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The influence of individuals' capability to use generative AI on their idea generation: The mediating role of cognitive information processing styles

Abstract

Purpose – This study investigates how individuals' capability to use generative artificial intelligence (GenAI) influences their idea generation and explores the cognitive mechanisms underlying this relationship. Drawing on cognitive experiential theory, which posits that individuals rely on two distinct and stable information processing styles (rational and experiential), this study examines how these styles mediate the link between GenAI usage capability and idea generation and all underlying relationships between these constructs.

Design/methodology/approach – This study employs a quantitative research design based on survey data from 399 business consultants located in Germany, Austria, and Switzerland at a leading global consultancy. Partial least squares structural equation modeling (PLS-SEM) is applied to test the hypothesized structural relationships.

Findings – The findings demonstrate that (1) individuals' capability to use GenAI enhances their idea generation; (2) individuals' capability to use GenAI influences both information processing styles; (3) rational information processing style enhances idea generation and not experiential information processing; (4) significant mediation effect of individuals' tendency to rely on the rational system that translates GenAI usage capability into idea generation.

Originality/value – This study enriches GenAI research in innovation management by identifying individuals' capability to use GenAI as a critical antecedent of idea generation. This capability perspective complements recent studies focusing on the extent, frequency, or purpose of GenAI usage and its influence on creative outputs.

Keywords Innovation management; idea generation; generative AI; generative AI usage; AI capability; cognitive experiential theory

Paper type Research paper

1. Introduction

Generative artificial intelligence (GenAI) represents a disruptive innovation that offers enormous economic potential across various business functions within a company (e.g., Kanbach et al., 2024; Chen & Chan, 2024; Fosso Wamba et al., 2024). Unlike traditional AI, which primarily focuses on data analysis, pattern recognition, and predictions (Roberts & Candi, 2024), GenAI *generates* original and creative content (Banh & Strobel, 2023).

This *generative* ability has sparked renewed interest in using AI technologies as a tool for innovation (Piller et al., 2024), also illustrated through the significant research interest at the intersection of GenAI and innovation management (e.g., Chiarello et al., 2024; Cimino et al., 2024; Mariani & Dwivedi, 2024; Vitellaro et al., 2025; Sedkaoui & Benaichouba, 2024). Particularly, GenAI's impact on idea generation, a central aspect of organizational life (Vandenbosch et al., 2006), where novel ideas serve as "the lifeblood of successful innovations" (Berg, 2016, p. 433), has been extensively studied (e.g., Bouschery et al., 2023; Boussioux et al., 2024; Eisenreich et al., 2024; Meincke et al., 2024). Specifically, GenAI can facilitate idea generation by enabling users to explore extensive solution and problem spaces, drawing on vast and diverse knowledge bases and supporting the combination of existing knowledge elements to identify novel connections and insights (Bouschery et al., 2023; Boussioux et al., 2024).

Much of this research frames GenAI's role through human–GenAI collaboration (e.g., Bankins et al., 2024; Boussioux et al., 2024; Choudhary et al., 2023)—that is, on the individual level of, for example, employees or managers. This perspective emphasizes human intelligence and GenAI's joint creative potential. Yet, despite the growing body of research emphasizing human–GenAI collaboration, surprisingly little attention has been given to individuals' capability to use GenAI. GenAI usage capability, understood as "the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2022, p. 4), is likely a critical antecedent to realizing the potential benefits of human–GenAI collaboration. Thus, this capabilities view offers a valuable perspective within innovation management (Held & Heubeck, 2025).

However, existing studies often conceptualize GenAI usage in terms of frequency, extent, or purpose (e.g., Zhang et al., 2025) or treat GenAI as a uniform intervention (e.g., Eisenreich et al., 2024; Meincke et al., 2024). These conceptualizations of GenAI usage neglect interindividual differences in users' capability to engage with GenAI technology. By assuming a homogeneous level of user competence, these studies overlook that the creative value derived from GenAI may depend on individuals' capability to use the technology. This is surprising given that interacting with GenAI systems inherently requires the formulation of structured input prompts—a process central to how generative models produce relevant and high-quality output (Banh & Strobel, 2023; Feuerriegel et al., 2024). To realize the innovation potential of human–GenAI collaboration, it is essential to understand whether and how individuals' capability to use GenAI influences their idea generation. To address this gap, we pose our first research question (RQ):

RQ1. *To what extent does an individual's capability to use GenAI foster their idea generation?*

While individuals' capability to use GenAI may provide the foundation for generating ideas, idea generation is fundamentally a cognitive process (Paulus & Brown, 2007; Garbuio & Lin, 2021), originating in the mind of an individual (Amabile, 1983; Campbell, 1960). Building on this perspective, it is relevant not only to determine whether individuals have the capability to use GenAI but also to determine the cognitive mechanisms through which this capability translates into idea generation.

Epstein's cognitive experiential theory[1] is a suitable theoretical lens to investigate this mechanism (Epstein, 1973, 2003, 2014). Rooted in psychology, the cognitive experiential theory is a dual-process theory stating that humans process information (e.g., GenAI-generated output text) through two distinct cognitive systems: the *experiential system*—an intuitive, emotion-driven process relying on associative memory—and the *rational system*—a deliberate, analytical process guided by logic and reasoning (Epstein, 1973, 2010; Kahneman, 2011).

The relative influence of each system on a given behavior, like idea generation, is shaped by the individual (Epstein, 2014). In other words, individuals differ in their preference regarding their information processing mode (i.e., experiential or rational). While some individuals are more inclined toward the rational system, others rely more on the experiential system.

The experiential and rational information processing systems are crucial for idea generation, as they foster complementary cognitive operations that collectively enhance creativity (Baldacchino et al., 2023; Eling et al., 2015). The experiential system is vital for idea generation because it facilitates intuitive judgments and associative memory, enabling the spontaneous emergence of novel ideas (Bălău et al., 2019; Epstein, 2003). Conversely, the rational system is essential for idea generation as it enables problem structuring and deductive reasoning (Luoma & Martela, 2021; Marques et al., 2022), supporting the development of new ideas.

Including cognitive experience theory in our study context is valuable as it helps to understand which information processing system is the main driver for promoting idea generation. We, thus, formulate our second RQ:

RQ2. *To what extent does an individual's tendency to rely on experiential and rational information processing systems promote their idea generation?*

Although information processing styles are generally regarded as relatively stable preferences, they are not entirely fixed (Epstein, 2003). Repeated engagement with external structures—such as GenAI tools—can modulate these preferences and become functionally integrated into cognitive processes (Reiser, 2004; Clark & Chalmers, 1998). Thus, individuals process information not in isolation but instead in close coupling with their environment (Hollan et al., 2000). We propose that as individuals develop GenAI usage capability, GenAI becomes an integral component of their approach to understanding problems and generating solutions, thereby shaping their tendency to rely on information processing styles. We pose our third RQ:

RQ3. *To what extent does an individual's capability to use GenAI influence their tendency to rely on experiential and rational information processing systems?*

We use partial least squares structural equation model (PLS-SEM) analysis on a large-scale sample of 399 consultants from a leading global consultancy in the DACH region (Germany, Austria, Switzerland) to test our research model. We chose this sample because the consultants in our study already use GenAI in their daily work and operate across a wide range of industries, thereby covering a broad spectrum of application contexts and problem types relevant to GenAI-supported idea generation. As GenAI is a relatively new phenomenon, the consultants likely differ in their capability to use the technology.

Our study makes several significant theoretical contributions to existing innovation management literature studying GenAI (e.g., Cimino et al., 2024; Mariani & Dwivedi, 2024; Roberts & Candi, 2024; Vitellaro et al., 2025; Sedkaoui & Benaichouba, 2024). First, our findings demonstrate that individuals' capability to use GenAI promotes their idea generation. Therefore, we extend previous research results highlighting this technology's enormous potential for idea generation (e.g., Eisenreich et al., 2024; Meincke et al., 2024). We enrich the research field by highlighting a critical, yet previously overlooked, perspective on GenAI and its potential for idea generation: the individuals' capability to use the technology. Therefore, we complement studies investigating the frequency, extent, or purpose of GenAI usage for creative outcomes like idea generation (e.g., Zhang et al., 2025). This extension is essential as it underscores that the creative value derived from GenAI is not solely a function of the technology itself but critically depends on the human's capability to engage with it effectively. Our study also addresses an observation by Holzner et al. (2025), which shows that empirical research on GenAI and the potential for creative outcomes such as idea generation remains fragmented and has predominantly focused on academic settings, while business professionals are vastly underrepresented.

Second, our findings show relevant underlying cognitive mechanisms in the interaction of individuals' GenAI capability and idea generation. Specifically, by building on cognitive experiential theory, we demonstrate that (1) individuals' capability to use GenAI promotes tendencies to rely on both information processing styles; (2) only the tendency to rely on rational information processing promotes idea generation, but conversely not experiential information processing; and (3) the tendency to rely on rational processing mediates the GenAI usage capability–idea generation link. Our findings thus extend previous research on cognitive styles and idea generation (e.g., Baldacchino et al., 2023; Eling et al., 2015; Yeo et al., 2024). In contrast to earlier studies that emphasize the experiential system as particularly relevant for idea generation (e.g., Bălău et al., 2019), our research finds no support for this link in the context of GenAI. Instead, our results indicate the tendency to rely on rational information processing as the key mediator in the context of GenAI usage capability and idea generation.

