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Entrepreneurial decision-making in the age of AI: Sector knowledge at the balance of intuition and analysis☆

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ABSTRACT

Artificial intelligence (AI) is shaping entrepreneurial decision making today, increasingly informing opportunities recognition, assessment, and exploitation. Yet prior sector knowledge of entrepreneurs remains a fundamental pillar in these cognitive activities, providing the experiential schemas and contextual understanding that anchor entrepreneurial judgment. This study examines the interaction between two forces – AI-driven analysis and sector knowledge – and their influence on entrepreneurial outcomes, encompassing the recognition, assessment, and exploitation of opportunities. Using a controlled laboratory experiment with 124 entrepreneurs, we manipulate AI usage and measure prior sector knowledge to identify the independent and joint effects of these factors on entrepreneurial decision outcomes. Results show that AI increases the number of opportunities recognized and enhances the depth of opportunity assessment, exploitation, and contextual understanding. At the same time, AI reduces novelty in recognition and innovation in exploitation. Sector knowledge restores this creative dimension, enabling entrepreneurs to integrate intuitive insights with AI-supported deliberation. Entrepreneurs who combine AI and expertise achieve the most balanced outcomes, excelling simultaneously in novelty, depth, contextual understanding, and innovation. These results extend dual-process theories of cognition by demonstrating that prior knowledge conditions how AI reshapes the balance between intuitive and deliberative processes. Practically, the study highlights that the strategic value of AI in entrepreneurship lies not in substituting for human judgment but in complementing it with sector-specific expertise that anchors both originality and analytical rigor.

1. Introduction

The rise of artificial intelligence (AI) is fundamentally transforming modern business and entrepreneurship over the last decades (Cristofaro & Giardino, 2025; Obschonka & Audretsch, 2020). The rapid emergence of computationally complex AI systems represents the culmination of decades of effort to create machine-based intelligence capable of complementing – or even surpassing – human cognition in specific domains (Townsend & Hunt, 2019). These developments are not simply technological milestones but catalysts for rethinking the foundations of entrepreneurial action, judgment, and decision-making in contexts of uncertainty and complexity. As AI-driven solutions evolve, their implications for entrepreneurship have become a central area of inquiry (e.g., Obschonka et al., 2025).[1]

AI is embedded in entrepreneurial processes, where sophisticated algorithms and machine learning techniques support strategic choices (Truong et al., 2023). Entrepreneurs can now derive insights from vast datasets, automate complex processes, and design innovative business models. By rapidly analyzing and interpreting data, AI enhances decision precision and enables entrepreneurs to identify opportunities that

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[1] In this study, we focus specifically on Generative AI (GenAI) tools, such as large language models (e.g., GPT-4), which generate novel text-based outputs. For readability, we use the shorthand "AI" throughout the paper to refer to this class of GenAI systems, rather than artificial intelligence technologies more broadly.

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might otherwise remain hidden (Chalmers et al., 2021; Shepherd & Majchrzak, 2022). Recent scholarship highlights AI's transformative role in entrepreneurship by offering data-driven insights that reduce uncertainty and enhance decision-making capacity (Dellermann et al., 2021; Giuggioli & Pellegrini, 2023; Kraus et al., 2020). Applications already extend to core practices such as market analysis and customer engagement (Usman et al., 2024), where predictive modeling and advanced analytics reveal trends, optimize resources, and anticipate customer needs. At the same time, Csaszar et al. (2024) show that AI not only supplies information but also enhances key cognitive processes central to entrepreneurial judgment.

However, the extent to which it promotes or constrains entrepreneurship remains unsettled. While AI seems to amplify creativity and decision quality (Townsend & Hunt, 2019), overreliance risks diminishing the role of human intuition and contextual interpretation (Cockburn et al., 2018; Usman et al., 2024). We propose that this tension is not inherent to AI itself but contingent on the knowledge base of the entrepreneur. Specifically, prior sector knowledge determines whether AI's outputs are interpreted as meaningful insights or followed mechanically, thereby shaping the balance between intuitive (System 1) and deliberative (System 2) thinking. Without contextual expertise, entrepreneurs may become overly dependent on AI's structured analysis, sacrificing novelty in opportunity recognition, innovation in exploitation, and contextual understanding. With sector knowledge, however, they are better positioned to integrate intuitive schemas with AI-supported deliberation, leveraging AI to expand the number of recognized opportunities, deepen assessments, and enhance exploitation strategies while sustaining originality. Thus, a critical question emerges: *How do AI assistance and prior sector knowledge interact to shape the balance between intuitive and deliberative thinking? and how does this cognitive balance influence entrepreneurial outcomes in opportunity recognition, assessment, and exploitation?*

