Futures 180 (2026) 103831

Contents lists available at ScienceDirect

Futures

journal homepage: www.elsevier.com/locate/futures

Generative artificial intelligence for managerial foresight

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A R T I C L E I N F O

Keywords:
Managerial Foresight
Artificial Intelligence
Decision making
Innovation
Innovative behavior
Behavioral strategy
ChatGPT

A B S T R A C T

As organizations increasingly integrate generative AI (GenAI) into decision processes, the nature of managerial foresight is undergoing a fundamental transformation. Although managerial foresight is widely associated with innovation, prior research has largely treated this relationship as direct or processual, overlooking the individual-level cognitive mechanisms through which managerial foresight translates into innovative behavior, particularly in AI-augmented contexts. This study develops and tests a cognitively grounded model linking managerial foresight to innovative behavior through cognitive engagement, and examines how GenAI conditions this relationship. Drawing on a 2 × 3 factorial experiment with 252 professionals evaluating product innovation scenarios, we manipulate GenAI usage (none, moderate, high). Results reveal a non-linear, inverse U-shaped moderating effect: moderate GenAI use strengthens the indirect effect of managerial foresight on innovative behavior via cognitive engagement, whereas both over-reliance and non-use attenuate it. Qualitative evidence shows that excessive GenAI use induces cognitive offloading and fixation, while its absence constrains exploratory thinking. These findings make three contributions. First, we reconceptualize managerial foresight as a cognitively effortful process, identifying cognitive engagement as a critical microfoundation of managerial foresight-driven innovation. Second, we theorize GenAI not as a uniformly beneficial tool, but as a contingent cognitive scaffold that reshapes managerial judgment, with effects depending on intensity of use. Third, we challenge prevailing assumptions of linear AI benefits by demonstrating that both underuse and overuse can undermine innovation. Practically, the study highlights the need to calibrate GenAI use, design managerial foresight practices that sustain cognitive effort, and develop managerial capabilities that prevent cognitive disengagement and overreliance.

1. Introduction

Managerial foresight is the capability of decision-makers to construct and use anticipatory information channels to detect early signals, explore unexperienced possibilities, and evaluate emerging future conditions to guide action under uncertainty (Fidler, 2011). This capability enables managers to complement backward-looking experience with forward-looking sensemaking, particularly during periods of discontinuous or non-linear change (Paliokaite et al., 2014; Rohrbeck et al., 2015; Fergnani, 2022; Dell'Era et al., 2025). It involves systematically sensing environmental changes, evaluating emerging trajectories, and leveraging insights to make choices that ensure adaptability and advantage (Rohrbeck & Gemünden, 2011; Marinković et al., 2022). At the managerial level, foresight is not merely distant scenario planning; it is associated with forward-looking thinking that challenges mental routines, enhances

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https://doi.org/10.1016/j.futures.2026.103831
Received 11 March 2025; Received in revised form 8 April 2026; Accepted 15 April 2026
Available online 17 April 2026
0016-3287/

imagination, and is widely regarded as supportive of innovation (Rohrbeck & Gemünden, 2011; Kapoor & Wilde, 2023).

Managerial foresight has been linked to innovative behavior – the intentional development and application of novel ideas, products, or processes to improve organizational performance (Iden et al., 2017; Tapinos & Pyper, 2018; Innes, 2024). It enables managers to construct alternative futures by integrating weak signals, reframing assumptions, and engaging in abstract, long-term thinking (Weick et al., 2005; Cristofaro, 2022; Vecchiato, 2012). Yet managerial foresight does not automatically generate innovation. Its efficacy appears to depend on cognitive engagement– the mental effort required to comprehend complexity, evaluate scenarios, and produce creative responses (Dweck & Leggett, 1988; Faiella & Corazza, 2025; Cristofaro et al., 2022). Behavioral decision theory suggests that managerial foresight prompts individuals to shift from intuitive, heuristic thinking (System 1) to deliberate, analytical reasoning (System 2), which supports innovation through critical evaluation and ideation (Kahneman, 2011).

Today, Generative AI (GenAI) is reshaping how managerial foresight is conducted (Cristofaro & Giardino, 2025). Technically, GenAI refers to AI systems—typically based on large language models—that generate context-specific outputs in response to user prompts by predicting subsequent elements in a sequence from patterns learned on large-scale training data (Finkenstadt et al., 2024; Kozachek, 2023). From a managerial foresight perspective, however, GenAI can be conceptualized as a prompt-configured cognitive infrastructure that supports the exploration of multiple plausible futures and extends managerial sensemaking under conditions of uncertainty, ambiguity, and incomplete information. In this role, GenAI does not replace managerial foresight judgment but reshapes the cognitive space in which future-oriented evaluation occurs, enabling managers to surface weak signals, recombine disparate insights, and contrast alternative future trajectories. Rather than forecasting outcomes, GenAI facilitates the recombination, comparison, and iterative evaluation of possible futures, functioning as a contingent support for future-oriented judgment whose effects depend critically on how it is configured, prompted, and engaged within managerial foresight practices (Doshi et al., 2025; Feher et al., 2025). Pratt et al. (2023) argue that GenAI can enable more inclusive and agile future exploration, and Rowland and Grüning (2025) demonstrate how AI-assisted brainstorming is associated with scenario thinking. Yet emerging research also signals risk. Users interacting with GenAI often exhibit lower cognitive engagement relative to comparison conditions such as search engines or learning directly (Chow, 2025; Inayatullah, 2023; Gerlich, 2025). Kozachek (2023) warns of "hallucinated foresight": plausible but misleading narratives rooted in training-data biases rather than real signals. As managerial foresight becomes hybridized, the challenge shifts from AI-enhanced capability to the preservation of human agency and reflexivity (Gordon et al., 2020; Saritas et al., 2022). Despite growing interest, the impact of GenAI on the relationship between managerial foresight and innovation remains insufficiently specified at the individual cognitive level. Managerial foresight research has largely emphasized organizational processes (Rohrbeck et al., 2015; Tapinos & Pyper, 2018), while innovation research has often overlooked the micro-level dynamics through which individuals process managerial foresight insights and generate innovation (Haefner et al., 2021). In this study, we address this gap by asking: *How does the use of generative AI condition the relationship between managerial foresight, cognitive engagement, and innovative behavior in innovation decisions?*

We examine this question using Kickstarter projects as proxies for early-stage innovation decisions. Managerial foresight simulation refers to the enactment of future-oriented evaluation under conditions of uncertainty and novelty (Köves et al., 2025); Kickstarter projects embody this by requiring respondents to interpret weak signals and assess future potential based on minimal, ambiguous information (Eisenbart et al., 2022). Our sample comprises 252 professionals with expertise in innovation, allowing us to examine experimentally induced differences in decision processes under controlled conditions, while maintaining managerial relevance.

We posit that AI's influence on managerial foresight-driven innovation follows an inverse U-shaped pattern: moderate GenAI use strengthens the indirect relationship between managerial foresight and innovative behavior via cognitive engagement, whereas excessive or absent use attenuates it by inducing overload or reinforcing fixation. We test this using a 2 × 3 factorial experimental design, manipulating managerial foresight prompts and GenAI usage levels and complementing this with open-ended responses and interviews to qualitatively contextualize experiential patterns such as cognitive overload, fixation bias, and reduced agency. Drawing on behavioral decision theory (Kahneman, 2011), prospective sensemaking (Klein et al., 2006; Weick et al., 2005; Cristofaro, 2022), and construal-level theory (Trope & Liberman, 2010), we theorize and empirically examine how managerial foresight activates

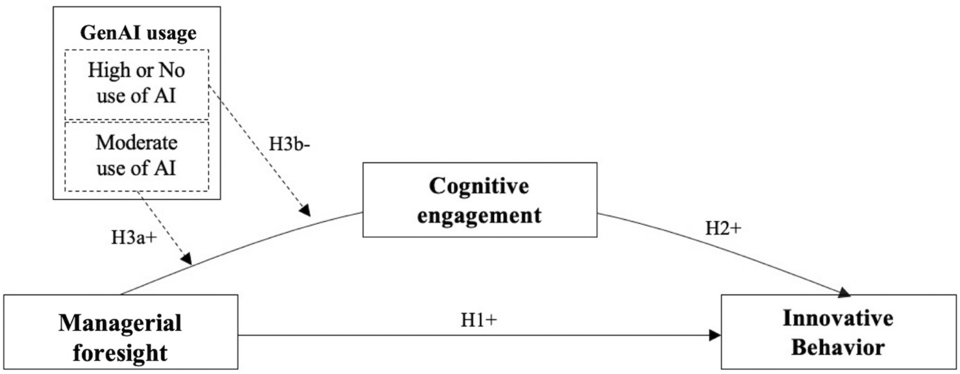

Fig. 1. Conceptual model.
Source: own elaboration

cognitive engagement by shifting individuals from heuristic-driven (System 1) to analytical (System 2) processing. On this basis, the study advances managerial foresight theory by clarifying cognitive engagement as a mediating microfoundation through which managerial foresight affects innovative behavior (Faiella & Corazza, 2025); conceptualizes GenAI as a conditional amplifier of managerial foresight, beneficial under moderate use but potentially impairing cognition when overused (Finkenstadt et al., 2024; Pratt et al., 2023; Chow, 2025); and contributes to practical managerial foresight methodology by delineating design boundaries for GenAI integration and guiding responsible use of large language models in futures thinking.

