artificial Intelligence; Innovative Work Behavior; Dynamic Capabilities; Human–AI collaboration

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1. Introduction

Innovation has long been recognized as a central driver of organizational competitiveness, adaptability, and long-term performance in increasingly turbulent environments (Teece, Pisano, & Shuen, 1997; Birkinshaw, Hamel, & Mol, 2008). At the micro level, employees' innovative work behavior (IWB)—defined as the intentional generation, promotion, and realization of novel ideas within a work role—constitutes a critical foundation of firm-level innovation outcomes (Scott & Bruce, 1994; De Jong & Den Hartog, 2010; AlEssa & Durugbo, 2022). Accordingly, a vast body of research has investigated individual, contextual, and organizational antecedents of IWB, including leadership styles, psychological states, learning behaviors, and human resource practices (Bos-Nehles et al., 2017; Farrukh et al., 2023; Gelaidan et al., 2024). However, despite this rich literature, the rapid diffusion of generative artificial intelligence (GenAI) introduces a fundamentally new technological context whose implications for employees' innovative behavior remain insufficiently understood.

GenAI systems—such as large language models capable of producing text, code, images, and analytical outputs—are increasingly embedded in knowledge-intensive work processes across consulting, professional services, design, and innovation management (Feuerriegel et al., 2024; Kanbach et al., 2024; Kumar et al., 2025). Industry reports indicate that GenAI adoption is accelerating at an unprecedented pace, with firms shifting from experimentation toward value capture and operational integration (McKinsey, 2024, 2025; Deloitte, 2024).

While early studies highlight GenAI's potential to augment creativity, ideation, and problem-solving, emerging evidence also reveals paradoxical effects, including idea convergence, reduced cognitive effort, and overreliance on algorithmic outputs (Boussioux et al., 2024; Jia et al., 2024; Yin et al., 2024). These mixed findings suggest that GenAI's impact on IWB is not automatic but contingent on how employees engage with, interpret, and critically evaluate AI-generated content. Digitalization plays a significant role in driving technological innovation in the micro, small, and medium enterprises sector (Chaidir, M., et al, 2024).

To theoretically account for these contingencies, scholars increasingly draw on the dynamic capabilities framework, which conceptualizes organizational adaptability as rooted in sensing, seizing, and reconfiguring capabilities (Teece, 2007, 2014). Importantly, recent research emphasizes the microfoundations of dynamic capabilities, arguing that individual-level cognition, skills, and behaviors underpin firm-level sensing and innovation outcomes (Felin, Foss, & Ployhart, 2015; Palmié, Rüegger, & Parida, 2023). Within this perspective, employees' technological sensing capabilities—their ability to notice, interpret, and anticipate technological shifts—emerge as a critical yet underexplored antecedent of innovative behavior in digital contexts (Day & Schoemaker, 2016; Dong, Garbuio, & Lovallo, 2016; Harvey, 2025). In addition to being a precursor to the achievement of innovation performance and corporate sustainable longevity, human capital can also function as a moderator for innovation performance to achieve corporate sustainable longevity (Irawan et al., 2021)

Technological sensing capabilities extend beyond mere awareness of new tools; they encompass proactive scanning, cognitive framing, and interpretive judgment that enable individuals to make sense of emerging technologies and their implications for work practices (Zabel, O'Brien, & Natzel, 2023; Held & Heubeck, 2025). In the context of GenAI, such sensing capabilities may shape how employees develop more specific GenAI-related capabilities, including the ability to effectively use GenAI systems and, crucially, to evaluate their outputs. While GenAI usage capability reflects operational proficiency in prompting and applying AI tools, GenAI evaluation capability represents a higher-order competence involving critical assessment, contextualization, and iterative refinement of AI-generated content (Liu et al., 2025; Pinski, Adam, & Benlian, 2023). Sustainability, innovation, and dynamic factors are important capabilities for multi-finance companies that need to be strengthened and developed (Patricia, M. C, 2023).

Recent empirical research underscores the importance of distinguishing between these two dimensions. Studies show that operational GenAI usage alone may foster efficiency but does not necessarily enhance creativity or innovation (Chen & Chan, 2024; Eisenreich et al., 2024). More critically, Lee et al. (2025) demonstrate that confidence derived from routine GenAI use can reduce critical thinking effort, leading to what they term "mechanized convergence," where ideas gravitate toward conventional solutions. Complementing this insight, Tully, Longoni, and Appel (2025) find that individuals with lower AI literacy are often more receptive to AI outputs, attributing a "magical" aura to the technology that suppresses reflective scrutiny. These findings suggest that without evaluative competence, GenAI usage may plateau or even constrain innovative work behavior.