To address these questions, we conducted a series of laboratory experiments with 124 entrepreneurs to examine how AI assistance, in interaction with prior sector knowledge, influences entrepreneurial decision-making. The results reveal a clear trade-off: AI enhances the number and depth of opportunities and exploitation strategies by stimulating deliberative thinking, yet constrains creativity and originality. Sector knowledge restores this creative dimension, enabling entrepreneurs to balance intuitive and deliberative cognition. Crucially, entrepreneurs with both AI and sector expertise achieved the strongest performance – excelling in novelty, depth, contextual understanding, and innovation across all phases.

Theoretically, this study advances dual-process theories of cognition in entrepreneurial decision making by showing how AI reshapes the balance between intuitive (System 1) and deliberative (System 2) thinking in entrepreneurial contexts (Cristofaro & Giannetti, 2021; Grégoire et al., 2011; Mitchell et al., 2002). It further highlights prior sector knowledge as a key moderating factor, clarifying how domain expertise conditions the integration of AI-driven insights. Practically, the findings guide entrepreneurs and organizations in leveraging AI strategically: using it to complement, rather than replace, human intuition, thereby preserving creativity while benefiting from structured analysis. In doing so, this study directly responds to Townsend and Hunt's (2019) call to examine how AI reshapes entrepreneurial theory and practice, particularly in addressing "modal uncertainty". It also engages with the agenda set out by Obschonka et al. (2024) by contributing evidence to fill three pressing gaps: the lack of theoretical frameworks for entrepreneurship in the age of AI, the methodological ambiguity in studying AI mobilization, and the limited evidence on how AI is transforming entrepreneurial practices.

Taken together, these contributions point to a broader insight: entrepreneurship in the age of AI is no longer only about adopting new technologies but about reimagining the cognitive foundations of judgment and action. Entrepreneurship has always lived at the edge of reason and imagination. The rise of AI sharpens this edge: while algorithms deliver depth and precision, only human intuition, enriched by prior knowledge, can turn patterns into breakthroughs. The future of entrepreneurial decision-making will be forged in this balance between machine intelligence, human insight, and domain expertise.

The remainder of this paper is structured as follows. Section 2 reviews the theoretical background, focusing on entrepreneurial decision-making, dual-process theories of cognition, and the role of AI in shaping opportunity processes. Section 3 outlines the research design, sample, and methods. Section 4 presents the empirical results, followed by Section 5, which discusses the contributions of this work. Section 6 concludes by outlining implications, limitations, and directions for future research.

2. Theory and hypotheses

Entrepreneurial decisions are commonly categorized into opportunity recognition (discovering and identifying potential business opportunities), opportunity assessment (evaluating venture ideas based on specific criteria), and opportunity exploitation (activities to derive economic returns from opportunities) (e.g., Cristofaro & Giannetti, 2021; Maine et al., 2015; Shepherd et al., 2015; Truong et al., 2023). These decisions unfold under conditions of bounded rationality (Simon, 1947), where computational, informational, and biological limits prevent fully optimized choices. To navigate such constraints, human beings rely on a dual-process architecture of cognition: System 1, which is intuitive, fast, and automatic, and System 2, which is deliberate, analytical, and effortful (Kahneman, 2011).

System 1 relies on heuristics and past experiences, enabling rapid assessments and decisive actions in ambiguous environments (De Winnaar & Scholtz, 2020; Eisenhardt & Zbaracki, 1992). Prior sector knowledge plays a pivotal role here, providing entrepreneurs with domain-specific frameworks that enhance their ability to recognize patterns and contextual cues, strengthening their intuitive decision-making processes (Fuentes Fuentes et al., 2010). However, overreliance on System 1 can lead to cognitive biases, such as overconfidence or anchoring, which may distort judgment. System 2, in contrast, mitigates these biases by enabling deeper evaluation, validation, and strategic alignment through broader data integration and scenario analysis (Evans, 2008). Entrepreneurs with prior sector knowledge are better positioned to combine the strengths of both systems, using intuitive insights to complement deliberate, analytical reasoning (Cristofaro & Giannetti, 2021).