2. Conceptual model and hypothesis development

The following sub-sections develop our hypotheses based on the relationships among the constructs shown in Fig. 1.

Our conceptual model rests on the intersection of behavioral decision theory, sensemaking, and Construal-Level Theory (CLT). Behavioral decision theory explains how managerial foresight can interrupt intuitive, heuristic-driven responses (System 1) and can activate analytical, effortful reasoning (System 2), thereby supporting cognitive engagement as a prerequisite for innovative behavior (Kahneman, 2011). Sensemaking theory adds a processual and narrative lens, showing how managers interpret ambiguous signals and construct meaning in dynamic environments (Klein et al., 2006; Weick, 1995; Maitlis & Christianson, 2014; Cristofaro, 2022). In our model, managerial foresight is theorized to reshape cognition by prompting deliberate reflection, expanding mental models, and incorporating weak signals and emerging possibilities (Vecchiato, 2012; Weick et al., 2005; Cristofaro, 2022), which is expected to be associated with a cognitive shift from fast, automatic to slow, analytical processing (Kahneman, 2011). This theoretical logic underpins the proposed direct relationship between managerial foresight and innovative behavior, as well as the indirect relationship via cognitive engagement.

GenAI is introduced as a moderator of the managerial foresight–cognitive engagement–innovation pathway. It may amplify or attenuate this cognitive shift by accelerating pattern recognition, surfacing analogies, and synthesizing cross-domain inputs (Schwarz et al., 2023), but its effects are expected to be non-linear. Drawing on cognitive load theory and dual-process models, the model suggests that moderate GenAI usage scaffolds attention, supports scenario elaboration, and encourages reflective abstraction (Makridakis, 2017; Wilson & Daugherty, 2018), whereas high usage may increase the likelihood of cognitive overload, cognitive offloading, and suppressed effortful reasoning (Davenport & Kirby, 2016; Roetzel, 2019; Gerlich, 2025), and no GenAI may reinforce habitual thinking and fixation (Marinkovic et al., 2022). CLT sharpens this argument by explaining how managerial foresight increases psychological distance and high-level construal, which are conducive to innovation (Trope & Liberman, 2010), while the overuse of GenAI may reduce construal level by fragmenting attention (Faiella & Corazza, 2025).

Accordingly, the model posits: (1) a positive relationship between managerial foresight and innovative behavior, (2) a mediating role of cognitive engagement in this relationship, and (3) a curvilinear moderating effect of GenAI usage, whereby moderate GenAI strengthens cognitive engagement and innovative behavior, while underuse and overuse constrain imagination or overload cognition.

2.1. *Managerial foresight and innovative behavior*

Managerial foresight rests on three core principles: recognizing multiple possible futures under uncertainty, identifying and analyzing key drivers of change, and assuming that the future can be actively influenced. It thus helps scan for and construct possible futures (Vecchiato, 2012), enabling organizations to anticipate opportunities and challenges (Gordon et al., 2020). By detecting emerging trends, technologies, and shifting customer needs, managerial foresight has been shown to reduce perceived uncertainty (Feher et al., 2024) and create conditions conducive to innovation (Sarpong & Maclean, 2011; Von der Gracht et al., 2010; Rohrbeck & Gemünden, 2011; Rohrbeck & Kum, 2018). It broadens perceptions (Burt & Wright, 2006), and enables change of entrenched mental models (Wack, 1985).

Prospective sensemaking (Klein et al., 2006; Weick, 1995; Weick et al., 2005; Cristofaro, 2022) clarifies this link by showing how actors actively construct future possibilities from weak signals and evolving cues. Rather than merely interpreting the present, they project themselves into future states, structure ambiguous developments, and align strategies accordingly (Iden et al., 2017; Marinković et al., 2022). In this way, managerial foresight provides not just information but narrative frames that can connect emerging opportunities to concrete innovation pathways.

CLT adds a complementary mechanism positing that distant future events elicit abstract, high-level thinking, whereas near-term concerns trigger concrete, detail-focused processing (Trope & Liberman, 2010). Because managerial foresight inherently extends temporal horizons, it is expected to encourage higher-level, big-picture cognition that supports creativity, problem reframing, and experimentation (Schwarz et al., 2023; Faiella & Corazza, 2025).

Empirical studies corroborate the positive association between managerial foresight and innovation. Rohrbeck and Schwarz (2013), examining 77 large European firms, demonstrate that managerial foresight is associated with an enhanced ability to perceive and respond to environmental change, enabling organizations to explore new fields, identify promising innovations, and challenge R&D throughout product development. Schwarz et al. (2023) find that among design-thinking professionals, managerial foresight – particularly trend research and scenario planning – positively correlates with the success of innovation projects and should be integrated into their methodological toolbox.

In summary, by scanning potential futures and integrating emerging trends, disruptions, and opportunities (Vecchiato, 2012; De Moor et al., 2014; Buehring & Liedtka, 2018), managerial foresight is expected to support innovative behavior – encompassing idea generation, promotion, and implementation (Eidinow & Ramirez, 2016). Building on this, we hypothesize:

H1. *: Managerial Foresight positively influences Innovative behavior.*

2.2. The mediating role of cognitive engagement

Managerial foresight is widely regarded as a key driver of innovation, as it enables firms and individuals to identify emerging technological, market, and societal shifts that can be leveraged for creative solutions (Vecchiato, 2015). However, while managerial foresight provides a foundation for innovation, few studies examine the cognitive processes through which it translates into innovative behavior (Rohrbeck et al., 2015).

In this vein, engaging in managerial foresight exposes individuals to complex, uncertain information about the future, which is likely to require a high level of cognitive engagement, as they must analyze weak signals, evaluate uncertainties, and integrate interdisciplinary knowledge (Day & Schoemaker, 2016). We refer to this as 'cognitive engagement' – a central concept in Behavioral Decision Theory and related behavioral strategy research (Powell et al., 2011; Cristofaro et al., 2024). Cognitive engagement involves the active mental effort required to interpret complex information, weigh alternatives, and critically analyze insights (Dweck & Leggett, 1988). It enables decision-makers to transition from intuitive System 1 processing to deliberate System 2 thinking (Kahneman, 2011). Thus, managerial foresight is theorized to foster cognitive engagement by encouraging individuals to challenge assumptions, develop new mental models, and explore alternative pathways (Gavetti & Levinthal, 2000; Rohrbeck & Kum, 2018).

This engagement is associated with higher levels of exploratory thinking, a prerequisite for innovative behavior (Sonnentag, 2003). Cognitively engaged individuals exhibit greater creative problem-solving, experimentation, and persistence (Zhou & George, 2001). Accordingly, cognitive engagement represents a plausible mediating mechanism linking managerial foresight to innovative behavior.

Engaging in managerial foresight therefore requires more than passive observation; it necessitates active cognitive engagement. This engagement involves overcoming heuristic biases and engaging in deliberate, analytical processing (Kahneman, 2011). By investing sustained mental effort, decision-makers are more likely to generate innovative solutions. Accordingly, we propose:

H2. *: Cognitive engagement mediates the relationship between managerial foresight and innovative behavior.*

2.3. The moderating role of generative artificial intelligence

The integration of AI into decision-making and innovation has substantially altered how individuals and organizations approach managerial foresight. GenAI, in particular, offers advanced data processing, predictive analytics, and pattern recognition that can either enhance or inhibit cognitive engagement (Makridakis, 2017). AI-driven insights have been shown to increase users' engagement in complex problem-solving (Kumar et al., 2024) and, when embedded in managerial foresight infrastructures such as Cisco's Technology Radar, can support collective sensemaking and innovation (Boe-Lillegraven & Monterde, 2015; Zirar, 2023).