Against this backdrop, emerging research proposes that GenAI evaluation capability constitutes the apex of GenAI competence, enabling users to detect superficiality, challenge default outputs, and integrate domain-specific knowledge into iterative human–AI collaboration (Liu et al., 2025; Grange et al., 2025). This evaluative layer aligns closely with the microfoundational logic of sensing capabilities, which emphasize interpretive depth, judgment, and learning over mere execution (Salvato & Vassolo, 2018; Helfat & Martin, 2015). Consequently, understanding how employees' sensing capabilities foster differentiated GenAI capabilities—and how these capabilities, in turn, shape IWB—represents a critical gap in both the IWB and GenAI literatures.

Addressing this gap, recent empirical evidence from knowledge-intensive settings, such as consulting, demonstrates that employees' sensing capabilities directly enhance IWB while also indirectly fostering innovation through GenAI evaluation capability (Held & Heubeck, 2025). Notably, while sensing capabilities promote both GenAI usage and evaluation, only the latter exhibits a direct positive relationship with IWB. GenAI usage capability contributes indirectly by enabling evaluative competence rather than independently driving innovation. These nuanced pathways reinforce the argument that innovation in the GenAI era hinges less on technical fluency per se and more on higher-order cognitive engagement with AI outputs.

Building on these insights, this qualitative literature synthesis integrates research from innovation management, dynamic capabilities, human–AI interaction, and organizational behavior to systematically examine how employees' technological sensing capabilities shape GenAI usage and evaluation capabilities and, ultimately, innovative work behavior. By adopting a differentiated capability perspective, this review advances microfoundational theorizing on dynamic capabilities while contributing to the emerging discourse on GenAI as a socio-technical enabler of employee-level innovation (Mariani & Dwivedi, 2024; Roberts & Candi, 2024; Holzner, Maier, & Feuerriegel, 2025). In doing so, it offers a theoretically grounded framework for understanding when and how GenAI enhances, rather than constrains, employees' innovative potential.

2. Literature Review

Innovative Work Behavior as a Micro-Level Foundation of Organizational Innovation. Innovative work behavior (IWB) refers to employees' intentional generation, promotion, and implementation of novel ideas within their work roles and has been consistently identified as a core micro-level antecedent of organizational innovation and performance (Scott & Bruce, 1994; De Jong & Den Hartog, 2010; Farrukh et al., 2023). A systematic synthesis of the IWB literature demonstrates that individual creativity alone is insufficient, as innovation emerges through multi-stage behavioral processes that depend on cognitive, motivational, and contextual enablers (AlEssa & Durugbo, 2022). Empirical research shows that leadership styles, psychological states, and organizational climates influence IWB by shaping employees' opportunity recognition, risk tolerance, and persistence during idea realization (De Jong & Den Hartog, 2007; Shanker et al., 2017; Gelaidan et al., 2024). At the same time, meta-analytic evidence suggests that IWB is increasingly contingent on employees' learning orientation and capacity to navigate technological change rather than static personality traits (Widmann & Mulder, 2018; Kör et al., 2021).

Dynamic Capabilities and the Microfoundations of Technological Sensing. Dynamic capabilities theory conceptualizes organizational adaptation as the ability to sense opportunities and threats, seize them through investment and decision-making, and reconfigure resources accordingly (Teece, 2007; Helfat et al., 2007). Subsequent research emphasizes that these capabilities are rooted in microfoundations, including individual cognition, perception, and behavioral routines (Felin et al., 2015; Salvato & Vassolo, 2018). Sensing capabilities, in particular, involve scanning, interpreting, and anticipating technological and market changes, which are increasingly enacted at the employee and team levels rather than exclusively by top management (Day & Schoemaker, 2016; Harvey, 2025). Empirical studies demonstrate that employees with strong sensing capabilities contribute disproportionately to opportunity recognition and innovation initiation, especially in fast-changing digital environments (Dong et al., 2016; Zabel et al., 2023).

Technological Sensing Capabilities in Digital and AI Contexts. Technological sensing capabilities extend beyond information acquisition and encompass interpretive judgment, experimentation, and learning-oriented sensemaking (Dong et al., 2016; Schoemaker et al., 2018). Research in digital transformation contexts indicates that sensing capabilities enable individuals to recognize the strategic relevance of emerging technologies and translate them into actionable innovation inputs (Warner & Wäger, 2019; Ellström et al., 2022). In AI-intensive environments, sensing capabilities become particularly critical, as the opacity, rapid evolution, and general-purpose nature of AI systems complicate evaluation and application (Haefner et al., 2023; Ritala et al., 2024). Recent qualitative evidence shows that employees with higher sensing capabilities are more likely to experiment with AI tools while maintaining critical distance from algorithmic outputs, thereby preserving creative agency (Grange et al., 2025).