2. Theoretical background

2.1. GenAI and individuals' GenAI usage capability

GenAI represents a powerful subcategory of AI (Schryen et al., 2025), with the introduction of applications such as ChatGPT, Dall-E, and Gemini driving the augmentation of human capabilities (Hermann & Puntoni, 2024). GenAI is defined as "computational techniques that are capable of generating seemingly new, meaningful content such as text, images, or audio from training data" (Feuerriegel et al., 2024, p. 111). While GenAI may seem like a recent breakthrough, it is built on decades of research. The development of the technology dates back to the 1950s and 1960s with early statistical language models, which have since evolved through advancements in deep learning and neural networks (Susarla et al., 2023). The recent breakthrough in GenAI can be attributed to four key factors: (1) the massive scaling of computational power; (2) advancements in model architecture; (3) the ability to pre-train models on vast amounts of unlabeled data; and (4) refinements in training techniques (Brynjolfsson et al., 2023).

Within the domain of GenAI, Large Language Models (LLMs), exemplified by the rise of OpenAI's ChatGPT, are the most prominent class. LLMs serve as versatile tools that facilitate the execution of diverse linguistic tasks across a broad range of applications (Susarla et al., 2023; Hermann & Puntoni, 2024). These models are built on transformer architecture, which utilizes self-attention mechanisms to process text sequences, making it particularly effective for capturing long-range dependencies within language data (Vaswani et al., 2017). Generative pre-trained transformers (GPTs) are designed to generate original content by predicting the next word in a sequence based on the context provided (Vaswani et al., 2017). This predictive ability is made possible through extensive pretraining on vast, diverse datasets encompassing billions of words across multiple domains (Banh & Strobel, 2023; Brynjolfsson et al., 2023). Pretraining allows GPTs to internalize complex linguistic patterns, enabling them to generate text that is both syntactically coherent and semantically meaningful (Susarla et al., 2023).

GenAI's generative capabilities make it highly relevant for creative processes (e.g., Chen & Chan, 2024; Liu et al., 2023; Magni et al., 2024). GenAI's ability to produce novel outputs and adapt to diverse contexts positions it as a disruptive tool for unlocking new opportunities in areas such as idea generation (Bouschery et al., 2023; Piller et al., 2024).

A key feature of GPTs is their adaptability, especially through prompting. Prompting is a crucial mechanism in GenAI, enabling pre-trained models to adapt to new tasks with minimal or no additional training by using carefully crafted instructions provided by users to guide output generation (Liu et al., 2023). Building on this, the interaction between humans and GenAI is increasingly characterized by co-creative processes, in which user input through prompts shapes the generated outputs and thereby contributes to the model's performance (Feuerriegel et al., 2024).

GenAI models produce probabilistic rather than deterministic outputs, as they rely on probability distributions shaped by the underlying language model and the specific input prompts used (Liu et al., 2023). Thus, the same prompt can produce different yet equally valid results each time, while different prompts can also lead to the same outcome. This makes prompt formulation a trial-and-error process, where rephrasing and tweaking keywords help refine the final output (Banh & Strobel, 2023).

To capture the user-side variability in these interactions, we draw on the concept of GenAI usage capability, which we define as "the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently" (Wang et al., 2022, p. 4). This construct originates from the broader notion of AI literacy and reflects both the technical and cognitive skills required to interact effectively with GenAI. In other words, we argue that an effective GenAI outcome is not simply a product of the algorithm's capacity but hinges on the user's ability to guide, interpret, and refine the model's responses. GenAI does not think or decide—it responds to what the user provides. Much like a skilled interviewer elicits insightful answers by asking the right questions, it is the competent user who unlocks the creative potential of the model.

2.2. Idea generation

Idea generation, the initial step in the broader idea journey—which includes the phases of idea generation, elaboration, championing, and implementation—involves creating novel and useful ideas that form the foundation for further development and implementation (Perry-Smith & Mannucci, 2017). In this sense, ideas are "discrete, or enumerated, descriptions of solutions to a problem posed" (Kornish & Hutchison-Krupat, 2017, p. 634). This problem can be implicit or explicit (Mannucci & Perry-Smith, 2022). For instance, a marketing manager could persistently be interested in the competition's campaigns (i.e., implicit problem) or could design a campaign to enhance brand awareness (i.e., explicit problem). Combining and reorganizing information and existing concepts, idea generation can solve these problems (Amabile, 1983; Jong & Hartog, 2010).

At its core, idea generation is a cognitive process grounded in psychology (Paulus & Brown, 2007). In other words, idea generation occurs within the individual's mind (Amabile, 1983; Campbell, 1960). This underlines the critical role of the individual creator in the idea-generation phase (Mannucci & Perry-Smith, 2022). Although ideas can be generated in a team (e.g., Harvey, 2014; Mannucci, 2017), cognitive processes at the individual level play a fundamental role in the origin of ideas (Rietzschel et al., 2010).

However, individual idea generation benefits from social contexts facilitating collaboration and knowledge sharing (Amabile et al., 1996; Mannucci & Perry-Smith, 2022; Woodman et al., 1993). Empirical evidence further highlights that exposure to others' ideas can stimulate originality in idea generation (Wang et al., 2018). From a firm's perspective, there are several ways to foster idea generation actively and systematically. For example, firms can utilize formally planned activities, such as brainstorming, or informal activities, such as extra free time for employees, to ideate. Additionally, they can seek to close gaps in the existing innovation portfolio or generally foster idea generation through market scouting and technology (Gurtner & Reinhardt, 2016).

The relevance of idea generation and novel ideas for firms is widely accepted in the literature (e.g., Girotra et al., 2010; Gurtner & Reinhardt, 2016; Ng et al., 2022; Wang et al., 2024). Novel ideas are described as "the lifeblood of successful innovations" (Berg, 2016, p. 433) and as a central aspect of organizational life (Vandenbosch et al., 2006). Idea generation is considered essential for the innovation process, as it begins with an idea, and all subsequent phases and the ultimate success depend on the initial idea (Kornish & Ulrich, 2014; Toubia & Netzer, 2017). Further, idea generation is crucial for the designing and marketing of new products and marketing strategies (Toubia, 2006).

Therefore, we argue that idea generation is a critical driver of organizational success and represents a cognitive process in an individual's mind. Understanding whether and how individuals' GenAI usage capability can influence and enhance this process and uncovering the underlying mechanisms is valuable and will be further examined in the following sections.

2.3. Cognitive experiential theory

Cognitive experiential theory, first introduced by Epstein (1973), has significantly developed since its introduction (Epstein, 1994, 2003, 2014). Over time, numerous researchers have expanded and adapted this theory (e.g., Sloman, 1996; Strack & Deutsch, 2004). Generally, the cognitive experiential theory is often considered part of the broader family of dual-process theories (e.g., Kahneman, 2003), according to which humans possess two independent yet interactive cognitive systems for processing information: the *experiential (intuitive) system* and the *rational (analytical) system* (Epstein, 2003, 2014).

The experiential system, also known as “System 1,” operates automatically, associatively, and affect-laden, often functioning beneath the threshold of conscious awareness (Epstein, 2010; Epstein et al., 1996; Kahneman, 2011). Evolutionary in origin, this system is shared with other species and is critical in enabling rapid, adaptive responses to environmental stimuli (Epstein, 1994). Driven by emotions, the experiential system learns effortlessly from experience and encodes these lessons automatically (Epstein, 2003). As a result, individuals often experience the outputs of this system as a sense of “just knowing” without a clearly identifiable rational basis (Kahneman, 2011; Kahneman & Klein, 2009). By quickly scanning memory for analogous past experiences, this system retrieves associated emotional cues to inform decision-making, relying on prior outcomes as a guide (Epstein, 2014).

In contrast, the rational system, “System 2,” operates with deliberation, relying on logic and systematic reasoning to process information and guide decision-making (Epstein et al., 1996; Evans & Stanovich, 2013). Functioning as an inferential mechanism, it adheres to established rules of reasoning and evidence, reflecting its relatively recent emergence in evolutionary terms (Epstein, 2003). In its controlled and rule-governed nature, the rational system is characterized by deliberate monitoring and systematic analysis designed to address complex problems

(Kahneman, 2003). This system operates more slowly and demands more cognitive resources (Epstein, 2010; Kahneman, 2011). Often described as a verbal reasoning system, it depends heavily on language and abstract symbols, such as words and numbers, to perform its functions (Epstein, 2014). Table 1 provides a comparative overview of the key attributes of the experiential and rational systems.

Insert Table 1 about here

The experiential and rational systems have unique value and significance, and neither is inherently superior to the other (Epstein, 2014). Instead, research suggests that individuals capable of flexibly integrating both systems, depending on the situational demands, tend to excel in navigating complex decision environments (Bakken et al., 2024). The interaction of both systems and their balance derive optimal outcomes across diverse organizational contexts (Luoma & Martela, 2021). Operating in parallel, these systems interact bidirectionally, engaging in competitive, cooperative, or collaborative dynamics (Hodgkinson & Sadler-Smith, 2018). The relative influence of each system on a given behavior or decision is shaped by the individual and the specific situational context (Epstein, 2014). While some individuals are more inclined toward the rational system, others may rely more heavily on the experiential system. In addressing complex and analytical problems, the rational system plays a dominant role, whereas emotional responses are predominantly governed by the experiential system (Epstein, 2014).