Recent advances in GenAI – encompassing large language models and multimodal agents – have rapidly reshaped managerial foresight practices (Pratt et al., 2023; Kozachek, 2023). These tools synthesize trends, simulate scenarios, and visualize futures at scale. Pratt et al. (2023) demonstrate how GenAI can facilitate managerial foresight through recombination and analogy, while cautioning against the passive, automation-driven use of this technology. Finkenstadt et al. (2024) find that GenAI "companions" may act as co-sensemakers yet also pose risks of over-reliance and declining judgment. Inayatullah (2023) illustrates how GenAI can be integrated into methods such as Causal Layered Analysis, but notes that it often remains normatively neutral and may lack surface-level contextual managerial foresight and temporal depth; Kozachek (2023) likewise emphasizes limitations in these areas. Overall, GenAI emerges as a conditional enabler, whose benefits depend on the intensity of use, critical reflection, and integration strategy.

At high reliance levels, decision-makers may delegate too much responsibility to GenAI, reducing "the thoughtfulness and willingness to exert the effort necessary to comprehend complex ideas" (Dweck & Leggett, 1988: 60) and potentially stifling out-of-the-box thinking (Jarrahi, 2018). Excessive automation has been associated with lower cognitive engagement (Davenport & Kirby, 2016) and may trigger "cognitive overload" (Roetzel, 2019) – a state where information demands exceed working-memory capacity, impairing attention and judgment (Rudolph et al., 2009; Kozachek, 2023; Inayatullah, 2023). Conversely, when GenAI is underutilized or absent, managerial foresight may remain constrained by bounded rationality (Simon, 1998): decisions rely on incomplete information and outdated methods, reinforcing presentism and limiting the scope for innovation (Brynjolfsson & McAfee, 2014; Cristofaro, 2016; Rudolph et al., 2009).

Three theoretical perspectives clarify this moderating role. From a prospective sensemaking view (Weick et al., 2005), moderate GenAI use can scaffold sensemaking by structuring ambiguity, surfacing weak signals, and stimulating associative thinking (Pratt et al., 2023; Inayatullah, 2023), whereas excessive use may overload actors and undermine coherent strategies (Iden et al., 2017; Kozachek, 2023). Construal-Level Theory suggests that managerial foresight requires abstract, high-level thinking (Trope & Liberman, 2010). GenAI can expand psychological distance, but overuse may anchor users to generic, presentist outputs (Finkenstadt et al., 2024; Kozachek, 2023). In contrast, no GenAI may reinforce fixation (Faiella & Corazza, 2025). Behavioral Decision Theory (Kahneman & Tversky, 1979; Simon, 1947) highlights reliance on heuristics under uncertainty; GenAI can help mitigate availability and confirmation biases by generating divergent options and reframing problems (Pratt et al., 2023; Finkenstadt et al., 2024), yet overuse may foster "decision inertia" and cognitive offloading, reducing brain engagement (Time/(Gerlich, 2025), whereas too little GenAI may heighten cognitive load and bounded rationality.

Accordingly, decision-makers must calibrate the use of GenAI to avoid overload and disengagement. Organizations tend to perform better when GenAI complements rather than replaces human intelligence (Wilson & Daugherty, 2018); thus, when they use GenAI responsibly (Feher et al., 2025). Supportive GenAI can enhance intuition and analytical capacity (Davenport & Ronanki, 2018), and firms that allow GenAI to generate insights while humans retain decision authority have been found to exhibit higher innovative behavior (Iansiti & Lakhani, 2020). Thus, GenAI is expected to moderate the managerial foresight–innovation link by shaping the degree and quality of cognitive engagement. We therefore propose:

H3a. *Moderate use of GenAI, by enhancing cognitive engagement, positively influences the relationship between managerial foresight and innovative behavior.*

H3b. *High or no use of GenAI, by limiting cognitive engagement, negatively influences the relationship between managerial foresight and innovative behavior.*

3. Methodology

3.1. Research design, participants, and procedures

This study employs a mixed-methods design that integrates a 2 × 3 between-subjects experiment with an embedded qualitative component to investigate how managerial foresight and GenAI usage are associated with differences in innovation-related cognition. Responding to calls for experimental foresight research (Derbyshire et al., 2023), we designed a controlled scenario-based task in which participants evaluated product innovation opportunities under varying conditions. A between-subjects factorial structure allows estimation of both main and interaction effects between managerial foresight (present vs. absent) and GenAI usage (none, moderate, high), while avoiding learning and carryover effects typical of within-subjects designs (Montgomery, 2017) and enabling the examination of the expected inverted U-shaped relationship between GenAI usage and innovative behavior (Eisenbart et al., 2022).

The two manipulated variables were: (1) managerial foresight (present vs. absent) and (2) GenAI usage (none, moderate, high). In practice, we implemented four conditions: (a) no managerial foresight/no GenAI; (b) managerial foresight/no GenAI; (c) managerial foresight with moderate GenAI; and (d) managerial foresight with high GenAI. The individual was the unit of analysis, as managerial foresight is theorized to reshape cognitive frames even in non-collective settings. Open-ended survey questions and a subset of semi-structured interviews, administered immediately after the task, were used to contextualize and interpret mechanisms underlying quantitative patterns.

Cochran's formula indicated a minimum of 209 participants (margin of error = 0.03; alpha = 0.01) for hypothesis testing (Cochran, 1977). Through our professional networks, we recruited 252 professionals with responsibility for assessing market potential and making new product decisions, thereby exceeding the threshold. Participants came from diverse industries and managerial roles, with relatively homogeneous age and experience, and were randomly assigned to the four conditions (63 per group). For detailed demographics, see Appendix A.

The experiment took place at an Italian university in September 2023. After a briefing on purpose, instructions, and the role of GenAI, participants were asked to imagine themselves as managers seeking growth opportunities through product innovation. They were presented with one focal consumer product from a newly established Italian company (see Section 3.3) and asked to generate and justify extensions over a period of 90 min. To enhance motivation, they were informed that the "best extension" would be rewarded and that the top ten performers would receive a € 20 gift voucher, based on evidence of self-beneficial incentives (VonGunten & Scherer, 2019).

Managerial foresight was manipulated via a written prompt. In managerial foresight conditions, before generating extensions, participants envisioned the company's future over the next decade, reflecting on internal (e.g., resources, scale-up difficulties) and external (technological, socio-economic, political) factors. In GenAI conditions, this exercise could be conducted with assistance from ChatGPT. Participants with AI access completed an online survey and were allowed to use GenAI; those in non-AI conditions completed a paper-based version and were explicitly instructed not to use GenAI or other online sources.

ChatGPT was selected because it represents state-of-the-art natural language processing, is widely adopted across industries, and supports interactive, text-based managerial foresight conversations (PCMag, 2024; Statista, 2023). We provided step-by-step access instructions and standardized interaction guidelines (see Section 3.3), defining a single interaction as a user prompt followed by an AI response. Clarification questions were invited before the task began.

Immediately after the task, all participants answered open-ended questions on how GenAI (when applicable) influenced their thinking, whether they felt supported or overwhelmed, and how they approached generating extensions. A subset participated in semi-structured interviews. Interviews were audio-recorded, transcribed, and analyzed using thematic analysis (Braun & Clarke, 2006). Triangulating these qualitative insights with experimental data clarified why different GenAI usage levels produced distinct effects on cognitive engagement and innovative behavior and helped rule out simple alternative explanations, thereby enhancing the external validity of our findings.

3.2. Measurements

We sourced the focal product from Kickstarter, a leading crowdfunding platform. Kickstarter products are suitable for our purposes because they represent early-stage ideas with high uncertainty, limited market validation, and evolving technological contexts – conditions that mirror the real-world challenges of managerial foresight. Such ideas typically require further funding and refinement before market introduction (Peterson & Wu, 2021); prior research also shows that crowdfunding pitches share a comparable evolutionary state (Kornish & Ulrich, 2014). In this study, participants were introduced to a project centered on a new vacuum cleaner (Skadu M1), developed by the start-up Hyper Lychee (founded in 2020). The original Kickstarter description was anonymized and provided to all participants to stimulate potential extensions.