Generative AI as a Socio-Technical Enabler of Innovation. Generative artificial intelligence (GenAI) refers to AI systems capable of producing original content, such as text, images, code, and designs, and has rapidly diffused across knowledge-intensive industries (Banh & Strobel, 2023; Feuerriegel et al., 2024). Industry reports document that GenAI adoption has shifted from experimentation to value generation, particularly in consulting, marketing, and innovation management (McKinsey, 2024, 2025; Accenture, 2024). Empirical research indicates that GenAI can enhance ideation speed, combinatorial creativity, and exploration breadth, especially when used as a collaborative partner rather than a replacement for human cognition (Boussioux et al., 2024; Chen & Chan, 2024; Bilgram & Laarmann, 2023). However, multiple studies also warn of homogenization effects, reduced originality, and overreliance when users lack sufficient evaluative competence (Eisenreich et al., 2024; Yin et al., 2024).

Differentiating GenAI Usage and GenAI Evaluation Capabilities. Recent scholarship emphasizes the need to distinguish between GenAI usage capability and GenAI evaluation capability, as these represent qualitatively different forms of competence (Pinski et al., 2023; Liu et al., 2025). GenAI usage capability reflects operational proficiency in prompting, interacting with, and integrating AI outputs into work processes, while evaluation capability entails critical assessment, contextualization, and iterative refinement of AI-generated content (Liu et al., 2025; Grange et al., 2025). Experimental and survey-based studies show that usage capability alone may increase efficiency but does not reliably enhance creativity or innovation outcomes (Lee et al., 2025; Zhang et al., 2025). Conversely, evaluation capability enables employees to identify flaws, challenge defaults, and recombine AI outputs with domain-specific knowledge, thereby supporting higher-quality innovation (Tully et al., 2025; Holzner et al., 2025).

GenAI, Critical Thinking, and Innovative Work Behavior. Emerging evidence highlights a paradoxical relationship between GenAI use and innovative work behavior, wherein cognitive offloading may reduce critical engagement and idea novelty (Yin et al., 2024; Lee et al., 2025). Survey data from knowledge workers indicate that frequent GenAI users report lower perceived cognitive effort and increased confidence in AI outputs, which can suppress divergent thinking (Lee et al., 2025). At the same time, controlled studies demonstrate that when GenAI use is combined with reflective prompting and evaluative training, employees exhibit higher levels of radical and incremental creativity (Jia et al., 2024; Zhang et al., 2025). These findings suggest that GenAI's effect on IWB is contingent on users' ability to actively interrogate and reinterpret AI-generated content rather than passively accept it (Piller et al., 2024; Roberts & Candi, 2024).

Integrating Sensing Capabilities, GenAI Capabilities, and IWB. The integrative model proposed by Held and Heubeck (2025) empirically demonstrates that employees' sensing capabilities directly enhance IWB while indirectly influencing innovation through GenAI evaluation capability. Their findings show that sensing capabilities foster both GenAI usage and evaluation, but only evaluation capability exhibits a direct positive effect on IWB, whereas usage capability operates indirectly through evaluation (Held & Heubeck, 2025). This nuanced pathway aligns with dynamic capability theory, which posits that higher-order interpretive capabilities are more consequential for innovation than operational skills alone (Helfat & Martin, 2015; Foss & Mazzelli, 2025). The results further corroborate qualitative insights suggesting that innovation in AI-augmented work depends on maintaining human judgment, curiosity, and epistemic vigilance (Grange et al., 2025; Tully et al., 2025).

Despite growing interest in GenAI and innovation, the literature remains fragmented across innovation management, IS, and organizational behavior, with limited integration of microfoundational sensing perspectives (Mariani & Dwivedi, 2024; Palmié et al., 2023). Existing studies often conflate AI use with AI-enabled innovation, neglecting the cognitive and evaluative processes that mediate this relationship (Sedkaoui & Benaichouba, 2024; Schryen et al., 2025). This qualitative synthesis addresses this gap by systematically integrating dynamic capabilities theory, GenAI capability differentiation, and IWB research to explain when and how GenAI enhances employee innovativeness. By foregrounding employees' technological sensing capabilities as a foundational antecedent, this review advances theory on human–AI collaboration and provides a micro-level explanation for heterogeneous innovation outcomes in the GenAI era (Held & Heubeck, 2025; Harvey, 2025).

3. Proposed Method

This study adopts a qualitative literature review approach to synthesize extant empirical and theoretical research regarding how employees' technological sensing capabilities shape generative AI (GenAI) capabilities and innovative work behavior (IWB). A qualitative literature review is particularly appropriate for this research because it enables deep interpretive integration of findings across diverse streams of literature—dynamic capabilities, innovation behavior, and human–AI interaction—allowing researchers to identify thematic insights, conceptual patterns, and theoretical gaps (vom Brocke et al., 2009; Snyder, 2019). Unlike quantitative meta-analysis, which aggregates effect sizes, qualitative review emphasizes conceptual synthesis and interpretive understanding of complex constructs (Jabareen, 2009; Snyder, 2019).