A compelling example of a competitive situation involving the parallel execution of the two systems during information processing is as follows: Imagine a manager confronted with the challenging decision of implementing layoffs during financial hardship. The manager’s rational system underscores the necessity of reducing the workforce to stabilize the company and secure its survival, drawing upon precise financial data to support this course of action. Simultaneously, the experiential system triggers empathy and concern for the well-being of employees and their families, resulting in a conflict between logical analysis and emotional response. This tension is often described as a struggle between "head and heart" (Lieberman, 2002).

From an innovation management perspective, cognitive experiential theory provides valuable implications for understanding human behavior in work-related contexts. For instance, intuition, a core aspect of the experiential system, has been found essential for fostering creativity, entrepreneurial thinking, and innovation, which are central to business success (Baldacchino et al., 2023). Intuitive processing allows leaders and employees to effectively draw on past experiences and implicit knowledge to navigate uncertainty and complexity across various organizational settings, including professional service contexts such as healthcare (Calabretta et al., 2017; Marques et al., 2022). The rational system, in contrast, empowers employees to adopt deliberate and systematic approaches to problem-solving and conflict resolution (Cerni et al., 2014). By integrating the logical structure of this system, businesses can strengthen decision-making processes, minimize errors, and better align actions with organizational goals (Armstrong et al., 2012; Cerni et al., 2014). While situational demands may activate either system, individuals differ in their dispositional tendency to rely more strongly on experiential or rational processing (Epstein et al., 1996).

3. Hypotheses development

In this section, we develop our research hypotheses, resulting in the research model depicted in Figure 1.

Insert Figure 1 about here

We argue that an individual's capability to use GenAI fosters their idea generation. GenAI, guided by human interactions like prompt refinement, can enhance creative problem-solving by navigating larger problem spaces and expanding the range and quality of potential solutions (Bouschery et al., 2023; Boussioux et al., 2024). Moreover, GenAI supports the generation of novel ideas by identifying connections between seemingly unrelated pieces of information and presenting them as coherent and structured suggestions (Lee & Chung, 2024). This human–GenAI collaboration is characterized by co-creative processes in which user input through prompts influences the generated outputs (Feuerriegel et al., 2024). In other words, the quality of GenAI-supported outcomes fundamentally depends on the user's ability to apply and exploit (Gen-)AI tools effectively (Wang et al., 2022). Thus, the user's capability directly influences the effectiveness of using GenAI. GenAI technologies may further support individuals in idea generation by handling convergent thinking tasks, freeing cognitive capacity for divergent, creative thinking (Grilli & Pedota, 2024). Moreover, individuals can expand the diversity of their idea outputs by combining their judgment and the technologies' generative ability (Meincke et al., 2024). Furthermore, GenAI can amplify individuals' idea generation by enhancing content and context awareness, supporting the exploration of different solution pathways during idea generation (Sundberg & Holmström, 2024; Holmström & Carroll, 2024). GenAI supports individuals in overcoming cognitive blind spots by leveraging extensive datasets and generating novel combinations of ideas, which humans might overlook due to cognitive biases (Joosten et al., 2024). However, the outcome quality of GenAI systems is inherently shaped by the user's ability to prompt, interpret, and refine model interactions (Banh & Strobel, 2023).

Additionally, the application of GenAI in early innovation phases has been shown to reduce resource-related barriers and improve accessibility, enabling individuals to generate ideas more efficiently and effectively (Bilgram & Laarmann, 2023). Further, Haase and Hanel (2023) demonstrate that GenAI can match human creative outputs by recombining knowledge into novel ideas, particularly for everyday tasks. This suggests that individuals' GenAI usage capability enhances their idea-generation output beyond typical cognitive limitations. Therefore, we hypothesize:

H1. *Individuals' capability to use GenAI fosters their idea generation.*

We further hypothesize that both information processing systems—the experiential and the rational—promote individuals' idea generation. This argumentation is based on the view that idea generation is fundamentally a cognitive process (Paulus & Brown, 2007; Campbell, 1960). Cognitive experiential theory posits that individuals differ in their stable preferences for processing information stimuli (e.g., GenAI output), either intuitively via the experiential system or analytically via the rational system (Epstein, 2003, 2014). These styles contribute differently but complementarily to idea generation and creativity, fostering distinct cognitive operations (e.g., Baldacchino et al., 2023; Eling et al., 2015; Moore et al., 2014).

The experiential system facilitates intuitive judgments and associative memory, allowing novel ideas to emerge spontaneously (Bălău et al., 2019). Additionally, it promotes divergent thinking by bypassing rigid cognitive constraints and supporting rapid pattern recognition (Epstein, 2003; Marques et al., 2022). Intuitive processing is particularly valuable in early-stage idea generation, where flexibility, associative recombination of information, and spontaneous insight are essential (Sowden et al., 2015). This process allows individuals to access implicit knowledge and emotionally charged cues from experience, which fosters originality and fluency in idea generation. Empirical studies show that individuals relying on intuitive processing often generate more original solutions than those guided solely by analytical reasoning (Gonçalves & Cash, 2021). Likewise, experienced entrepreneurs frequently draw on emotionally charged insights to identify opportunities in uncertain environments (Baldacchino et al., 2023).

The rational system, in contrast, contributes to idea generation by enabling problem structuring, causal reasoning, and deductive hypothesis building—cognitive operations that directly support creative output (Luoma & Martela, 2021; Marques et al., 2022). Especially in organizational settings marked by complexity and resource constraints, individuals use analytical strategies such as logical decomposition and scenario modeling to articulate potential innovations (Calabretta et al., 2016). Rational cognitive styles have been found to promote intrapreneurial idea initiation through goal-directed reasoning (Marques et al., 2022). Entrepreneurs applying structured search and analytical decomposition tend to generate more feasible and high-quality ideas, particularly when building on domain-specific expertise (Gemmell et al., 2012). Analytical processing further shapes idea generation by guiding attention, identifying constraints, and enabling the logical recombination of knowledge (Hodgkinson & Sadler-Smith, 2018). These capabilities are especially relevant when idea generation depends on abstraction, rule-based inference, and conceptual coherence (Luoma & Martela, 2021).

In sum, while experiential cognition may trigger spontaneous idea generation, the rational system enables structured exploration and concept formation through deliberate, rule-based reasoning. Based on this argumentation, we formulate the following hypotheses:

H2a. *Individuals' tendency to process information intuitively promotes idea generation.*

H2b. *Individuals' tendency to process information rationally promotes idea generation.*

While information processing styles are typically conceptualized as relatively stable preferences, they are not entirely fixed (Epstein, 2003). These stable traits can be modulated through repeated engagement with external structures that shape cognitive activity (Reiser, 2004). Such external structures can be tools and artifacts situated in the environment—ranging from notebooks to computational systems like GenAI tools—and become functionally integrated into human cognitive processes (Clark & Chalmers, 1998). Individuals do not process information in isolation but form tightly coupled cognitive systems with their environments (Hollan et al., 2000). In this context, GenAI tools represent a particularly dynamic form of such an environment that actively shapes how users engage with information. Developing the capability to use GenAI effectively means interacting with it as a cognitive partner that continuously structures and simplifies mental tasks. Hollan et al. (2000) note that such external scaffolding can shape individuals' thinking, particularly when the interaction becomes routine and goal-directed.

GenAI systems support cognitive processes such as learning and reflection by providing users context-specific guidance and tailored feedback that helps them internalize new knowledge (Alavi et al., 2024). We argue that when individuals become skilled in using these systems, GenAI can become a regular part of understanding problems and developing solutions, supporting and gradually shaping their preferred ways of processing information.

For instance, individuals who primarily rely on rational-analytical strategies and learn to interact fluently with systems that produce intuitive, associative outputs may adapt behaviorally and become more confident and cognitively fluent in intuitive modes of thinking. Conversely, individuals with intuitive inclinations might be encouraged by tools that require logical prompt engineering or reward structured iteration to increasingly engage in analytical strategies. In both cases, the repeated use of GenAI in cognitively demanding tasks may act as a stabilizing influence, reinforcing the internalization of alternative processing routines.

Empirical evidence shows that skilled use of GenAI can shift users' cognitive focus from task execution toward reflective evaluation and oversight, altering how attention and effort are distributed in cognitive tasks (Lee et al., 2025). This suggests that the capability to use GenAI may not only affect situational thinking but could also, over time, influence more stable preferences in how individuals process information. Theoretically, repeated interaction with GenAI in problem-solving contexts can gradually internalize the tool's reasoning patterns and representational structures (Malloy & Gonzalez, 2024). Building on this, we argue that developing the capability to use GenAI proficiently may reshape individuals' dominant cognitive strategies by embedding external reasoning formats into their habitual processing routines.