Participants in the experimental groups additionally received a brief anonymized company description adapted from Kickstarter: "Company ABC is an Italian start-up set to revolutionize the way people execute daily tasks at home by building technologically and design-advanced products to improve the overall quality of life." The Italian setting was chosen to maximize contextual familiarity.

A panel of three experts assessed innovative behavior: two academics in business and management with expertise in new product development, and one academic judge from national start-up competitions (six years' experience). Following Eisenbart et al. (2022), experts evaluated each product extension on three criteria using a 1–3 scale: (a) Business Potential (revenue, market share, and sustainable value), (b) Market Differentiation (uniqueness of features or value propositions), and (c) Feasibility (technological, resource, and market viability, including barriers to entry). For each extension, criterion ratings were averaged across experts and summed, yielding an overall innovative score from 3 (minimum) to 9 (maximum). Inter-rater reliability was high (Cronbach's alpha = 0.89); disagreements were resolved through discussion and consensus.

GenAI usage was operationalized via pre-defined interaction bands with ChatGPT: No GenAI usage: no access to ChatGPT; participants relied solely on their own cognition and experience; Moderate GenAI usage: between 5 and 15 interactions with ChatGPT; High GenAI usage: at least 16 interactions, with no upper limit. Participants in the GenAI conditions were required to provide printed screenshots of their ChatGPT sessions, marking the start and end of each AI-assisted sequence. They were instructed to use GenAI exclusively for managerial foresight about the company's future; non-compliance led to exclusion. For non-AI conditions, use of GenAI or any external online source was explicitly prohibited, and three researchers monitored compliance during the experiment. Confidentiality and anonymity were emphasized to reduce social desirability bias.

Cognitive engagement was measured as time-on-task (in minutes), from task initiation to completion. The time spent provides an objective indicator of the depth and persistence of cognitive processing, avoiding the biases inherent in self-report measures. Prior work shows that longer time-on-task is associated with deeper cognition and improved innovative outcomes (Helme & Clarke, 2001; Järvelä et al., 2008). In a managerial foresight context – where participants must integrate analytical and creative thinking – time-on-task is a meaningful proxy for the mental effort invested in generating and elaborating product extensions. The experimental protocol was pilot-tested with 16 doctoral students and two junior lecturers at the Italian university where the survey was administered. Feedback from the pilot was used to refine instructions and ensure clarity of the GenAI guidelines. The pilot also assisted in training the three expert raters. Experts received detailed evaluation guidelines based on established frameworks (Eisenbart et al., 2022) and used the pilot extensions to practice scoring and align interpretations.

Thresholds for GenAI usage levels (no, moderate, high) were derived empirically from the pilot data. Participants completed the innovation-oriented task with unrestricted access to GenAI, and we then examined the relationship between the number of interactions and innovative behavior scores using visual inspection (Fisch, 2001). Two authors and two external academics (experts in statistics with 15 years of experience in visual analysis) independently inspected the plots and identified breakpoints where patterns in innovative behavior shifted. Agreement was excellent (Cronbach's alpha = 0.95), and discrepancies were resolved through discussion. The analysis revealed that participants with up to 15 interactions exhibited distinct performance patterns compared to those with more than this threshold, supporting the 5–15 range for moderate usage and a threshold of 16 or higher for high usage. While visual inspection is not a fully rigorous change-point method, it provides an intuitive and exploratory basis for identifying meaningful thresholds, in line with Fisch (2001), and ensures that our GenAI usage bands are empirically grounded rather than arbitrary.

3.3. Group parity verification

We verified the comparability of groups along three dimensions: random assignment, managerial foresight-related cognitive capability, and GenAI literacy.

First, participants were randomly allocated to the four experimental conditions. Randomization helps equalize "nuisance characteristics" across treatments and reduces the influence of extraneous variables (Wickens & Keppel, 2004). In between-subjects designs, manipulating the independent variables under random assignment strengthens internal validity and supports causal inference (Wehnert et al., 2019), as recommended in experimental managerial foresight guidelines (Derbyshire et al., 2023; Eisenbart et al., 2022). This design choice increases confidence that observed differences in innovative extensions are attributable to managerial foresight prompts and the use of GenAI.

Second, to rule out systematic differences in participants' ability to conceive of futures and understand cause–and–effect relationships, we analyzed the future-oriented extensions across conditions; group-level comparisons revealed no statistically significant differences in these baseline parameters. In addition, participants in GenAI conditions were screened for compliance via verified screenshots, while non-AI groups were supervised in offline settings to prevent unauthorized AI use. This multi-pronged approach helps reduce sampling distortion, supports construct validity, and enhances the relevance of our findings to managerial populations.

Third, we assessed GenAI literacy using a validated 12-item self-report scale (Wang et al., 2022), which shows strong internal consistency (Cronbach's alpha = 0.83). Self-assessed digital competence is highly correlated with actual skill in professional samples, making it suitable for large-scale field experiments. To further mitigate self-report bias, we included a single-item measure of familiarity with ChatGPT (mean = 5.9/7). We examined the data for outliers or inconsistencies during data cleaning and found no problematic patterns.

4. Results

4.1. Preliminary analyses and group comparisons

The transcripts of all extensions were read independently by two researchers, who were unaware of the groups from which they originated. They then individually coded the extensions using an inductive approach. The codes and criteria were exchanged to ensure clarity in the coding scheme. A final set of criteria was established for coding the extensions. Any discrepancies in the coding results between the researchers were discussed until only a few instances of misalignment remained. Subsequently, a third researcher verified the consistency of each code with the defined criteria. Complete alignment was achieved through a final round of discussion among all coders. We considered an instance of a future extension when it fulfills any of the following criteria: a) the purpose and/or application area of the product in question is changed; b) the form and/or functionality of the product is noticeably altered; c) a new commercialization strategy and/or market vertical is proposed; d) a new user group or use context is presented. To exemplify, an extension of the vacuum cleaner proposed by a subject was "Introducing a modular attachment system, exclusively designed for the vacuum cleaner. The system is engineered to address the diverse cleaning needs of modern households. It ensures that the vacuum cleaner is not just for floors. Still, for every nook and cranny of your home". This implies an extension of the offered functionality. No instance of the future extension was counted when the subjects offered no, or only minor, design changes, such as color options.

Before testing our hypothesized moderated mediation model, we conducted extensive preliminary analyses to ensure that the data met the requisite assumptions of normality, homoscedasticity, and absence of multicollinearity. Outliers were identified and addressed to prevent undue influence on the results. A one-way ANOVA was then performed to assess differences in innovative behavior across the four experimental conditions.

As summarized in Table 1, significant differences were observed among the groups. In the control condition (no managerial foresight, NF), participants exhibited a mean innovative behavior score of 5.10 (SD = 1.35). In contrast, those in the managerial foresight condition without GenAI usage recorded a higher mean of 6.25 (SD = 1.20), with an F-value of 14.67 and a p-value of 0.001 ($\eta^2 = 0.09$), indicating a statistically significant effect of the managerial foresight manipulation on innovative behavior. Notably, the group receiving both the managerial foresight prompt and moderate GenAI usage achieved the highest mean score (M = 7.20, SD = 1.25; F = 9.64, p = 0.002, $\eta^2 = 0.04$). Conversely, the managerial foresight condition with high GenAI usage produced a lower mean innovative behavior score (M = 5.35, SD = 1.32; F = 6.31, p = 0.012, $\eta^2 = 0.03$). These group comparisons provided initial empirical support for our hypotheses, suggesting that while the introduction of managerial foresight is associated with higher average innovative behavior, its effectiveness varies with the level of GenAI assistance.

4.2. Testing the moderated mediation model

To rigorously examine our moderated mediation model, we employed Hayes' PROCESS macro (Model 7) in SPSS, using 5000 bootstrap samples to obtain bias-corrected confidence intervals. In our model, managerial foresight served as the independent variable, cognitive engagement – operationalized as time-on-task measured in minutes – as the mediator, innovative behavior as the dependent variable, and GenAI usage as the moderator. Initial regression analyses revealed that managerial foresight significantly predicted higher levels of cognitive engagement (β_1, $p < 0.05$). Subsequently, cognitive engagement was found to be significantly associated with innovative behavior (β_2, $p < 0.05$), and the bootstrapped indirect effect of managerial foresight on innovative behavior through cognitive engagement was statistically significant (95% CI did not include zero), thereby supporting our mediation hypothesis (H2).