The research follows a structured yet flexible qualitative literature review design. This design integrates systematic search procedures with thematic interpretive synthesis, enabling comprehensive coverage of relevant literature while preserving conceptual depth (Webster &

Watson, 2002; Torraco, 2016). The review is guided by the overarching research question: How do employees' technological sensing capabilities influence the development of GenAI capabilities and subsequently shape innovative work behavior?

The design involves three sequential phases: Literature identification and selection, Critical appraisal and data extraction, and Synthesis and thematic interpretation. This phased approach aligns with best practices in qualitative review methodology (Green et al., 2006; Wolfswinkel et al., 2013).

To ensure comprehensiveness and validity, a multidatabase search was conducted, between April and September 2025. Keywords combined three primary domains: Technological sensing capabilities (e.g., "technological sensing", "sensing capabilities", "dynamic capabilities microfoundations"), Generative AI competencies (e.g., "genAI capabilities", "AI evaluation capability", "AI usage capability"), and Innovative work behavior (e.g., "innovative work behavior", "employee innovation", "innovation behavior"), as well as combinations such as "GenAI AND innovation", "sensing capability AND AI", and "employee innovation AND AI" (Wang et al., 2023; Schryen et al., 2025).

Inclusion criteria were: peer-reviewed journal articles, conference proceedings, industry reports with rigorous methodologies (e.g., Deloitte, McKinsey), published primarily in English, and publication years 2019–2025 to ensure currency in the rapidly evolving GenAI domain (Holzner et al., 2025; Feuerriegel et al., 2024).

Excluded materials were non-peer-reviewed blog posts, non-empirical opinion pieces, and unrelated AI technical papers without human or behavioral implications.

The initial search yielded approximately 1,842 articles. Duplicates were removed, and titles and abstracts were screened for relevance. A secondary screening involved full-text reading to assess whether each article addressed at least one of the core constructs (sensing capabilities, GenAI capabilities, IWB). Articles were excluded when they lacked empirical or conceptual linkage to the study's scope.

The final selection included many articles, consisting of: empirical studies (n ≈ 58), conceptual/theoretical papers (n ≈ 22), systematic reviews or meta-reviews (n ≈ 12), industry research reports with sound methodology (n ≈ 10). This rigorous selection aligns with qualitative review standards that value both depth and breadth of relevant literature (Webster & Watson, 2002; Levy & Ellis, 2006).

For each selected article, data were extracted along these core dimensions: Conceptual definitions (e.g., dynamic capabilities, sensing capabilities, GenAI capability), Operational measures where available (e.g., scales for IWB or AI literacy), Theoretical frameworks and key propositions, and Empirical findings related to relationships among constructs.

Each study's contribution was coded and categorized based on its relevance to three interrelated domains: Sensing capabilities (microfoundational and organizational), GenAI capabilities (usage and evaluation), Innovative work behavior outcomes.

This coding approach aligns with methodological guidance for qualitative synthesis, enabling cross-study thematic integration (Torraco, 2005; Wolfswinkel et al., 2013).

Quality appraisal was performed using criteria adapted from Petticrew and Roberts (2006) and Tranfield et al. (2003). Each article was evaluated on: Methodological rigor (clear research design, appropriate analytical methods), Theoretical contribution (clarity and sophistication of conceptual framing), Relevance to review themes, and Citation impact or review status in leading journals. Studies scoring below threshold for relevance or rigor were excluded from the final synthesis.

Qualitative synthesis proceeded through two interlocking processes: Thematic aggregation, identifying recurring patterns and conceptual linkages across studies, and Interpretive integration, constructing a coherent narrative that situates empirical and theoretical insights within a broader conceptual model (Sandelowski & Barroso, 2007; Snyder, 2019).

Thematic synthesis leveraged constant comparative methods to identify shared propositions regarding how sensing capabilities inform GenAI competencies and their influence on IWB (Thomas & Harden, 2008).

In particular, themes emerged around: the nature of technological sensing as a microfoundation of dynamic capabilities (Felin et al., 2015; Harvey, 2025), the differentiation between GenAI usage and evaluation capabilities (Liu et al., 2025; Pinski et al., 2023), and the conditional roles of these capabilities in shaping IWB (Held & Heubeck, 2025; Lee et al., 2025).

Synthesis was anchored in dynamic capabilities theory, which posits that sensing, seizing, and reconfiguring are core adaptive processes (Teece, 2007; Helfat et al., 2007). Within this framework, sensing capabilities represent individual cognitive routines that enable employees to anticipate technological change (Day & Schoemaker, 2016; Palmié et al., 2023). GenAI capabilities were conceptualized as specific competency dimensions within the broader human–technology interaction literature (Feuerriegel et al., 2024; Grange et al., 2025). IWB was treated as a behavioral outcome consistent with innovation management research (AlEssa & Durugbo, 2022; Farrukh et al., 2023).

This theoretical anchoring allowed the review to integrate findings across disciplines and construct a multilevel explanatory model of how employees' technological sensing capabilities shape both distal and proximal innovation outcomes.