Thus, the capability to use GenAI is not just a matter of performance optimization; it may gradually shape the cognitive scaffolding through which individuals perceive, interpret, and solve problems. When used skillfully, GenAI systems may influence how information is processed more generally, potentially altering users' dominant cognitive inclinations. We, thus, hypothesize:

H3a. *Individuals' capability to use GenAI promotes their tendency to process information intuitively.*

H3b. *Individuals' capability to use GenAI promotes their tendency to process information rationally.*

4. Method

4.1. Data collection and sample

To validate the research model empirically, we conducted a survey involving consultants from a leading global consultancy within the DACH region (Germany, Austria, Switzerland). This globally recognized firm operates in more than 100 countries, employs several hundred thousand professionals, and achieves annual revenues in the tens of billions of dollars.

Our study focused on this company's strategy, consulting, and innovation divisions. Despite operating under shared corporate protocols, consultants in this firm work across heterogeneous industries and project types and exhibit substantial dispersion in GenAI-related skills and usage patterns, providing the necessary variance to test our theorized mechanisms empirically. As the needs of the clients of the consultants are constantly changing (e.g., new regulations, new technologies, new business models, new products, new competitors), the problems are also very diverse, continually evolving, and the consultants need to generate new ideas. They are confronted with new problems on a day-to-day basis.

Moreover, studying consultants in the context of digital transformation, which also entails GenAI, aligns closely with established approaches in prior research (e.g., Warner & Wäger, 2019; Williams & van Triest, 2023). Consultants are essential in facilitating the adoption and implementation of GenAI solutions across industries (Deloitte, 2024). Industry analyses further highlight that consulting firms have positioned themselves as leaders in adopting and deploying GenAI technologies (McKinsey, 2024a). Accenture reported generating over three billion dollars in bookings from GenAI-driven initiatives in recent years, underscoring the extensive practical experience consultants have gained with this transformative technology (Accenture, 2024). These findings demonstrate that consultants are theoretically knowledgeable and possess substantial hands-on expertise, further validating their relevance as subjects for our research.

The survey design and preliminary testing phase occurred between April and June 2024. To ensure clarity and validity, pre-tests were carried out with two professors, a doctoral researcher, and two consultants representative of the target group. After minor refinements to the survey, we conducted the data collection in July 2024. We distributed personalized email invitations containing a survey link to 1,032 consultants, ultimately receiving 399 completed responses (response rate 38.7%). Table 2 provides an overview of the sample's demographics, illustrating a balanced distribution across industries and experience levels.

Before commencing the analysis, we tested the data for common method bias and non-response bias. Harman's single-factor test was used to assess common method bias, with the threshold set at 50%. The resulting factor accounted for only 16,72% of the variance, indicating no significant issue with common method bias. To evaluate non-response bias, we compared responses from early participants (first 33%) to late ones (final 33%) using t-tests on key constructs. No significant differences were observed, confirming that non-response bias was not a concern in this dataset.

Insert Table 2 about here

4.2. Variable measurements

The measurement items utilized in this study were carefully derived from well-validated and widely recognized scales (Wang et al., 2022; Epstein et al., 1996; Jong & Hartog, 2010). These items were designed using a 5-point Likert scale, with response options ranging from 1, indicating "Strongly Agree," to 5, representing "Strongly Disagree." A comprehensive summary of the constructs and their corresponding measurement items is provided in the Appendix.

To assess the construct *GenAI usage capability*, we extracted and slightly modified a similar construct from the AI literacy scale proposed by Wang et al. (2022). GenAI usage capability is defined as “the ability to apply and exploit (Gen) AI technology to accomplish tasks proficiently” (Wang et al., 2022, p. 4). It is measured by three items, which determine an individual’s perceived ability to use GenAI applications effectively, their ease or difficulty in learning to use new GenAI tools, and their ability to use these applications to increase work efficiency.

We used the scale of Epstein et al. (1996) to measure the constructs *experiential information processing system* and *rational information processing system*. Both constructs were measured with five items each. The experiential system captures individuals’ dispositional tendency to rely on automatic, intuitive, and affectively influenced processes, emphasizing heuristic-based and context-specific approaches driven by associative memory. The rational system reflects individuals’ dispositional propensity to engage in deliberate, analytical, and logical reasoning, characterized by abstract principles and systematic information processing.

To measure the construct *idea generation*, we utilized the five proposed items of Jong and Hartog (2010) as part of their broader conceptualization of innovative work behavior (IWB). This dimension captures an early phase of the innovation process by reflecting an individual’s actions to combine and reorganize information to produce novel and useful solutions, including new products, services, or improvements in work processes. We deliberately focused on the idea generation dimension—rather than the complete IWB construct—because we aim to investigate how GenAI tools can support in early creative phases of innovation processes (e.g., Eisenreich et al., 2024; Meincke et al., 2024). By isolating idea generation as the relevant outcome variable, we ensure a conceptually aligned and theoretically meaningful assessment of how GenAI usage capability translates into innovation-related performance.

4.3. Model evaluation

We used structural equation modeling (SEM) to analyze the data and conducted our calculations using the statistical software SmartPLS 4. Our approach closely followed the guidelines of Hair et al. (2022), applying the partial least squares (PLS) path modeling approach. The selection of PLS-SEM for our analysis is driven by its suitability for research approaches that emphasize both explanation and prediction (Gudergan et al., 2025; Hair & Sarstedt, 2021; Sarstedt & Danks, 2022). Further, PLS-SEM combines the strengths of exploratory and confirmatory research (Sharma et al., 2024). PLS-SEM demonstrates significant advantages over covariance-based structural equation modeling by offering enhanced predictive capabilities and greater flexibility, particularly in exploratory research contexts (Hair et al., 2019). Additionally, PLS-SEM facilitates the simultaneous estimation of all relationships among constructs, enabling a comprehensive examination of complex models (Becker et al., 2023). For this study, PLS-SEM is particularly well-suited to assess the intricate relationships between individuals' GenAI usage capability, the experiential and rational information processing systems, and idea generation. By estimating direct and indirect effects, PLS-SEM provides robust insights into the underlying mechanisms that connect these constructs.

5. Results

5.1. Measurement model

We applied the standard PLS-SEM algorithm to calculate the measurement model. The evaluation of quality criteria encompassed indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, following the procedure of Hair et al. (2022). The results of these assessments are presented in Tables 3 and 4.

Insert Table 3 about here

In the first step, we assessed indicator reliability. A common rule of thumb is a value of > 0.708 for the external loadings of the indicators. However, values between 0.4 and 0.7 can also be sufficient, and these indicators should only be excluded if the deletion leads to an increase in internal consistency or convergent validity (Hair et al., 2022). The outer loadings for the construct GenAI usage capability all exceeded 0.708. For the construct experiential information processing, the second outer loading of 0.678 is minimally below the limit value but in the range of 0.4 and 0.7 and, therefore, acceptable. For the construct rational information processing, all outer loadings exceed 0.7, except for the fifth indicator, which we removed (outer loading of 0.294). The construct idea generation has three outer loadings above 0.708, and Item 1 (outer loading of 0.624) and Item 5 (outer loading of 0.699) are minimally below the value of 0.708 but in the range of 0.4–0.7 and, therefore, acceptable. We can state that indicator reliability is consequently ensured in our model.

Next, we evaluated the internal consistency reliability. We examined the composite reliability and Cronbach's alpha to determine the internal consistency reliability. For both, we set the usual target value of > 0.7 (Hair et al., 2022). All our constructs exceed 0.7. Hence, we can state that our model's internal consistency and reliability are assured.

We examined the average variance extracted (AVE) as a key metric to evaluate convergent validity. An AVE value exceeding 0.50 was established as the acceptable threshold, ensuring that the constructs demonstrate sufficient shared variance with their indicators (Hair et al., 2022). All constructs surpass this 0.50 benchmark, indicating that convergent validity is not a concern in our measurement model.

Last, we assessed the discriminant validity of the constructs by utilizing the Heterotrait-Monotrait Ratio (HTMT). We use the widely used cut-off value of 0.85 (Henseler et al., 2015). Table 4 contains the HTMT and illustrates that every value is below 0.85, indicating that discriminant validity is ensured for our measurement model.

Insert Table 4 about here

5.2. Structural model

After evaluating the measurement model, we assessed the structural model. In the first step, we calculated the variance inflation factor (VIF) to check for potential collinearity issues among the predictor constructs. The VIF values presented in Table 5 indicate that none exceeds the threshold of 3, confirming the absence of collinearity issues in the structural model (Hair et al., 2019).

Insert Table 5 about here

In the subsequent phase of our analysis, we applied the standard bootstrapping algorithm with 5,000 resamples to estimate the structural model. This approach allowed us to assess R^2 values, path coefficients, and corresponding significance levels. To interpret the significance levels, we categorized the p-values as follows: results were considered extremely significant when $p \leq 0.001$, highly significant when $p \leq 0.01$, and significant when $p \leq 0.05$. Table 6 provides an overview of path coefficients and corresponding significance levels, which are also illustrated in Figure 2. In addition, Table 7 summarizes the hypothesis test results.