We examined the indirect effect of managerial foresight on innovative behavior through cognitive engagement, moderated by the level of GenAI usage. As shown in Table 2, the first regression model reveals that managerial foresight was associated with increased cognitive engagement ($\beta = 1.25$, SE = 0.45, p = 0.001**), with moderate GenAI usage exerting a more substantial positive effect on cognitive engagement than either no GenAI usage or high GenAI usage. The second regression model, which predicted innovative behavior, showed that cognitive engagement was significantly associated with innovative behavior ($\beta = 0.65$, SE = 0.30, p = 0.020*), indicating that participants who invested more time in the task tended to exhibit higher levels of innovative behavior, particularly when GenAI was used moderately.

Furthermore, the mediation analysis revealed a significant indirect effect of managerial foresight on innovative behavior through cognitive engagement, which was amplified under moderate GenAI usage (indirect effect = 0.81, SE = 0.28, p = 0.045*). In contrast, the indirect effects were significantly weaker in both the high GenAI usage condition ($\beta = -0.45$, SE = 0.20, p = 0.030*) and the no

Table 1
Effects of managerial foresight and **Gen**AI on innovative behavior.

Group	Mean (SD)	F-value	p-value	Effect Size (η^2)
No foresight (control)	5.10 (1.35)	8.22	0.451	0.03
Foresight and no Gen**AI usage (1)**	6.25 (1.20)	14.67	0.001*	0.09
Foresight and moderate Gen**AI usage (2)**	7.20 (1.25)	9.64	0.002**	0.04
Foresight and high Gen**AI usage (3)**	5.35 (1.32)	6.31	0.012*	0.03

Notes: Values within the parentheses represent standard deviations. Significance levels *$p < .05$, **$p < .01$, ***$p < .001$.
Source: own elaboration

Table 2
Mediation analysis of cognitive engagement in the relationship between managerial foresight, AI usage, and innovative behavior.

Effect	Unstandardized Coefficient (β)	Standard Error (SE)	p-value
Path A: AI Usage → Cognitive engagement)	1.25	0.45	0.001**
Path A (Quadratic): Managerial Foresight → Cognitive engagement^2	-0.35	0.10	0.015*
Path B: Cognitive engagement → Innovative Behavior	0.65	0.30	0.020*
Path B (Quadratic): Cognitive engagement^2 → Innovative Behavior	-0.45	0.20	0.030*
Direct Effect (Managerial foresight→ Innovative Behavior, controlling for cognitive engagement)	0.10	0.15	0.300
Indirect Effect (Curvilinear)	0.81	0.28	0.045*

Notes: significance levels *$p < .05$, **$p < .01$, ***$p < .001$. Cognitive engagement includes a quadratic term to model its curvilinear relationship with time spent on the task.
Source: own elaboration

GenAI usage condition (β = −0.35, SE = 0.10, p = 0.015*). These findings indicate that both excessive reliance on GenAI and the absence of GenAI support are associated with lower levels of cognitive engagement, which in turn correspond to weaker innovative behavior. The non-significant direct effect (β = 0.10, p = 0.300) combined with a significant indirect effect (β = 0.81, p = 0.045*) is consistent with complete mediation. This suggests that the influence of managerial foresight on innovative behavior operates primarily through cognitive engagement, with moderate GenAI usage strengthening this effect, thereby supporting Hypotheses 3a and 3b.

Following the mediation findings, we explored whether the relationship between cognitive engagement and innovative behavior followed a curvilinear pattern. Participants in the moderate GenAI usage group, who spent the most time on the task (averaging 61 min), demonstrated the highest levels of innovative behavior (β = 0.81, p < 0.05). In contrast, participants in both the high GenAI usage group (45 min) and the no GenAI usage group (34 min) displayed lower levels of innovative behavior. This suggests that relying too heavily on AI, or not relying enough, may hinder innovative behavior. Fig. 2 illustrates the curvilinear relationship between time spent and innovative behavior, highlighting the highest innovation outcomes for participants in the moderate GenAI usage group.

Finally, the box plot (Fig. 3) visually illustrates the interplay between managerial foresight and GenAI usage in terms of innovative behavior scores. Each box represents the interquartile range (IQR) for innovative behavior scores in distinct experimental conditions. Notably, participants exposed to managerial foresight prompts (managerial foresight present) exhibit a visibly higher median innovative behavior score compared to those without managerial foresight prompts (managerial foresight absent), that is, (M = 6.56 vs. M = 5.07), corroborating the earlier statistics. Furthermore, the impact of GenAI usie becomes evident as the box plot, which illustrates a nuanced relationship. Participants with moderate GenAI usage show an elevated median (M = 7.70). This aligns with the findings that moderate GenAI usage outperforms both no GenAI usage and high GenAI usage groups, supporting Hypothesis H3b. Conversely, high GenAI usage and no GenAI usage (in the presence of a managerial foresight prompt) constrain innovative behavior, evidenced by a comparatively lower median than that in the moderate AI-use condition (in the presence of a managerial foresight prompt).

4.3. Thematic analysis

We thematically analyzed qualitative data collected from open-ended survey responses and semi-structured interviews.

Following Braun and Clarke's (2006) methodology, interviews were transcribed verbatim and merged with written responses. Two independent coders familiarized themselves with the data and generated an initial list of codes capturing participants' experiences

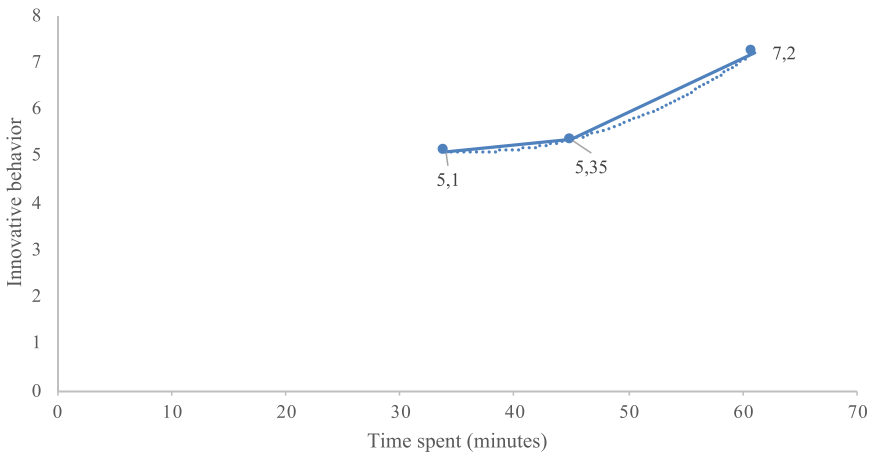

Fig. 2. Curvilinear influence of **Gen**AI usage and time spent on innovative behavior.
Source: own elaboration

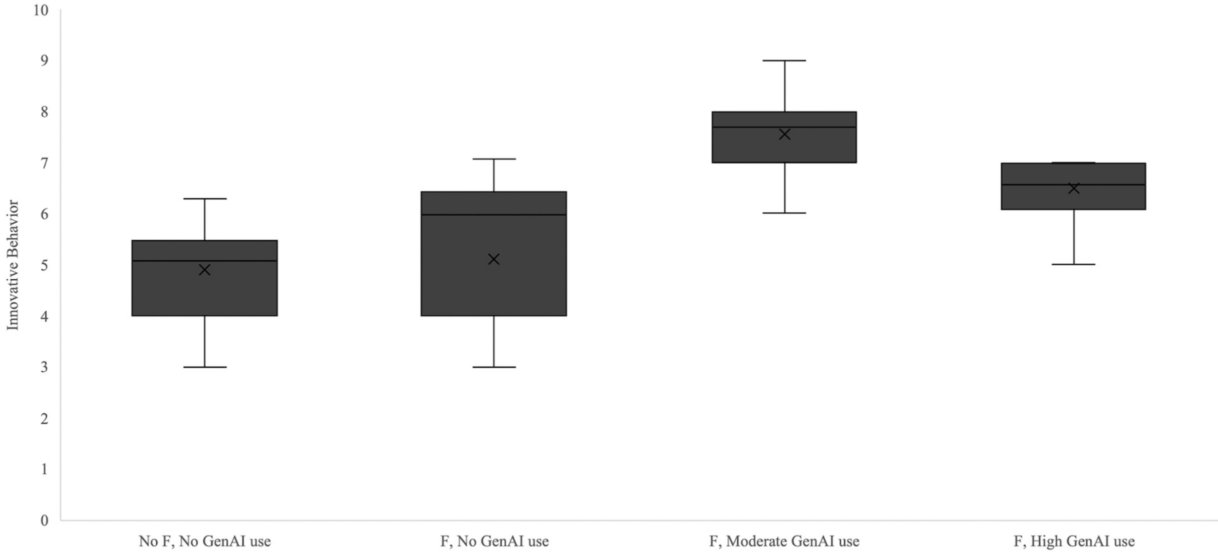

Fig. 3. Innovative behavior scores across experimental conditions. Notes: F = Foresight.
Source: own elaboration