The complementary roles of System 1 and System 2 allow entrepreneurs to adapt their decision-making processes to uncertainty and complexity. System 1 provides speed and flexibility, while System 2 introduces rigor and refinement, collectively shaping how opportunities are recognized, assessed, and exploited. When supported by prior sector knowledge, these cognitive systems enable entrepreneurs to combine intuition and analysis, ensuring adaptability and relevance in entrepreneurial decisions. Indeed, prior sector knowledge has been identified as a critical enabler in all phases – opportunity recognition, assessment, and exploitation – enhancing intuitive and analytical processes (Fuentes Fuentes et al., 2010). Furthermore, it equips entrepreneurs to identify patterns, contextualize opportunities, and exploit possibilities in ways that might remain overlooked (Fuentes Fuentes et al., 2010; Shane, 2000).

Following opportunity evaluation research (Grégoire & Shepherd, 2012; Shane & Venkataraman, 2000; Shepherd et al., 2015), entrepreneurial decisions are often judged along creative, analytical, and contextual dimensions – namely, novelty, feasibility/viability, and environmental fit. In this study, we operationalize these dimensions as novelty, depth, and contextual understanding. While novelty reflects the originality of opportunity recognition, depth captures the elaboration of feasibility and strategic viability, and contextual understanding reflects alignment with environmental and market conditions. These three variables therefore do not represent new constructs but established evaluative dimensions of entrepreneurial decision-making, adapted for empirical testing in an AI-supported context. See Appendix A for a synthesis and description of investigated variables.

2.1. Opportunity recognition, AI, and prior knowledge

The emergence of AI as a tool for entrepreneurial decision-making has significantly impacted how entrepreneurs recognize opportunities. AI, particularly through natural language processing models, processes vast amounts of data, uncovering patterns and insights humans might overlook. As Kraus et al. (2020) point out, datafication and predictive analytics enhance decision-making, particularly in opportunity recognition. This is because, by analyzing large datasets, AI can identify trends and market gaps, enabling entrepreneurs to uncover previously hidden opportunities (Pietronudo et al., 2022).

Shepherd and Majchrzak (2022) further highlight AI's role in identifying anomalies and unexpected patterns in unstructured data, such as customer sentiment or psychographic shifts. This ability allows entrepreneurs to refine and exploit emerging opportunities. Additionally, AI-driven insights can boost entrepreneurs' creativity and confidence by providing a broader range of information, inspiring them to think outside the box (Usman et al., 2024). Social signal processing – AI's capacity to detect and analyze social cues – also supports opportunity recognition by offering insights into emerging market needs (Liebregts et al., 2020).

However, as Grilli and Pedota (2024) cautioned, AI's reliance on structured processes may inadvertently limit divergent thinking, channeling creativity into predefined pathways. While AI excels in analytical tasks, it struggles to replicate the human capacity for intuition and novel, context-dependent ideas. This trade-off underscores the need to balance AI-driven insights with human cognitive flexibility to maintain unpredictability and originality in opportunity recognition.

In entrepreneurship research, this dimension of originality is captured by the construct of novelty, defined as the distinctiveness or uniqueness of a venture idea relative to existing products, services, or practices, and conceptually distinct from mere newness in time (Frederiks et al., 2019). Importantly, novelty is rarely assessed in isolation but is typically considered alongside feasibility and value when judging the overall attractiveness of an opportunity (Davidsson et al., 2021; Scheaf et al., 2020). Entrepreneurs may also apply novelty as one evaluative "rule" within broader rule-based decision frameworks, integrating it with other considerations such as resource efficiency or risk mitigation (Wood & Williams, 2014). In this study, we therefore treat novelty as a tractable indicator of originality in opportunity recognition – an actor-independent attribute of venture ideas that signals distinctiveness, while remaining interdependent with complementary evaluative criteria.