Insert Table 6 about here

Insert Figure 2 about here

The results of the path analysis reveal nuanced insights into the relationship between GenAI usage capability and both information processing systems. Specifically, the analysis indicates that the capability to use GenAI accounts for 1.6% of the variance observed in the experiential information processing system, demonstrating a modest but measurable impact. Similarly, GenAI usage capability explains 1.3% of the variance within the rational information processing system, suggesting its role in influencing both information processing systems. The R^2 values of the mediators are relatively low, which is expected when modeling cognitive processes influenced by various contextual and individual factors. More importantly, their inclusion increases the R^2 of the final dependent variable (idea generation) from 7.3% to 19.2%, demonstrating their substantive role in the explanatory model and their contribution to understanding the relationship between GenAI usage capability and idea generation.

Insert Table 7 about here

5.3. Mediation effects

Our mediation analysis demonstrates a significant indirect effect of individuals' GenAI usage capability on idea generation via the tendency to rely on rational information processing (β = 0.042, p = 0.038). In contrast, the indirect effect through the tendency to rely on experiential information processing is not significant (β = 0.010, p = 0.242). These results highlight that only rational information processing mediates the relationship between individuals' GenAI usage capability and idea generation in our model. Table 8 summarizes the indirect effects.

Insert Table 8 about here

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6. Discussion

This study investigates how individuals' capability to use GenAI influences their idea generation, a core activity in innovation management. Addressing a critical gap in current research, we shift the focus from general usage metrics (frequency, extent, or purpose) to individuals' capability to skillfully engage with GenAI technology. Drawing on cognitive experiential theory, we further examine the cognitive mechanisms that underlie the relationship between GenAI usage capability and idea generation.

Our analysis is based on survey data from 399 business consultants located in Germany, Austria, and Switzerland at a leading global consultancy. We analyzed the data using PLS-SEM. Our findings mainly confirmed our theoretically grounded hypotheses. Specifically, we found that individuals' capability to use GenAI improves their idea generation (H1). We further found that (1) individuals' capability to use GenAI promotes tendencies to rely on both information processing styles (H2a and H2b); (2) only the tendency to rely on rational information processing promotes idea generation, not experiential information processing (H3a and H3b); and (3) the tendency to rely on rational processing mediates the GenAI usage capability–idea generation link.

These findings offer novel insights into the intersection of GenAI usage capability, cognitive information processing styles, and idea generation. As theoretically expected, individuals with higher levels of GenAI usage capability have improved idea generation, supporting the notion that technical and cognitive proficiency in interacting with GenAI tools is essential to unlock their creative potential. Notably, our findings reveal an asymmetry in the role of the two cognitive systems. While prior research frequently underscores the relevance of intuitive, associative processing for creativity and idea generation (e.g., Bălău et al., 2019; Epstein, 2003), our results suggest that in the specific context of GenAI-supported idea generation, rational information processing plays the more decisive role in driving idea generation based on GenAI usage capability.

6.1. Theoretical contributions

Our study offers several significant theoretical contributions to the growing body of innovation management literature in the context of GenAI (e.g., Cimino et al., 2024; Mariani & Dwivedi, 2024; Roberts & Candi, 2024; Vitellaro et al., 2025). Most notably, we provide empirical evidence that individuals' capability to use GenAI promotes their idea generation. This finding allows us to expand existing studies emphasizing GenAI's immense potential to foster idea generation (e.g., Eisenreich et al., 2024; Meincke et al., 2024). We enrich the research field by highlighting a critical, yet previously overlooked, perspective on GenAI and its creative potential for idea generation: the individuals' capability to use the technology. Therefore, we complement studies investigating GenAI usage's frequency, extent, or purpose for creative outcomes like idea generation (e.g., Zhang et al., 2025). This perspective adds depth to understanding how GenAI contributes to idea generation, emphasizing that its creative value is closely linked to human capabilities rather than being an automatic byproduct of the technology itself. Moreover, our research directly responds to the observation of Holzner et al. (2025), who emphasize that existing empirical literature on GenAI and its potential for creative outcomes, such as idea generation, is not only fragmented but also predominantly focused on data from academic settings. By shifting the focus to business consultants—a group largely underrepresented in prior research—we help close this gap and contribute to a more comprehensive understanding of GenAI's role in real-world innovation contexts.

Second, we found relevant underlying cognitive mechanisms in the link between individuals' GenAI usage capability and idea generation. Drawing on cognitive experiential theory, we provide evidence for a more nuanced understanding of this relationship. Specifically, our results show that (1) individuals' capability to use GenAI promotes their tendencies to rely on both information processing styles; (2) only the tendency to rely on rational information processing promotes idea generation, not experiential information processing; and (3) the tendency to rely on rational processing mediates the GenAI usage capability–idea generation link.

These findings extend existing research on cognitive styles and their role in idea generation (e.g., Baldacchino et al., 2023; Eling et al., 2015). Whereas prior studies have often emphasized the value of experiential thinking for idea generation (e.g., Bălău et al., 2019), our results present a different picture within the context of GenAI usage capability and idea generation. Contrary to earlier assumptions, the experiential system does not appear to be a significant driver of idea generation in this setting. Instead, our evidence highlights a stronger reliance on rational information processing as the decisive factor, positioning it as the key cognitive path through which GenAI usage capability translates into idea generation.

6.2. Practical contributions

Our findings have practical implications that can help companies and consultants ensure a targeted approach to GenAI. First, our results demonstrate that an individual's capability to use GenAI promotes their idea generation. In other words, the creative value of GenAI critically depends on the human capability to engage with it effectively. That means companies should invest in their employees and support them in systematically building their GenAI usage capability. A key lever for this is training in *prompt engineering*—the ability to formulate clear and targeted instructions that guide GenAI systems. As McKinsey (2024b) notes, effective prompts benefit from defined roles ("You are a consultant…"), clear output formats, and iterative refinement. These simple but powerful techniques help users get more accurate and helpful responses, turning GenAI into a productive support tool. To enable such upskilling at scale, companies can rely on established programs such as the Fraunhofer Institute's compact online course[2] "*Prompting für generative KI*," which introduces essential prompting strategies through hands-on examples. Structured offerings like this can help organizations anchor GenAI's competence in everyday workflows and unlock its innovation potential through user proficiency.

Second, our study contributes to building a deeper understanding of the cognitive mechanisms underlying GenAI-supported idea generation. From a managerial perspective, this knowledge is essential for unlocking the full creative value of GenAI technologies. We show that individuals' capability to use GenAI directly enhances their idea generation and increases their tendency to rely on experiential and rational information processing systems. However, only the rational system—characterized by deliberate, analytical thinking—was found to promote idea generation in the GenAI context. From a practical perspective, it suggests that organizations should consider the psychological dimensions of GenAI use—how people think, reason, and process information when interacting with these systems. Understanding GenAI as part of a human–technology cognitive system can help organizations approach its implementation more holistically and recognize that meaningful outcomes rely not only on access to powerful tools but also on the cognitive information processing styles of those who use them.

6.3. Limitations and future research

Our study faces some limitations that open avenues for future research. First, as a result of our quantitative survey approach, our data was collected at a single point in time. This limits the validity of the results. Future studies could further explore temporal developments through longitudinal or experimental designs. Second, the reliance on self-reported data may introduce biases such as common method variance or social desirability. Although we conducted established diagnostic tests, which did not indicate problematic bias, such risks can never be entirely excluded. Future research could strengthen measurement validity by combining self-assessments with behavioral indicators or third-party evaluations. Third, the consultants in our sample likely work on client issues that are at least partially pre-structured, limiting the possibility for genuine problem identification, which could restrict the generalizability of our findings to contexts with more open-ended problem spaces. Fourth, as our data come from consultants working for a single global consultancy with formalized hiring and quality-assurance protocols, unobserved firm-level standardization may attenuate individual variability, limiting the generalizability of our findings to organizations with less codified problem-solving routines.

Fifth, this study concentrates on cognitive information processing styles as mediating mechanisms. Although this lens offers explanatory value, other psychological or contextual variables, such as individual learning orientation or situational task complexity, may also influence how GenAI usage capability affects idea generation and deserve further attention. Finally, this study focuses exclusively on the idea-generation phase and does not consider subsequent stages of the innovation process. However, recent research shows that transformer-based language models, such as those used in GenAI applications, can support individuals in generating, evaluating, and prioritizing large sets of ideas (Just et al., 2024). Future research could, therefore, extend our model by examining how individuals' GenAI usage capability influences later phases of the innovation process, such as idea evaluation.

Endnotes

[1] The theory was originally introduced by Epstein as cognitive experiential self-theory but was later shortened to cognitive experiential theory. Today, both terms are used interchangeably in research.