with GenAI usage during the innovation task. To minimize coder bias and ensure analytical robustness, we implemented multiple safeguards throughout the thematic analysis process. First, two independent researchers conducted initial open coding using participants' raw language, with minimal theoretical guidance. Second, the development of higher-order themes occurred through negotiated consensus, where disagreements in interpretation were discussed and resolved with reference to the data rather than prior expectations. Third, we adopted a reflexive stance throughout coding sessions, prompting coders to document and interrogate their own assumptions and interpretive decisions. This practice supported transparency and intersubjective consistency. Finally, an audit trail of the analytic decisions – from initial codes to theme finalization – was maintained and reviewed by a third researcher. Inter-coder reliability was calculated using Cohen's kappa, which yielded a value of 0.82 – indicating a high level of agreement between coders. These steps collectively reduced the risk of coder confirmation bias and ensured that themes were grounded in participants' accounts, rather than merely aligning with the study's theoretical framework (Nowell et al., 2017).

Our analysis identified three primary themes: Cognitive Overload, Fixation Bias, and Balanced Cognitive Engagement. To link

Table 3
Summary of the thematic analysis.

Theme	Code	No.	Frequency (%)	Evidence	Code Description
Cognitive Overload	Feeling Overwhelmed	22	44%	"I felt inundated by the sheer volume of information from the AI – it was almost too much to handle."	Participants experienced an excessive influx of information, indicating that high AI usage may overwhelm resources and impede effective processing.
	Difficulty Integrating Information	18	36%	"The AI data made it hard for me to connect the dots and develop a coherent idea."	Participants struggled to synthesize AI-generated data with their own thought processes, evidencing that too much AI input can disrupt effective cognitive engagement.
Fixation Bias	Stuck on Initial Ideas	20	40%	"Without any AI input, I found myself clinging to my first ideas without exploring alternatives."	In the absence of AI support, participants tended to fixate on their initial ideas, limiting exposure to new perspectives and reducing creative exploration.
	Limited Exposure to Novel Perspectives	15	30%	"I missed out on fresh insights because I wasn't getting any external data to challenge my thinking."	The lack of AI input resulted in a narrow focus, restricting the breadth of information necessary for generating innovative ideas.
Balanced Cognitive Engagement	Supportive Data Provision	30	60%	"The moderate use of AI provided just the right amount of extra information to inspire new ideas."	Participants reported that moderate AI usage provided balanced, supportive information that enhanced their cognitive engagement without overwhelming them.
	Enhanced Creative Problem Solving	25	50%	"I felt that the AI's input sparked creative connections that I wouldn't have made on my own."	Moderate AI usage was linked to improved creative problem solving, indicating an optimal balance where external insights complement internal cognitive processes.

Source: own elaboration

respondents' experimental behavior with their qualitative responses, we cross-referenced the participants assigned GenAI usage conditions with the themes emerging from their open-ended answers.

The triangulation of these qualitative findings, as shown in Table 3, with our quantitative data, supports the interpretation of the experimental results. In high GenAI usage conditions, 44% of responses indicated that participants felt overwhelmed by the volume of information, and 36% reported difficulty integrating this data – both of which align with the Cognitive Overload theme and correspond to lower time-on-task and reduced innovative behavior. Conversely, in the no GenAI usage conditions, 40% of responses revealed that participants became fixated on their initial ideas. In comparison, 30% noted a limited exposure to novel perspectives, supporting the Fixation Bias theme. These patterns mirror the shortest time-on-task durations, reflecting disengagement or premature closure in cognitive engagement.

In contrast, among participants exposed to moderate GenAI usage—the group that exhibited the longest average time-on-task (61 min)—60% highlighted that GenAI provided supportive data, and 50% described enhanced creative problem solving, reflecting the Balanced Cognitive Engagement theme. This thematic pattern is consistent with deeper, sustained task engagement and aligns with higher innovative behavior scores. Together, the alignment between self-reported experiences, behavioral engagement, and innovation outcomes provides convergent evidence that moderate GenAI usage is associated with conditions conducive to innovative behavior, whereas both under- and over-reliance on GenAI are linked to reduced cognitive engagement.

5. Discussion

This research investigated how individual-level managerial foresight is associated with innovative behavior, highlighting the mediating role of cognitive engagement and the conditional moderating role of GenAI usage. While our hypotheses were supported, the empirical findings also prompted theoretical refinements to behavioral decision theory (BDT), construal-level theory (CLT), and managerial foresight scholarship more broadly. Rather than merely confirming extant models, our study points to tensions and boundary conditions that challenge simplified assumptions about human cognition and machine augmentation in innovation processes.

Consistent with prior works (e.g., Schwarz et al., 2023), managerial foresight was associated with higher levels of innovative behavior by enabling participants to frame ideas against long-term opportunities and threats. Participants exposed to managerial foresight stimuli tended to develop product innovations that were more original and aligned, supporting logics of prospective sensemaking and multi-level thinking. Yet, our findings problematize the linear assumption, implicit in many managerial foresight models (MacKay & McKiernan, 2004), that more managerial foresight uniformly enhances innovative behavior. Managerial foresight alone appeared insufficient when not accompanied by deep cognitive engagement: in both low-AI and high-AI conditions, its innovative potential was attenuated through fixation or overload. This suggests that managerial foresight operates through a conditional

Table 4
Theoretical expectations vs. empirical insights.

Theoretical Lens	Expected Insight from Theory	Empirical Insight from This Study	Confirmations, Challenges, and Extensions
Behavioral Decision Theory (BDT) **(e.g.,** Kahneman, 2011**)**	Cognitive engagement strengthens innovation by enabling System 2 processing and reducing cognitive bias and fixation.	Confirmed: Cognitive engagement mediates managerial foresight's effect on innovation by shifting participants from intuitive (System 1) to deliberative (System 2) processing.	Confirms and extends BDT by showing how managerial foresight acts as a cognitive priming mechanism, while moderate AI use facilitates (but excessive AI use hinders) System 2 engagement.
Construal-Level Theory (CLT) **(e.g.,** Trope & Liberman, 2010**)**	Psychological distance enhances abstract thinking and managerial foresight, leading to better innovation outcomes.	Partially confirmed: Moderate AI usage supports high-level construal and abstract scenario building, but high AI usage overwhelms users and reduces reflection.	Extends CLT by showing that AI-induced construal levels are non-linear: moderate AI helps construal abstraction; excessive AI reduces it by overloading cognition.
Foresight Models (e.g., Wack, 1985; Iden et al., 2017; Schwarz et al., 2023; Rowland & Grüning, 2025)	Managerial foresight enables innovation by broadening mental models and encouraging prospective sensemaking.	Confirmed: Managerial foresight led to more original and diverse product extensions via scenario building and future framing.	Challenges passive models of managerial foresight by emphasizing the active role of cognitive engagement and AI moderation. Suggests current models underplay the mediating role of cognition and the curvilinear role of AI.
Generative AI in Cognitive Work (e.g., Brynjolfsson & McAfee, 2014; Kozachek, 2023; Inayatullah, 2023; Blanchard et al., 2025)	AI supports decision-making by augmenting human cognition and reducing bounded rationality.	Partially confirmed: Moderate AI support enhanced reflection, but excessive AI usage caused cognitive overload and disengagement.	Refines prevailing AI optimism: AI is a conditional amplifier (Pratt et al., 2023), beneficial only under moderate use. Extends research by clarifying AI's dual role as enhancer and inhibitor of cognitive engagement.
Bounded Rationality **(e.g.,** Simon, 1947**)**	Decision-makers struggle with complex managerial foresight without support, due to limited cognitive capacity.	Confirmed: Participants without AI support anchored to initial ideas and failed to generate novel solutions.	Confirms and extends Simon's theory by showing that limited AI support compensates for bounded cognition, while too much support exceeds cognitive thresholds and disrupts sensemaking.