Building on this conceptualization, the reliance on AI raises further challenges, including the risk of over-dependence on data-driven insights that can suppress human intuition and creativity (Chukwuka & Igweh, 2024). In fact, AI primarily supports System 2 thinking by providing structured, logical insights that enhance analysis (Chukwuka & Igweh, 2024). However, over-reliance on AI may inhibit System 1 thinking – intuitive, rapid, and experience-based processes – critical for recognizing unconventional opportunities and dealing with uncertainty (Dane & Pratt, 2007; Shepherd & Patzelt, 2018). Therefore.

H1. *Entrepreneurs using AI tools identify a greater number (volume) of business opportunities but ones that are less innovative compared to those relying solely on their cognition, as AI's data-driven approach fosters greater reliance on deliberative thinking rather than forward-looking intuition*

The interaction between prior sector knowledge and the dual-process framework of cognitive functioning offers significant insights into how entrepreneurs recognize opportunities when using AI. Shane (2000) posits that prior sector knowledge enables entrepreneurs to identify opportunities aligned with their existing expertise, suggesting that such sector knowledge enhances intuitive decision-making by drawing on stored heuristics and pattern recognition. This aligns with the view that experienced entrepreneurs often rely on System 1 thinking to act decisively in familiar contexts (Dane & Pratt, 2007; Kahneman, 2011).

In contrast, entrepreneurs without prior sector knowledge are less equipped to rely on intuition due to a lack of domain-specific heuristics (Cristofaro & Giannetti, 2021). In such cases, AI tools support System 2 thinking by providing data-driven, structured, and analytical insights (Chukwuka & Igweh, 2024). These insights help compensate for the absence of prior sector knowledge, enabling non-experts to engage in deliberative processes to evaluate opportunities more systematically.

However, this reliance on deliberative thinking introduces a trade-off. Entrepreneurs with prior sector knowledge can integrate AI outputs into their existing cognitive frameworks, combining intuition and analysis to find innovative opportunities. Conversely, entrepreneurs without prior sector knowledge may become overly dependent on AI-driven deliberation, potentially leading to a higher volume of identified opportunities but with limited depth or originality. This differentiation underscores the moderating role of prior sector knowledge in shaping the balance between intuitive and deliberative thinking during AI-assisted opportunity recognition. Building on these insights, we propose the following hypothesis.

H2. *Entrepreneurs with prior sector knowledge will balance intuitive and deliberative thinking when recognizing opportunities using AI, resulting in fewer but more innovative opportunities. Conversely, entrepreneurs without prior sector knowledge will predominantly rely on deliberative thinking, leading to a greater number of recognized opportunities but with limited novelty.*

2.2. Opportunity assessment, AI, and prior knowledge

AI's role in opportunity assessment is particularly beneficial for entrepreneurs seeking to evaluate venture ideas with precision and confidence. In this phase, AI contributes depth, understood as the extent to which evaluations incorporate multiple dimensions such as feasibility, market alignment, strategic fit, and long-term viability. Depth reflects the elaboration and refinement of opportunity concepts, grounded in a coherent understanding of their assumptions and implications. Opportunity evaluation is a dynamic process in which entrepreneurs continuously revise their beliefs through planning and refinement (McCann & Vroom, 2015). As such, depth is closely linked to cognitive elaboration and entrepreneurial learning, capturing how ideas are progressively sharpened by testing assumptions, exploring contingencies, and refining linkages between resources, markets, and value propositions (Healey et al., 2021; Scheaf et al., 2020). In our study, we therefore conceptualize depth as the degree of elaboration and cognitive sophistication in opportunity assessments, focusing on how AI and sector knowledge influence evaluations across multiple dimensions and over long-term horizons.

AI enhances depth by providing structured, data-driven insights that reduce perceived uncertainty, a significant barrier to entrepreneurial decision-making (Dellermann et al., 2021). Uncertainty often deters even skilled professionals from pursuing new ventures; however, AI's capability to analyze relevant datasets and predict the potential success of opportunities can provide entrepreneurs with a clearer and more comprehensive understanding of the entrepreneurial opportunity viability (Davidsson et al., 2020). This capability is exemplified in the study by Shepherd and Majchrzak (2022), which highlights AI's ability to augment opportunity assessment through structured feedback. For instance, AI tools can synthesize extensive market and operational data, enabling entrepreneurs to address gaps in their business strategies and deepen their evaluations.