[2] Frauenhofer Institute: Prompt Engineering - Techniken für Generative KI https://www.bigdata-ai.fraunhofer.de/de/data-scientist/schulungssuche/KompakteinstiegPromptingFuerGenerativeKI.html (last accessed 02 June 2025)

Tables and Figures

Table *1.* *Comparison of the attributes of experiential and rational information processing.*

Experiential system	Rational system
Solves problems in living by what was automatically learned from experience	Solves problems by conscious reasoning
Nonverbal: Encodes information often in images	Verbal: Encodes information in abstract symbols, including words and numbers
Emotional	Affect free
Associative connections between stimuli, responses, and outcomes	Cause-and-effect relations among stimuli, responses, and outcomes
Behavior mediated by automatic representations of events and feelings	Behavior mediated by conscious appraisal of events
Holistic	Analytic
Effortless and minimally demanding cognitive resources	Effortful and demanding cognitive resources
Rapid processing: Oriented toward immediate action; impulsive	Slower processing and capable of long-delayed action
Self-evidently valid: Experiencing is believing	Requires validation by logic and evidence

Source: Adapted from Epstein (2014, p. 12)

Table *1.* *Sample characteristics.*

Variable		**No.**	**%**
Gender	Female	167	41.9
	Male	230	57.6
	Non-binary	2	0.0
Education (highest level)	High School Diploma	10	2.5
	Bachelor's Degree	48	12.0
	Master's Degree/Diploma	306	76.7
	Doctorate	34	8.5
	Others	1	0.0
Work experience (in years)	Less than 1	5	1.3
	1–3	64	16.0
	3–5	67	16.8
	5–10	116	29.1
	More than 10	147	36.9
Company affiliation (in years)	Less than 1	63	15.8
	1–3	127	31.8
	3–5	62	15.5
	5–10	90	22.6
	More than 10	57	14.3
Career Level	Analyst	87	21.8
	Consultant	108	27.1
	Manager	91	22.8
	Senior Manager	57	14.3
	Principal	27	6.8
	Managing Director	29	7.3
Industry expertise	Health and Public Sector	162	40.6
	Finance	175	43.9
(more than one answer possible)	Communications and Media	113	28.3
	IT and Software	127	31.8
	Resources	105	26.3
	Consumer Goods	153	38.3
	Mobility and Automotive	176	44.1

Note: $N = 399$
Source: Authors' own work

Table 2. *Measurement model evaluation.*

Construct and indicator	Factor loading	Composite reliability	Cronbach's α	AVE
GenAI usage capability		0.727	0.711	0.628
GenAI usage capability 1	0.841			
GenAI usage capability 2^{R}	0.784			
GenAI usage capability 3	0.750			
Experiential information processing		0.883	0.883	0.608
Experiential information processing 1	0.776			
Experiential information processing 2	0.678			
Experiential information processing 3	0.816			
Experiential information processing 4	0.874			
Experiential information processing 5	0.743			
Rational information processing		0.762	0.760	0.582
Rational information processing 1^{R}	0.779			
Rational information processing 2^{R}	0.799			
Rational information processing 3	0.764			
Rational information processing 4	0.705			
Idea generation		0.769	0.763	0.514
Idea generation 1	0.624			
Idea generation 2	0.737			
Idea generation 3	0.779			
Idea generation 4	0.736			
Idea generation 5	0.699			

Notes: $N = 399$; ^{R} = inversed item
Source: Authors' own work

Table 3. *Heterotrait-Monotrait Ratio.*

	Constructs	1	2	3	4
1	Experiential information processing				
2	GenAI usage capability	0.153			
3	Idea generation	0.138	0.315		
4	Rational information processing	0.093	0.140	0.501	

Source: Authors' own work

Table *4.* *Variance Inflation Factors.*

	VIF
Rational information processing → Idea generation	1.014
Experiential information processing → Idea generation	1.017
GenAI usage capability → Rational information processing	1.000
GenAI usage capability → Experiential information processing	1.000
GenAI usage capability → Idea generation	1.028

Source: Authors' own work

Table 5. *Direct effects.*

Direct effects	***β***	***p***	***t***
GenAI usage capability → Experiential information processing	0.126	0.019	2.338
GenAI usage capability → Rational information processing	0.114	0.026	2.231
GenAI usage capability → Idea generation	0.178	0.001	3.270
Experiential information processing → Idea generation	0.076	0.143	1.465
Rational information processing → Idea generation	0.366	< 0.001	6.933

Source: Authors' own work

Table 7. *Hypothesis test results.*

Hypothesis	**Result**
H1. Individuals' capability to use GenAI fosters their idea generation.	Supported
H2a. Individuals' tendency to process information intuitively promotes idea generation.	Rejected
H2b. Individuals' tendency to process information rationally promotes idea generation.	Supported
H3a. Individuals' capability to use GenAI promotes their tendency to process information intuitively.	Supported
H3b. Individuals' capability to use GenAI promotes their tendency to process information rationally.	Supported

Source: Authors' own work

Table 8. *Indirect effects.*

Indirect effects	***β***	***p***	**t**
GenAI usage capability → Rational information processing → Idea generation	0.042	0.038	2.070
GenAI usage capability → Experiential information processing → Idea generation	0.010	0.242	1.170

Source: Authors' own work

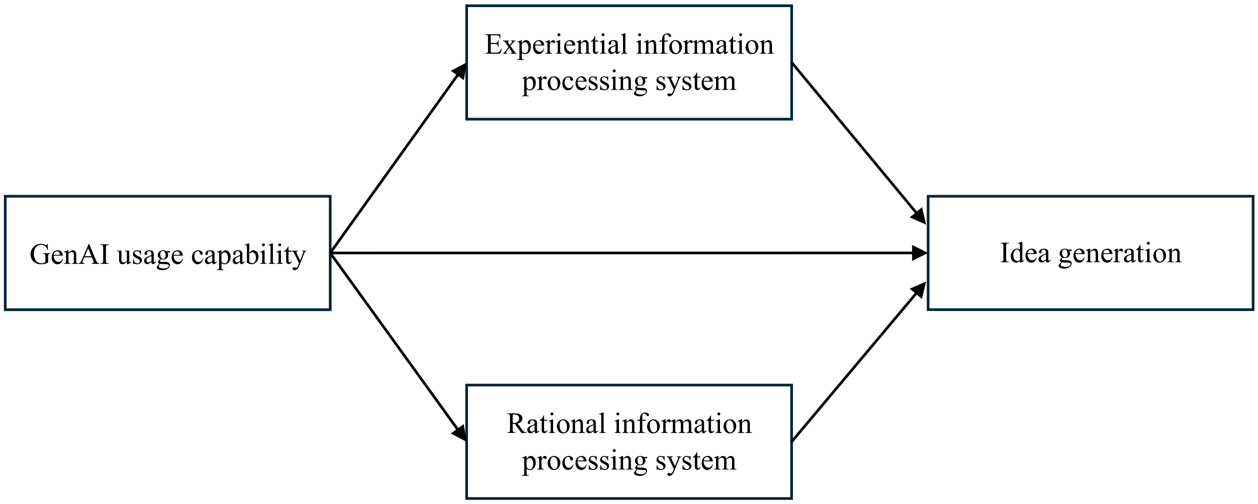

Fig. 1. Research model.
Source: Authors' own work

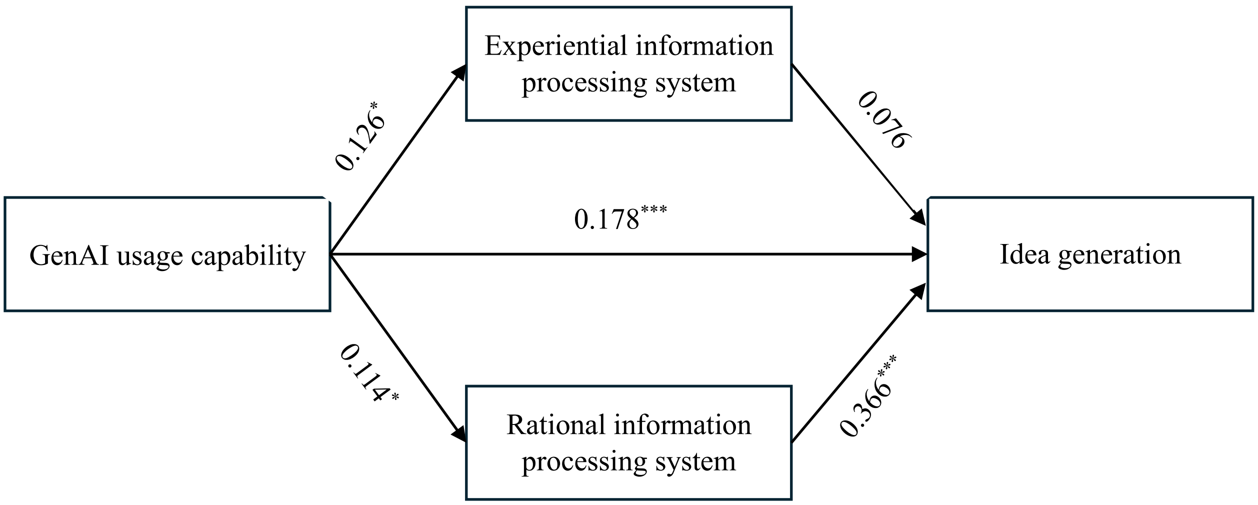

Fig. 2. Research model with path results (*p < 0.05, **p < 0.01, ***p < 0.001).
Source: Authors' own work

Appendix. Measurement scales

Construct	Item
GenAI usage capability	U1: I can skillfully use GenAI applications to help me with my daily work.
	U2: It is usually hard for me to learn to use a new GenAI application.[R]
	U3: I can use GenAI applications to improve my work efficiency.
Experiential information processing system	E1: I trust my initial feelings about people.
	E2: I believe in trusting my hunches.
	E3: My initial impressions of people are almost always right.
	E4: When it comes to trusting people, I can usually rely on my "gut feelings."
	E5: I can usually feel when a person is right or wrong even if I can't explain how I know.
Rational information processing system	R1: I don't like to have to do a lot of thinking.[R]
	R2: I try to avoid situations that require thinking in depth about something.[R]
	R3: I prefer to do something that challenges my thinking abilities rather than something that requires little thought.
	R4: I prefer complex to simple problems.
	R5: Thinking hard and for a long time about something gives me little satisfaction.[1]
Idea generation	I1: I search out new working methods, techniques or instruments.
	I2: I generate original solutions for problems.
	I3: I create new ideas.
	I4: I find new approaches to execute tasks.
	I5: I mobilize support for innovative ideas.