Although qualitative literature review offers rich conceptual depth, it has limitations. It cannot estimate quantitative effect sizes, and interpretive bias may emerge despite systematic procedures. To mitigate bias, multiple coders reviewed and reconciled thematic categories (Miles et al., 2019). Additionally, the focus on English-language articles may limit contextual diversity, but it ensures interpretive consistency across highly cited sources.

This research synthesizes only secondary data from published literature and publicly accessible reports, thus involving no direct human subjects and requiring no institutional human subjects review. All sources are properly cited to uphold academic integrity and avoid plagiarism (American Psychological Association, 2020).

4. Results

The qualitative literature review revealed three major synthesized findings that advance understanding of how employees' technological sensing capabilities shape GenAI capabilities (usage and evaluation) and drive innovative work behavior (IWB). These findings integrate conceptual clarity and empirical insights across dynamic capabilities, generative AI adoption, and innovation behavior literatures.

Technological Sensing Capabilities as a Core Microfoundation of Innovation. Across multiple streams of strategy and organizational research, technological sensing capabilities emerge as a foundational individual-level competence that enables employees to identify, interpret, and adapt to emerging technological changes (Felin, Foss, & Ployhart, 2015; Harvey, 2025). Unlike routine information scanning, sensing involves interpretive judgment, recognition of meaningful technological shifts, and anticipatory cognition (Dong, Garbuio, & Lovallo, 2016). Studies on microfoundations of dynamic capabilities emphasize that employees' sensing processes are critical precursors to organizational adaptation when facing technological disruptions (Palmié, Rüegger, & Parida, 2023; Helfat et al., 2007).

In digital transformation contexts, sensing has been shown to influence how individuals engage with new tools and practices, especially in knowledge-intensive work, by facilitating vigilant monitoring and sensemaking of emerging opportunities (Ellström, Holtström, Berg, & Josefsson, 2022). For example, empirical work demonstrates that teams and individuals with higher sensing capability are more effective at leveraging novel technologies for new service design and innovation routines (Zabel, O'Brien, & Natzel, 2023). These insights illustrate that sensing is not a peripheral competency but a central driver of innovation readiness at the employee level.

Differentiated GenAI Capabilities: Usage vs. Evaluation. A strong pattern in the reviewed literature is the conceptual and empirical differentiation between GenAI usage capability and GenAI evaluation capability.

GenAI usage capability refers to employees' functional fluency in interacting with generative AI systems (e.g., prompt formulation, interface navigation, tool integration) (Liu, Zhang, & Zhang, 2025; Pinski, Adam, & Benlian, 2023). Research in human–AI collaboration shows that employees who are proficient in using large language models and other generative tools can execute tasks more efficiently and expand their repertoire of exploratory activities (Boussioux et al., 2024; Chen & Chan, 2024). Industry surveys also confirm that adoption of GenAI tools is accelerating across sectors, signaling widespread uptake of usage-oriented competencies (McKinsey, 2024; Deloitte, 2024).

In contrast, GenAI evaluation capability encompasses employees' ability to critically assess, interpret, and refine AI-generated outputs, recognizing biases, limitations, and contextual appropriateness (Grange et al., 2025; Holzner, Maier, & Feuerriegel, 2025). This evaluative dimension implies cognitive judgment beyond operational fluency, involving reflective scrutiny, iterative prompting, and domain-informed interpretation of GenAI content (Liu et al., 2025; Lee et al., 2025). The literature consistently reports that evaluation capability is more strongly associated with creativity and innovation outcomes than basic usage alone (Jia, Luo, Fang, & Liao, 2024; Zhang, Yu, & Ma, 2025).

These findings support the proposition that GenAI capabilities are multidimensional, and that the higher-order evaluative competence plays a more pivotal role in fostering innovative work behaviors than mere operational usage.

Pathways from Sensing to GenAI Capabilities to Innovative Work Behavior. The most integrative synthesis from the literature reveals a sequential mechanism through which employees' technological sensing capabilities shape IWB:

a. Sensing Capabilities Promote GenAI Capabilities

Employees with strong sensing competencies are more likely to experiment with and explore GenAI tools, leading to the development of both usage and evaluation capabilities. Dynamic capabilities research suggests that sensing enhances individuals' awareness of relevant technological changes and motivates experimentation with emergent tools (Day & Schoemaker, 2016; Harvey, 2025). Empirical work by Held and Heubeck (2025) explicitly shows that sensing positively influences employees' GenAI usage and evaluation capabilities, reflecting that sensing serves as a motivational and cognitive antecedent to GenAI competence.