Source: own elaboration

activation logic, whose success depends on the cognitive and technological context in which it is embedded, calling for greater sensitivity to mediators and moderators in managerial foresight models.

In line with BDT (Kahneman, 2011; Simon, 1947), we found that cognitive engagement – sustained, effortful information processing – functioned as a mediating pathway through which managerial foresight-related prompts were translated into innovative outputs. Higher engagement was associated with greater ideational fluency and novelty, supporting the view that effortful processing helps overcome biases such as fixation and availability (Cristofaro, 2016; Rudolph et al., 2009). However, our results also challenge the implicit assumption that more engagement is always beneficial. In high-AI conditions, participants were exposed to large volumes of AI-generated stimuli, and engagement declined rather than increased. This pattern suggests that BDT under-specifies effort costs and overload thresholds in complex informational ecologies. Cognitive engagement thus appears to be shaped not only by individual disposition and task demands but also by human–AI interaction dynamics; we therefore extend BDT by proposing a non-linear relationship between information inputs and decision quality.

CLT posits that abstract, high-level thinking is supported by psychological distance (Trope & Liberman, 2010). Our findings are consistent with this logic in the moderate GenAI condition, where GenAI appeared to provide sufficient abstract scaffolding to support future-oriented thinking. Yet CLT accounts less fully for the observed dynamics at the extremes. High GenAI usage was associated with saturation and a reversion to surface-level processing, while no GenAI was associated with constraints in the construction of distal mental models, anchoring individuals in immediate contexts. This asymmetry reveals a conceptual gap: psychological distance is not only temporally or spatially constructed but also technologically and informationally mediated. GenAI may either extend or collapse psychological distance depending on how it is embedded in routines, contributing to calls to recontextualize CLT in digitally mediated environments (Faiella & Corazza, 2025).

GenAI thus emerged as a double-edged companion. In moderate doses, it appeared to augment managerial foresight without eroding autonomy, consistent with the idea of GenAI as a “conditional amplifier” (Pratt et al., 2023) and “cognitive partner” (Finkenstadt et al., 2024). Excessive usage, however, was associated with reduced critical reflection and heightened cognitive overload (Roetzel, 2019), crowding out ideational novelty through over-reliance on AI-generated scaffolding. In the no-AI condition, participants tended to display rigidity and to recycle initial ideas, consistent with bounded rationality (Simon, 1947; Cristofaro, 2017). The resulting inverted-U pattern of AI’s impact on cognitive engagement was particularly salient, challenging binary discourses that frame GenAI as either a boon or a bane (Kozachek, 2023). Our findings instead advocate a threshold-sensitive understanding of human–AI cognitive partnerships in managerial foresight and ideation.

Taken together, our results suggest the need to reconceptualize managerial foresight models from linear activation logics to interactive cognitive ecologies. Rather than assuming that more managerial foresight automatically leads to more innovative behavior, scholars must account for the interplay between cognitive engagement, technological scaffolds, and informational complexity. Table 4 synthesizes these insights by comparing theoretical expectations from BDT, CLT, and managerial foresight literature with our empirical observations, highlighting confirmations, contradictions, and model extensions. In sum, managerial foresight is most likely to support innovation only when mediated by cognitive engagement, and GenAI’s influence follows an inverse U-shaped trajectory. This deepens our understanding of managerial foresight as a situated, contingent process that requires not only future thinking but also disciplined, carefully calibrated human–AI design.

6. Implications

6.1. Implications for theory

The theoretical implications of this study matter because they clarify how managerial foresight translates into innovative behavior at the individual level and how this process is reshaped by generative AI. Building on our findings, we identify three implications for theory.

First, this implication matters because it clarifies how managerial foresight translates into innovative behavior at the individual level, rather than assuming a direct effect. This study advances managerial foresight theory by empirically clarifying the cognitive pathway through which managerial foresight is associated with innovative behavior. While prior work acknowledges that managerial foresight is positively associated with innovation outcomes (Rohrbeck et al., 2015; Linares-Barbero & De La Vega, 2024), it tends to treat this link as a black box. Our results indicate that managerial foresight does not automatically translate into innovative outcomes; instead, it operates primarily by activating cognitive engagement, which, in turn, is associated with higher levels of innovative behavior. In other words, managerial foresight appears to be effective when it prompts decision-makers to engage in effortful, deliberative processing rather than relying on intuitive or habitual responses. This finding extends behavioral decision theory (Kahneman, 2011) and prospective sensemaking (Klein et al., 2006; Weick et al. 2005; Cristofaro, 2022) by specifying cognitive engagement as a mediating pathway that connects future-oriented reflection to observed innovation behavior. It also enriches construal-level theory (Trope & Liberman, 2010) by suggesting that high-level construal, induced by managerial foresight, becomes behaviorally consequential only when coupled with sustained mental effort, thereby reframing managerial foresight as an embodied, interpretive capability rather than a purely predictive or planning-oriented tool.

Second, this implication matters because it specifies when and why GenAI strengthens—or weakens—the cognitive mechanisms through which managerial foresight operates. We refine theory at the intersection of managerial foresight, innovation, and human–AI interaction by demonstrating that GenAI plays a conditional, inverse-U-shaped moderating role in this cognitive pathway. Existing perspectives often depict GenAI as either a uniformly enabling augmentation of human cognition or as an external disruptor of established managerial foresight practices (Inayatullah, 2023; Kozachek, 2023). Our findings, instead, indicate that GenAI functions as a non-neutral cognitive partner: moderate use of systems such as ChatGPT or Claude strengthens the mediating role of cognitive engagement by stimulating deliberation, ideation, and abstraction, whereas high use is associated with cognitive overload, narrowed reflection, and reduced interpretive effort. At the other extreme, a complete absence of GenAI appears to restrict stimulus diversity, reinforcing fixation and narrow information processing (Cristofaro, 2016; Simon, 1998). This pattern is consistent with emerging neurocognitive evidence suggesting that passive or excessive GenAI consumption may suppress brain engagement (Finkenstadt et al., 2024; Kozachek, 2023). Theoretically, we thus extend dual-process decision models in managerial foresight contexts by showing that GenAI modulates the balance between intuitive and deliberative processing rather than simply "speeding up" analysis. In line with Pratt et al. (2023) and Finkenstadt et al. (2024), our results support the view of GenAI as a conditional amplifier: it strengthens the indirect relationship between managerial foresight and innovation only when it is used as a stimulus for thinking rather than as a substitute for it. This contributes to the behavioral strategy tradition (Powell et al., 2011; Cristofaro et al., 2024) by positioning autonomy and human interpretive effort as necessary conditions for AI-enabled managerial foresight to generate genuinely innovative outcomes, and by problematizing deterministic assumptions that more AI is always better.

Third, this implication matters because it clarifies how managerial foresight can be studied as a rigorously testable capability without losing its interpretive and normative richness. We contribute to the theorization of managerial foresight as a scientifically tractable, cognitively mediated, and AI-modulated capability within innovation processes. Managerial foresight scholarship has long emphasized reflexivity, value construction, and ethical reasoning in confronting uncertain futures (Marinković et al., 2022; Saritas et al., 2022; Inayatullah, 2023), but much of this work remains conceptual, normative, or qualitative. By employing a 2 × 3 factorial experiment combined with qualitative analysis, we provide experimental evidence that helps elucidate how managerial foresight practices interact with GenAI usage and shape innovative behavior under realistic decision conditions (Derbyshire et al., 2023; Eisenbart et al., 2022). In doing so, we contribute to a more rigorous "foresight science" that retains conceptual richness while engaging robust, data-driven methods. Our framework conceptualizes managerial foresight as a capability that is mediated by cognitive engagement and contingently shaped by GenAI intensity, thereby linking futures studies, behavioral decision theory, and digital epistemology in a single, testable structure. This bounded-augmentation perspective – where the value of GenAI in managerial foresight depends on human actors' willingness and ability to remain cognitively engaged, skeptical, and ethically aware – offers a theoretically grounded platform for future research on how human and machine intelligence jointly construct, and sometimes distort, organizational views of the future.