[R] = inversed; [1] = Removed due to low outer loading of indicator < 0.50

References

Accenture. (2024). Accenture fiscal 2024 annual report. https://www.accenture.com/content/dam/accenture/final/accenture-com/a-com-custom-component/iconic/document/Accenture-Fiscal-2024-Annual-Report.pdf (last accessed 17 February 2025)

Alavi, M., Leidner, D. E., & Mousavi, R. (2024). Knowledge management perspective of generative artificial intelligence. *Journal of the Association for Information Systems*, *25*(1), 1–12. https://doi.org/10.17705/1jais.00859

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology*, *45*(2), 357–376. https://doi.org/10.1037/0022-3514.45.2.357

Amabile, T. M., Conti, R., Coon, H., Lazenby, J., & Herron, M. (1996). Assessing the work environment for creativity. *Academy of Management Journal*, *39*(5), 1154–1184. https://doi.org/10.5465/256995

Armstrong, S. J., Cools, E., & Sadler-Smith, E. (2012). Role of cognitive styles in business and management: reviewing 40 years of research. *International Journal of Management Reviews*, *14*(3), 238–262. https://doi.org/10.1111/j.1468-2370.2011.00315.x

Bakken, B. T., Hansson, M., & Hærem, T. (2024). Challenging the doctrine of “non-discerning” decision-making: Investigating the interaction effects of cognitive styles. *Journal of Occupational and Organizational Psychology*, *97*(1), 209–232. https://doi.org/10.1111/joop.12467

Bălău, G., Faems, D., & van der Bij, H. (2019). Team experiential cognitive style and team performance: The moderating impact of workplace setting. *Creativity and Innovation Management*, *28*(3), 343–354. https://doi.org/10.1111/caim.12319

Baldacchino, L., Ucbasaran, D., & Cabantous, L. (2023). Linking experience to intuition and cognitive versatility in new venture ideation: A dual-process perspective. *Journal of Management Studies*, *60*(5), 1105–1146. https://doi.org/10.1111/joms.12794

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

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, *45*(2), 159–182. https://doi.org/10.1002/job.2735

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

Berg, J. M. (2016). Balancing on the creative highwire: Forecasting the success of novel ideas in organizations. *Administrative Science Quarterly*, *61*(3), 433–468. https://doi.org/10.1177/0001839216642211

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

Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *Journal of Product Innovation Management*, *40*(2), 139–153. https://doi.org/10.1111/jpim.12656

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

Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at Work. (No. w31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161

Calabretta, G., Gemser, G., & Wijnberg, N. M. (2017). The interplay between intuition and rationality in strategic decision making: A paradox perspective. *Organization Studies*, *38*(3-4), 365–401. https://doi.org/10.1177/0170840616655483

Campbell, D. T. (1960). Blind variation and selective retention in creative thought as in other knowledge processes. *Psychological Review*, *67*, 380–400. https://doi.org/10.1037/h0040373

Cerni, T., Curtis, G. J., & Colmar, S. H. (2014). Cognitive-experiential leadership model: How leaders' information-processing systems can influence leadership styles, influencing tactics, conflict management, and organizational outcomes. *Journal of Leadership Studies*, *8*(3), 26–39. https://doi.org/10.1002/jls.21335

Chen, Z., & Chan, J. (2024). Large language model in creative work: The role of collaboration modality and user expertise. *Management Science*, Article mnsc.2023.03014. Advance online publication. 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*, 103002. https://doi.org/10.1016/j.technovation.2024.103002

Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2023). Human-AI ensembles: when can they work? *Journal of Management*, 51(2), 536-569. https://doi.org/10.1177/01492063231194968

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.* Advance online publication. https://doi.org/10.1108/MD-10-2023-1968

Clark, A., & Chalmers, D. (1998). The extended mind. *analysis*, *58*(1), 7-19.

Deloitte. (08/2024). 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 17 February 2025)

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*, 103123. https://doi.org/10.1016/j.technovation.2024.103123

Eling, K., Langerak, F., & Griffin, A. (2015). The performance effects of combining rationality and intuition in making early new product idea evaluation decisions. *Creativity and innovation management*, *24*(3), 464-477.

Epstein, S. (1973). The self-concept revisited. Or a theory of a theory. *The American Psychologist*, *28*(5), 404–416. https://doi.org/10.1037/h0034679

Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *The American Psychologist*, *49*(8), 709–724. https://doi.org/10.1037/0003-066X.49.8.709

Epstein, S. (2003). Cognitive-experiential self-theory of personality. In I. B. Weiner (Ed.), *Handbook of Psychology* (pp. 159–184). Wiley. https://doi.org/10.1002/0471264385.wei0507

Epstein, S. (2010). Demystifying intuition: What it is, what it does, and how it does it. *Psychological Inquiry*, *21*(4), 295–312. https://doi.org/10.1080/1047840X.2010.523875

Epstein, S. (2014). Cognitive-experiential theory: An integrative theory of personality. Oxford University Press.

Epstein, S., Pacini, R., Denes-Raj, V., & & Heier, H. (1996). Individual differences in intuitive–experiential and analytical–rational thinking styles. *Journal of Personality and Social Psychology*(71), Article 2, 390-405.

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science 8*(3), 223–241. https://doi.org/10.1177/1745691612460685

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

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676–5696. https://doi.org/10.1080/00207543.2023.2294116

Garbuio, M., & Lin, N. (2021). Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence. *Journal of Product Innovation Management*, *38*(6), 701–725. https://doi.org/10.1111/jpim.12602

Gemmell, R. M., Boland, R. J., & Kolb, D. A. (2012). The socio–cognitive dynamics of entrepreneurial ideation. *Entrepreneurship Theory and Practice*, *36*(5), 1053–1073. https://doi.org/10.1111/j.1540-6520.2011.00486.x

Meincke, L., Girotra, K., Nave, G., Terwiesch, C., & Ulrich, K. T. (2024). Using large language models for idea generation in innovation. *The Wharton School Research Paper*, https://doi.org/10.2139/ssrn.4526071

Girotra, K., Terwiesch, C., & Ulrich, K. T. (2010). Idea generation and the quality of the best idea. *Management Science*, *56*(4), 591–605. https://doi.org/10.1287/mnsc.1090.1144

Gonçalves, M., & Cash, P. (2021). The life cycle of creative ideas: Towards a dual-process theory of ideation. *Design Studies*, *72*, 100988. https://doi.org/10.1016/j.destud.2020.100988

Grilli, L., & Pedota, M. (2024). Creativity and artificial intelligence: A multilevel perspective. *Creativity and Innovation Management*, *33*(2), 234-247. https://doi.org/10.1111/caim.12580

Gudergan, S. P., Moisescu, O. I., Radomir, L., Ringle, C. M., & Sarstedt, M. (2025). Special issue editorial: Advanced partial least squares structural equation modeling (PLS-SEM) applications in business research. *Journal of Business Research*, *188*, 115087. https://doi.org/10.1016/j.jbusres.2024.115087

Gurtner, S., & Reinhardt, R. (2016). Ambidextrous idea generation—antecedents and outcomes *Journal of Product Innovation Management*, *33*(S1), 34–54. https://doi.org/10.1111/jpim.12353

Haase, J., & Hanel, P. H. (2023). Artificial muses: Generative artificial intelligence chatbots have risen to human-level creativity. *Journal of Creativity*, *33*(3), 100066. https://doi.org/10.1016/j.yjoc.2023.100066

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

Harvey, S. (2014). Creative synthesis: Exploring the process of extraordinary group creativity. *The Academy of Management Review*, *39*(3), 324–343. https://doi.org/10.5465/amr.2012.0224

Held, P., & Heubeck, T. (2025). GenAI and employee innovativeness: How employees' sensing capabilities and the capabilities to use and evaluate GenAI shape their innovative work behavior. *Digital Business*, *5*(2), 100149. https://doi.org/10.1016/j.digbus.2025.100149

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

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, *180*, 114720. https://doi.org/10.1016/j.jbusres.2024.114720

Hodgkinson, G. P., & Sadler-Smith, E. (2018). The dynamics of intuition and analysis in managerial and organizational decision making. *Academy of Management Perspectives*, *32*(4), 473–492. https://doi.org/10.5465/amp.2016.0140

Hollan, J., Hutchins, E., & Kirsh, D. (2000). Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *7*(2), 174-196. https://doi.org/10.1145/353485.353487

Holmström, J., & Carroll, N. (2024). How organizations can innovate with generative AI. *Business Horizons.* Advance online publication. https://doi.org/10.1016/j.bushor.2024.02.010

Holzner, N., Maier, S., & Feuerriegel, S. (2025). Generative AI and creativity: A systematic literature review and meta-analysis. *arXiv preprint arXiv:2505.17241*.