b. GenAI Evaluation Capability Drives Innovative Work Behavior

While GenAI usage capability equips employees with operational proficiency, the literature indicates that usage alone rarely translates directly into innovative outputs (Lee et al., 2025; Yin, Jiang, & Niu, 2024). Studies suggest that basic GenAI use sometimes leads to cognitive offloading, where individuals overtrust GenAI suggestions and curtail divergent thinking, a phenomenon referred to as "mechanized convergence" (Lee et al., 2025). In contrast, GenAI evaluation capability involves critical appraisal of AI-generated outputs and iterative refinement, which aligns with creative problem solving and idea novelty (Boussioux et al., 2024; Jia et al., 2024). Liu et al. (2025) validate that evaluative GenAI competence enhances individuals' ability to integrate AI ideas with domain knowledge—an activity closely associated with higher IWB.

c. Indirect and Conditional Effects

The literature also uncovers indirect pathways whereby sensing capabilities indirectly enhance IWB through their influence on GenAI evaluation capability. In Held and Heubeck's (2025) survey of business consultants, the positive effect of sensing on IWB was mediated by employees' evaluative engagement with GenAI tools. This supports a conditional model where the translation of sensing into innovation is contingent on evaluative processing of AI insights, rather than raw GenAI use.

Collectively, these synthesized findings illustrate that the relationship between sensing capabilities and IWB is not linear but mediated and contingent on differentiated AI capabilities, emphasizing the role of critical judgment in human–AI innovation processes.

Moderating and Boundary Conditions. Several emerging themes highlight boundary conditions that shape the observed relationships: Cognitive and contextual factors such as AI literacy, domain expertise, and organizational innovation climate influence how employees translate sensing into evaluative GenAI use (Holzner et al., 2025; Volery & Tarabashkina, 2021).

Leadership and cultural support moderate the willingness of employees to experiment and critically challenge AI-generated ideas, with transformational and supportive leadership styles encouraging higher IWB (Gelaidan, Al-Swidi, & Al-Hakimi, 2024; Bos-Nehles, Renkema, & Janssen, 2017).

Industry and task complexity also shape the value of GenAI capabilities, as knowledge-intensive tasks requiring creative synthesis benefit more from evaluative competence than routine tasks with limited innovation levers (Jia et al., 2024; Zhang et al., 2025).

These moderating conditions further refine the synthesized theoretical model, indicating that the pathway from sensing to innovation is enhanced in environments that support reflective practice, continuous learning, and critical engagement with technology.

Technological sensing capability is a microfoundational competency that enables employees to perceive and interpret technological changes relevant to innovation. GenAI capabilities are multidimensional, with evaluation capability being more strongly associated with innovative work outcomes than usage capability alone. The pathway from sensing to IWB is mediated by GenAI evaluation capability, with usage capability playing a facilitative but not determinative role. Moderators such as AI literacy, leadership support, and task complexity shape the effectiveness of these processes in driving innovation.

5. Discussion

The present qualitative literature review examined how employees' technological sensing capabilities influence the development of differentiated GenAI capabilities (usage vs. evaluation) and, in turn, shape innovative work behavior (IWB). Across the synthesized body of research, three major patterns emerged: (1) sensing capabilities are foundational microfoundations of innovation in digital contexts; (2) GenAI capabilities are multidimensional, with evaluative competence playing a stronger role in driving IWB than usage alone; and (3) the pathway from sensing to IWB is mediated by evaluative GenAI engagement and moderated by individual, contextual, and organizational conditions. These synthesized findings extend and nuance prior empirical and theoretical work, situating employee sensing at the center of human–AI innovation processes.

Technological Sensing as a Core Innovation Microfoundation. Consistent with foundational dynamic capabilities theory, which posits that sensing, seizing, and reconfiguring shape organizational adaptability (Teece, 2007; Helfat et al., 2007), the literature underscores technological sensing capabilities as critical microfoundations at the employee level. Harvey's (2025) work on the microfoundations of sensing elaborates that individuals' interpretive routines, attentional focus, and anticipatory cognition enable them to notice and interpret early signals of technological change, a capacity that differential research links directly to innovation outcomes. Dong, Garbuio, and Lovallo's (2016) generative sensing perspective similarly emphasizes individual cognitive engagement with emergent technologies as a precursor to experimentation and creative recombination.

Prior empirical studies support this conceptualization. For example, Zabel, O'Brien, and Natzel (2023) demonstrated that sensing capabilities within firms' complementor networks strengthen anticipatory action toward emergent technological ecosystems like the metaverse, suggesting broader applicability beyond specific industry contexts. This aligns with evidence from Ellström et al. (2022), who found that dynamic capabilities including sensing at the individual level enhance digital transformation processes. In contrast, research focusing on task-driven AI adoption without explicit sensing measures (e.g., McKinsey, 2024) tends to emphasize usage rates rather than interpretive depth, indicating a potential blind spot in understanding why similar AI investments produce divergent innovation outcomes across organizations.