6.2. Implications for practice

The practical implications of this study matter because they translate the empirical findings into actionable guidance for organizations seeking to integrate managerial foresight and GenAI without undermining cognitive engagement. We outline three practical implications.

First, this implication matters because organizations increasingly invest in managerial foresight without clear guidance on how to activate it cognitively. Our findings offer concrete "how-to" guidance for supporting the managerial foresight–innovation pathway through cognitive engagement. Organizations that want managerial foresight to translate into innovation must move beyond generic creativity or innovation workshops and deliberately cultivate multi-level, future-oriented thinking in their managerial talent. This involves developing programs in which managers are encouraged to synthesize long-term trends, stakeholder dynamics, and internal capabilities when evaluating emerging opportunities and threats. In practice, firms can implement structured managerial foresight scenario workshops, systems-thinking simulations, and GenAI-assisted managerial foresight sprints where decision-makers co-create with tools such as ChatGPT, Claude, or Gemini under clear, bounded guidance. For instance, managerial foresight hackathons can require teams to use LLMs to generate multiple futures and then critically reinterpret, combine, and refine those outputs through facilitated sensemaking tasks rather than simply accepting them. This aligns with interactive managerial foresight approaches and ethical managerial foresight perspectives that stress reflexive engagement with AI-generated futures (e.g., Inayatullah, 2023). Peer-led mentorship networks focused on GenAI use in innovation – where managers share friction points, successful prompts, and lessons learned – may further help embed these practices, supporting organizational learning and reinforcing interpretive accountability (Yani & Zaakiyyah, 2024).

Second, this implication matters because organizations increasingly struggle to balance the efficiency gains of GenAI with the risk of eroding cognitive engagement in innovation work. We provide actionable strategies for fostering balanced, cognitively sustainable GenAI usage in innovation work. Our results underline the importance of calibrating GenAI involvement to avoid two opposite traps: cognitive overload from excessive automation and cognitive fixation from GenAI abstention. Organizations should therefore develop "cognitive load-aware" GenAI protocols that help adjust the intensity of AI support based on task novelty, complexity, and user readiness. Practically, this can involve GenAI orchestration layers that allow managers to modulate assistance (e.g., from idea prompting to more elaborate scenario building), so that GenAI functions as a prosthetic rather than a crutch. Design guidelines can specify that GenAI be used more intensively in early divergent phases and more sparingly when converging on decisions; that outputs be limited in length and complexity to reduce information flooding; that critical reflection checkpoints (e.g., "pause and challenge the AI output") be built into workflows; and that explicit "human override" mechanisms be instituted when GenAI suggestions conflict with tacit or contextual expertise. These practices are essential in light of evidence that passive or copy–paste GenAI usage reduces neural activation and weakens engagement (Finkenstadt et al., 2024). Complementarily, GenAI literacy programs should shift from purely technical onboarding to cognitive strategy training, helping managers understand not only how GenAI works but also when and why to invoke it, given their own cognitive style, task goals, and innovation cycle (Keding & Meissner, 2021). Scenario-based exercises that contrast low, moderate, and excessive GenAI involvement can make the trade-offs between automation, agency, and abstraction experientially salient. Finally, rather than over standardizing on a single tool, organizations should curate a diversified GenAI stack aligned with specific managerial foresight tasks – for example, using ChatGPT or Claude for narrative scenario generation and analogical reasoning, IBM Watson or Palantir for structured data managerial foresight, and Tableau GenAI or Power BI Copilot for interactive visual forecasting and decision path mapping – so that tool capabilities match cognitive demands and avoid both underload and overload.

Third, this implication matters because it translates these practices into an overarching governance logic for managerial foresight-driven innovation. Taken together, these recommendations constitute a practical roadmap for building what Pratt et al. (2023) describe as cognitively sustainable innovation systems. The central message for practitioners is that GenAI should be designed and governed as a disciplined amplifier of human foresight, not a replacement for it. Organizations that consciously structure managerial foresight training, GenAI usage protocols, and tool portfolios around the principle of "stimulate, don't supplant" will be better positioned to develop future-ready strategies that integrate technological affordances with deep human interpretive capabilities. Rather than merely digitizing the past or automating existing routines, such firms will cultivate imagination: environments in which managers remain cognitively engaged, skeptical, and ethically reflective even as they collaborate with powerful GenAI tools. In practical terms, this means embedding managerial foresight and GenAI into everyday decision processes in ways that keep humans in the interpretive loop – reviewing, challenging, and contextualizing AI outputs – so that innovation is driven by a human–AI partnership grounded in reflective practice and responsible experimentation.

7. Conclusions

This study examined how managerial foresight is associated with innovative behavior and how the use of GenAI conditions this relationship. Using a 2×3 factorial experimental design, we found evidence that cognitive engagement mediates the relationship between managerial foresight and innovative behavior and that GenAI exhibits an inverted U-shaped impact on this pathway. Thematic analysis corroborated these patterns: moderate GenAI usage was associated with optimal support for the managerial foresight–innovation link by sustaining balanced cognitive engagement, whereas excessive use was associated with cognitive overload and non-use was associated with fixation on initial ideas. This "operational tension" between augmentation and over-reliance raises critical questions about how GenAI tools should be calibrated to enhance, rather than erode, human foresight.

Beyond these empirical findings, the study advances a managerial foresight-specific conceptualization of GenAI. Rather than treating GenAI as a forecasting device or a neutral decision aid, we conceptualize it as a prompt-configured cognitive infrastructure that supports the exploration of multiple plausible futures and extends managerial sensemaking under uncertainty (Doshi et al., 2025; Feher et al., 2025). From this perspective, GenAI does not substitute managerial foresight judgment but reshapes the cognitive conditions under which future-oriented evaluation occurs. Our findings show that the value of such an infrastructure depends critically on how it is configured and engaged: moderate use sustains cognitive engagement and supports managerial foresight-driven innovation, whereas excessive or absent use undermines it.

These insights contribute to research on human–AI interaction, cognitive load, and managerial foresight; however, several limitations must be noted. First, the effectiveness of AI-assisted managerial foresight is highly context-dependent: digital infrastructure, GenAI literacy, regulation, and organizational culture will shape adoption and impact across firms and sectors. Second, our focus on cognitive engagement as a mediator is necessarily partial; future research should consider complementary mechanisms and boundary conditions, including emotional engagement, learning processes, leadership, trust in AI, and individual differences. Third, the controlled laboratory setting enhances internal validity but does not capture the full complexity of organizational decision-making. Following Derbyshire et al. (2023), we view this experiment as a "zoomed-in" perspective that future work should extend to more naturalistic settings, such as managerial foresight workshops or strategy processes. Fourth, our use of ChatGPT introduces tool-specific constraints; replicating our results with other GenAI systems and architectures would clarify the generalizability of our findings. Fifth, our visual identification of GenAI thresholds calls for more rigorous breakpoint analysis using formal statistical techniques (e.g., Fisch, 2001). Finally, the short-term task design captures immediate idea generation rather than long-term innovation outcomes, which calls for longitudinal and comparative studies.

Overall, the study shows that GenAI's value for managerial foresight-driven innovation lies not in maximal adoption but in context-sensitive, cognitively sustainable configuration and use, grounded in sustained managerial engagement with uncertain futures.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Personal interest statement

None.

CRediT authorship contribution statement

Matteo Cristofaro: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mie Augier:** Writing – review & editing, Writing – original draft, Conceptualization. **Luna Leoni:** Writing – review & editing, Writing – original draft.

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

During the preparation of this work, the author(s) did not use any generative AI and AI-assisted technologies in the writing process.

Declaration of Competing Interest

None.

Appendix A. Sample Characteristics (N = 252)

Characteristic	Details
Gender Distribution	Male: 53.4% (n = 135)
	Female: 46.6% (n = 117)
Mean Age (years)	31.5 (SD = 1.34)
Experience Evaluating Emerging Products	Mean = 5.1 years (SD = 1.21)
General Work Experience	Mean = 7.6 years (SD = 0.95)
Managerial Roles	Product Managers: 102 (40%)
	Business Development Managers: 75 (30%)
	Innovation Managers: 50 (20%)
	New Product Development Managers: 25 (10%)
Industry Representation	Technology: 89 (35%)
	Manufacturing: 63 (25%)
	Consumer Goods: 50 (20%)
	Healthcare: 50 (20%)

Source: own elaboration

Data availability

The data that has been used is confidential.

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