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

Joosten, J., Bilgram, V., Hahn, A., & Totzek, D. (2024). Comparing the ideation quality of humans with generative artificial intelligence. *IEEE Engineering Management Review*, *52*(2), 153–164. https://doi.org/10.1109/EMR.2024.3353338

Just, J., Hutter, K., & Füller, J. (2024). Catching but a glimpse?—Navigating crowdsourced solution spaces with transformer-based language models. *Creativity and Innovation Management 33*(4), 718-741. https://doi.org/10.1111/caim.12612

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *The American Economic Review* 93(5), 1449–1475. http://www.jstor.org/stable/3132137

Kahneman, D. (2011). Thinking, fast and slow (First paperback edition). Psychology/economics. Farrar Straus and Giroux.

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree. *The American Psychologist*, *64*(6), 515–526. https://doi.org/10.1037/a0016755

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

Kornish, L. J., & Hutchison-Krupat, J. (2017). Research on idea generation and selection: Implications for management of technology. *Production and Operations Management*, *26*(4), 633–651. https://doi.org/10.1111/poms.12664

Kornish, L. J., & Ulrich, K. T. (2014). The importance of the raw idea in innovation: Testing the sow's ear hypothesis. *Journal of Marketing Research*, *51*(1), 14–26. https://doi.org/10.1509/jmr.12.0401

Lee, B. C., & Chung, J. J. (2024). An empirical investigation of the impact of ChatGPT on creativity. *Nature Human Behaviour*, *8*(10), 1906–1914. https://doi.org/10.1038/s41562-024-01953-1

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. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-22). https://doi.org/10.1145/3706598.3713778

Lieberman, J. D. (2002). Head over the heart or heart over the head? Cognitive experiential self-theory and extralegal heuristics in juror decision making. *Journal of Applied Social Psychology,* 32(12), 2526–2553. https://doi.org/10.1111/j.1559-1816.2002.tb02755.x

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

Luoma, J., & Martela, F. (2021). A dual-processing view of three cognitive strategies in strategic decision making: Intuition, analytic reasoning, and reframing. *Long Range Planning*, *54*(3), 102065. https://doi.org/10.1016/j.lrp.2020.102065

Magni, F., Park, J., & Chao, M. M. (2024). Humans as creativity gatekeepers: Are we biased against AI creativity? *Journal of Business and Psychology*, *39*(3), 643–656. https://doi.org/10.1007/s10869-023-09910-x

Malloy, T., & Gonzalez, C. (2024). Applying generative artificial intelligence to cognitive models of decision making. *Frontiers in Psychology*, *15*, 1387948. https://doi.org/10.3389/fpsyg.2024.1387948

Mannucci, P. V. (2017). Drawing snow white and animating Buzz Lightyear: Technological toolkit characteristics and creativity in cross-disciplinary teams. *Organization Science*, *28*(4), 711–728. https://doi.org/10.1287/orsc.2017.1141

Mannucci, P. V., & Perry-Smith, J. E. (2022). “Who are you going to call?” Network activation in creative idea generation and elaboration. *Academy of Management Journal*, *65*(4), 1192–1217. https://doi.org/10.5465/amj.2019.0333

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

Marques, C. S., Lopes, C., Braga, V., Ratten, V., & Santos, G. (2022). Intuition and rationality in intrapreneurship and innovation outputs: The case of health professionals in primary health care. *International Entrepreneurship and Management Journal*, *18*(2), 579–602. https://doi.org/10.1007/s11365-021-00761-7

McKinsey (2024a). 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. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (last accessed 17 February 2025)

McKinsey (2024b). What is prompt engineering? https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-prompt-engineering (last accessed 2 June 2025)

Moore, D., Sauder, J., & Jin, Y. (2014, August). "A Dual-Process Analysis of Design Idea Generation." Proceedings of the ASME 2014 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 7: 2nd Biennial International Conference on Dynamics for Design; 26th International Conference on Design Theory and Methodology. Buffalo, New York, USA. August 17–20, 2014. V007T07A017. ASME. https://doi.org/10.1115/DETC2014-34657

Ng, T. W. H., Shao, Y., Koopmann, J., Wang, M., Hsu, D. Y., & Yim, F. H. K. (2022). The effects of idea rejection on creative self-efficacy and idea generation: Intention to remain and perceived innovation importance as moderators. *Journal of Organizational Behavior*, *43*(1), 146–163. https://doi.org/10.1002/job.2567

Paulus, P. B., & Brown, V. R. (2007). Toward more creative and innovative group idea generation: A cognitive-social-motivational perspective of brainstorming. *Social and Personality Psychology Compass*, *1*(1), 248–265. https://doi.org/10.1111/j.1751-9004.2007.00006.x

Perry-Smith, J. E., & Mannucci, P. V. (2017). From creativity to innovation: The social network drivers of the four phases of the idea journey. *The Academy of Management Review*, *42*(1), 53–79. https://doi.org/10.5465/amr.2014.0462

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

Reiser, B. J. (2004). Scaffolding complex learning: The mechanisms of structuring and problematizing student work. *The Journal of the Learning Sciences* 13(3):273–304.

Rietzschel, E. F., Nijstad, B. A., & Stroebe, W. (2010). The selection of creative ideas after individual idea generation: Choosing between creativity and impact. *British Journal of Psychology, 101*(Pt 1), 47–68. https://doi.org/10.1348/000712609X414204

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

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

Schryen, G., Marrone, M., & Yang, J. (2025). Exploring the scope of generative AI in literature review development. *Electronic Markets*, *35*(1). https://doi.org/10.1007/s12525-025-00754-2

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*. https://doi.org/10.1108/EJIM-02-2024-0129

Sharma, P. N., Sarstedt, M., Ringle, C. M., Cheah, J.-H., Herfurth, A., & Hair, J. F. (2024). A framework for enhancing the replicability of behavioral MIS research using prediction oriented techniques. *International Journal of Information Management*, *78*, 102805. https://doi.org/10.1016/j.ijinfomgt.2024.102805

Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin*, *119*(1), 3–22. https://doi.org/10.1037/0033-2909.119.1.3

Sowden, P., Pringle, A., & Gabora, L. (2015). The shifting sands of creative thinking: Connections to dual process theory. *Thinking & Reasoning, 21*(1), 40-60. https://doi.org/10.1080/13546783.2014.885464

Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review 8*(3), 220–247. https://doi.org/10.1207/s15327957pspr0803_1

Sundberg, L., & Holmström, J. (2024). Innovating by prompting: How to facilitate innovation in the age of generative AI. *Business Horizons*, *67*(5), 561–570. https://doi.org/10.1016/j.bushor.2024.04.014

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus effect of generative AI: charting the path for responsible conduct of scholarly activities in information systems. *Information Systems Research*, *34*(2), 399–408. https://doi.org/10.1287/isre.2023.ed.v34.n2

Toubia, O. (2006). Idea generation, creativity, and incentives. *Marketing Science*, *25*(5), 411–425. https://doi.org/10.1287/mksc.1050.0166

Toubia, O., & Netzer, O. (2017). Idea generation, creativity, and prototypicality. *Marketing Science*, *36*(1), 1–20. https://doi.org/10.1287/mksc.2016.0994

Vandenbosch, B., Saatcioglu, A., & Fay, S. (2006). Idea management: A systemic view *Journal of Management Studies*, *43*(2), 259–288. https://doi.org/10.1111/j.1467-6486.2006.00590.x

Vaswani, A., Shazeer, N. M., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems*, 30. 31st Conference on Neural Information Processing Systems.* CA, USA: Long Beach.

Vitellaro, F., Schifilliti, V., Buratti, N., & Cesaroni, F. (2025). I won't become obsolete! Exploring the acceptance and use of GenAI by marketing professionals. *European Journal of Innovation Management.* https://doi.org/10.1108/EJIM-04-2024-0471

Wang, B., Rau, P.-L. P., & Yuan, T. (2022). 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, K., Nickerson, J., & Sakamoto, Y. (2018). Crowdsourced idea generation: The effect of exposure to an original idea. *Creativity and Innovation Management*, *27*(2), 196-208. https://doi.org/10.1111/caim.12264

Wang, T., Qi, T., Zhou, X., & Xin, X. (2024). Idea generation performance in open innovation communities: The role of user interaction. *Information & Management*, *61*(3), 103930. https://doi.org/10.1016/j.im.2024.103930

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

Williams, C., & van Triest, S. (2023). Understanding performance in professional services for innovation intermediation: Technology consultants vs. management consultants. *Technovation*, *126*, 102824. https://doi.org/10.1016/j.technovation.2023.102824

Woodman, R. W., Sawyer, J. E., & Griffin, R. W. (1993). Toward a theory of organizational creativity. *The Academy of Management Review*, *18*(2), 293–321. https://doi.org/10.2307/258761

Yeo, G. B., Celestine, N. A., Parker, S. K., To, M. L., & Hirst, G. (2024). A neurocognitive framework of attention and creativity: Maximizing usefulness and novelty via directed and undirected pathways. *Journal of Organizational Behavior*, *45*(6), 912–934. https://doi.org/10.1002/job.2787

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