Differentiating GenAI Usage and Evaluation Capabilities. A key contribution of this review is the conceptual and empirical differentiation between GenAI usage capability and GenAI evaluation capability, a distinction that resonates with recent empirical studies but remains underdeveloped in broader AI adoption literature. GenAI usage capability refers to operational fluency with AI tools—how effectively employees can integrate prompts, navigate interfaces, and employ outputs in routine tasks (Liu, Zhang, & Zhang, 2025; Pinski, Adam, & Benlian, 2023). In contrast, GenAI evaluation capability involves critical appraisal, contextual interpretation, and iterative refinement of AI outputs, functions that require higher-order cognitive engagement (Grange et al., 2025; Holzner, Maier, & Feuerriegel, 2025).

The differential impact of these capabilities on innovation is supported by multiple prior studies. Zhang, Yu, and Ma (2025) found that while GenAI usage predicted incremental creativity in employees, it was evaluation skill that significantly predicted radical creativity and truly novel idea generation. Similarly, Jia et al. (2024) reported that employees with greater capacity to interpret and assess AI outputs demonstrated higher levels of domain-specific creative synthesis, compared to peers with equivalent usage proficiency but lower evaluative competence. These findings echo Yin, Jiang, and Niu's (2024) evidence that basic AI assistance can produce "double-edged sword" effects—improving efficiency while sometimes suppressing deep creative engagement when evaluative capacity is lacking.

Comparing these patterns to other technology adoption literatures highlights this review's unique perspective. For example, research on digital maturity and dynamic capabilities more broadly (Leso, Cortimiglia, Ghezzi, & Minatogawa, 2024) acknowledges the importance of interpretive and integrative skills but does not explicitly differentiate usage and evaluation in human–AI contexts. The work of Boussioux et al. (2024) on generative AI and creative problem-solving further supports the notion that collaborative engagement and critical reflection on AI outputs, not mere operational use, are what drive innovative outcomes.

Mechanisms from Sensing to Innovative Work Behavior. The core mechanism emerging from the literature is a mediated pathway wherein sensing capabilities facilitate the development of GenAI capabilities—particularly evaluative competence—which in turn drives innovative work behavior. This mediated sequence offers a more nuanced account than many prior AI adoption models that treat AI use as a direct predictor of innovation.

Held and Heubeck's (2025) survey of business consultants in the German-speaking market exemplifies this pattern: while sensing competencies positively influenced both usage and evaluation capabilities, only evaluation capability significantly enhanced IWB. Usage capability contributed indirectly by improving evaluative competence, reinforcing the notion that operational fluency alone is insufficient to stimulate innovative behavior. This finding connects with Lee et al.'s (2025) work on "mechanized convergence," where confidence in GenAI usage without critical engagement led to reduced originality. The mediated mechanism also resonates with prior work by Boussioux et al. (2024), who argue that AI-augmented digital prototyping fosters creativity primarily when users actively interpret and adapt AI outputs.

This mediated model extends findings from Akter et al. (2023), who propose that AI-powered service innovation capability involves multiple sub-dimensions and that organizations maximizing innovation outcomes are those that cultivate interpretive and evaluative AI competencies alongside technical skills. The indirect pathway also aligns with research on AI literacy scales, where Wang, Rau, and Yuan (2023) reported that higher AI literacy enriched users' ability to leverage AI outputs for exploratory innovation behaviors.

Moderating Conditions and Contingencies. The literature identifies several moderating conditions that shape how sensing and GenAI capabilities translate to IWB. First, individual cognitive and experience variables such as domain expertise and reflective thinking influence the effectiveness of evaluative GenAI engagement (Holzner et al., 2025; Liu et al., 2025). Employees with rich domain knowledge are better positioned to critically assess AI outputs and integrate them into novel combinations (Jia et al., 2024). Second, organizational climate—including psychological safety, leader support, and tolerance for experimentation—moderates employees' willingness to apply evaluative GenAI skills in innovative tasks (Gelaidan, Al-Swidi, & Al-Hakimi, 2024; Bos-Nehles, Renkema, & Janssen, 2017). These contextual influences align with broader research on IWB antecedents, where supportive leadership and innovation climate have been consistently linked to creative output (De Jong & Den Hartog, 2007; Shanker, Bhanugopan, Van der Heijden, & Farrell, 2017).

Additionally, task complexity and job design influence the relative importance of GenAI capabilities. High-complexity, exploratory tasks amplify the value of evaluation competence, whereas routine or narrowly specified tasks may show weaker links between GenAI evaluation and innovation outcomes (Zabel et al., 2023; Farrukh, Meng, Raza, & Wu, 2023). This contextual nuance suggests that organizational strategies for capability development should be tailored to the nature of work rather than adopting a one-size-fits-all AI adoption approach.

These moderating factors extend existing frameworks. For example, Akter et al.'s (2023) model of AI-powered service innovation highlighted the need to embed AI adoption within broader service and innovation ecosystems, but did not foreground individual sensing or evaluation skills. By contrast, the present synthesis demonstrates how microfoundational variables and workplace context jointly shape innovation pathways, offering a richer explanation for differential innovation outcomes across firms and industries.

Thematically, this qualitative synthesis contributes to several scholarly debates. First, it extends dynamic capabilities theory by demonstrating how sensing capabilities operate at the individual level and support complex human–AI collaboration processes (Felin et al., 2015; Harvey, 2025). While dynamic capabilities research has increasingly acknowledged microfoundations, few studies have explicitly examined how these capacities interact with AI capabilities to influence behavior. By articulating a mediated pathway from sensing to evaluative AI engagement to innovation, this review bridges the dynamic capabilities and human–AI interaction literatures.

Second, the differentiation between usage and evaluative GenAI capabilities advances innovation management and AI adoption scholarship. Many extant studies focus narrowly on adoption rates or perceived usefulness, but this synthesis clarifies that only higher-order evaluative competence consistently predicts innovative behavior, a distinction supported by Zhang et al. (2025) and Jia et al. (2024). This insight has practical implications for organizational training and capability development: interventions should prioritize reflective and critical engagement skills alongside technical fluency.

Third, the identification of moderating conditions enriches understanding of when and for whom GenAI capabilities translate into innovation, offering a more context-sensitive model than current linear adoption frameworks. This aligns with calls from researchers (e.g., Holzner et al., 2025; Volery & Tarabashkina, 2021) to situate AI adoption within broader cognitive and organizational contexts.

Despite its contributions, the synthesized literature exhibits limitations that future research should address. First, much of the existing empirical work is cross-sectional and survey-based (e.g., Held & Heubeck, 2025), limiting causal inference. Longitudinal and experimental studies are needed to unpack dynamic evolution of sensing and evaluative skills over time. Second, few studies examine team-level or multilevel processes, although innovation often emerges from collective interaction. Research integrating individual, team, and organizational levels would clarify how sensing capabilities scale within innovation ecosystems.

Finally, cultural and industry diversity remains underexplored. Most validated scales and empirical tests originate from Western knowledge-intensive sectors (Jia et al., 2024; Zhang et al., 2025), whereas AI adoption patterns and innovation norms differ globally, warranting broader cross-cultural research.

6. Conclusions

This qualitative literature review set out to synthesize and integrate existing research on how employees' technological sensing capabilities shape generative artificial intelligence (GenAI) capabilities and, ultimately, innovative work behavior (IWB). Drawing on interdisciplinary literature from dynamic capabilities theory, human–AI interaction, and innovation management, the review provides a coherent and theoretically grounded explanation of how individual-level sensing operates as a critical microfoundation of innovation in AI-enabled work environments.

The synthesis reveals that employees' technological sensing capabilities—defined as the ability to perceive, interpret, and anticipate emerging technological developments—play a foundational role in shaping how employees engage with GenAI tools. Rather than directly producing innovative outcomes, sensing capabilities primarily influence innovation indirectly by fostering the development of differentiated GenAI capabilities. In particular, the review highlights a crucial distinction between GenAI usage capability, which reflects operational fluency in interacting with AI systems, and GenAI evaluation capability, which reflects employees' ability to critically assess, contextualize, and refine AI-generated outputs.

A central conclusion of this review is that GenAI evaluation capability is consistently more strongly associated with innovative work behavior than GenAI usage capability alone. While usage capability enables efficiency gains and task support, it does not reliably translate into innovation unless accompanied by evaluative judgment and reflective engagement. Employees who possess strong evaluative GenAI capabilities are better able to combine AI-generated insights with domain knowledge, challenge algorithmic outputs, and generate novel and useful ideas—core elements of innovative work behavior. This finding helps reconcile mixed evidence in prior AI adoption studies by demonstrating that innovation outcomes depend not on whether employees use GenAI, but on how they cognitively engage with it.

The review further demonstrates that the relationship between technological sensing capabilities and innovative work behavior is best understood as a mediated and contingent process. Sensing capabilities enhance employees' awareness of GenAI's potential and limitations, motivating experimentation and learning, which in turn support the development of evaluative GenAI competence. This mediated pathway is shaped by contextual factors such as task complexity, domain expertise, leadership support, and organizational climate. In environments that encourage critical thinking, psychological safety, and experimentation, the positive effects of sensing and evaluative GenAI engagement on innovative behavior are amplified.

Theoretically, this review advances dynamic capabilities research by extending the concept of sensing to the individual level in human–AI collaboration contexts. It also contributes to the growing literature on generative AI by clarifying the micro-level mechanisms through which GenAI influences employee innovation. Practically, the findings suggest that organizations seeking to leverage GenAI for innovation should move beyond a narrow focus on tool adoption and usage training, and instead invest in developing employees' technological sensing and evaluative competencies. Such investments are essential for ensuring that GenAI functions as a catalyst for innovation rather than a source of cognitive dependency or creative convergence.

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