The ability of AI to enhance depth in opportunity assessment is further demonstrated in the study by Csaszar et al. (2024). An experiment involving experienced evaluators from venture capital, private equity, and angel investing assessed 250 business plans submitted to a European start-up accelerator. Evaluators exposed to AI-generated and entrepreneur-generated plans (but not for the same businesses) consistently rated AI-generated plans higher on innovation, execution, investment potential, and viability. These findings indicate that AI tools help entrepreneurs develop more compelling and well-rounded strategic plans, improving the likelihood of attracting investor interest and advancing their ventures.

AI's capacity to foster depth in opportunity assessment relies heavily on its engagement with deliberative thinking, characterized by analytical, logical, and structured reasoning processes (Evans, 2008). This contrasts with intuitive thinking, which is rapid, heuristic-based, and influenced by prior experience. Entrepreneurs using AI are encouraged to rely more on deliberative processes, as the tools provide actionable data that enhances their ability to evaluate opportunities comprehensively. Therefore.

H3. *Entrepreneurs using AI develop deeper evaluated opportunities than those relying solely on their cognition, as AI's data-driven approach fosters greater reliance on deliberative thinking rather than forward-looking intuition.*

The entrepreneur's contextual understanding, defined as the degree to which opportunity ideas are situated within their broader technological, market, and environmental conditions (Grégoire & Shepherd, 2012; Keh et al., 2002; Wood et al., 2014), strongly influences the depth of opportunity assessments. It captures not only awareness of external conditions (see Shepherd et al., 2015). but also the interpretive work of mapping opportunity attributes onto demand patterns, technological trajectories, and institutional logics. In this way, contextual understanding functions as a bridge between external context and evaluative judgments, directly linking to broader constructs such as perceived uncertainty and opportunity-market fit.

Entrepreneurs with prior sector knowledge leverage this contextual understanding to enrich AI-driven deliberative insights with intuitive judgments (Shane, 2000). Their domain expertise enables them to critically interpret AI outputs, adding strategic depth to their assessments. This integration ensures that evaluations regarding feasibility and potential outcomes are comprehensive and aligned with the broader market or strategic context (Schleith et al., 2022). For example, an entrepreneur with prior sector knowledge can identify subtle risks or opportunities that AI might overlook, enhancing the relevance and robustness of their assessments. In contrast, entrepreneurs without prior sector knowledge depend heavily on AI to guide their evaluations (Fuentes Fuentes et al., 2010). While this reliance enables them to achieve a certain level of depth through structured, data-driven analysis, their lack of contextual understanding can limit their assessments' practicality and strategic relevance. These entrepreneurs may produce technically robust evaluations but lack the practical insight to address dynamic or complex scenarios (Groher et al., 2019).

This dynamic highlight the moderating role of prior sector knowledge in shaping the depth and contextual relevance of AI-assisted opportunity assessments. Entrepreneurs with prior sector knowledge integrate intuitive insights with AI-driven deliberative thinking, resulting in evaluations that are detailed, relevant, and well-aligned with strategy. Conversely, entrepreneurs without prior sector knowledge rely primarily on AI-driven deliberation, achieving depth in structured analysis but lacking the contextual grounding needed for broader strategic use. Therefore.

H4. *Entrepreneurs with prior sector knowledge integrate AI-driven deliberative insights with their contextual understanding during opportunity assessment, resulting in evaluations with greater depth and contextual relevance. Entrepreneurs without prior sector knowledge rely predominantly on AI-driven deliberation, producing evaluations that achieve depth in analysis but lack contextual grounding.*

2.3. Opportunity exploitation, AI, and prior knowledge

AI can transform entrepreneurial opportunity exploitation by helping entrepreneurs turn ideas into workable strategic plans. AI tools analyze data to provide actionable insights and strategic recommendations, enabling entrepreneurs to optimize resource allocation, identify market entry points, and develop growth strategies aligned with current market dynamics (Cockburn et al., 2018). According to Agrawal et al. (2022), AI's ability to predict outcomes based on data analysis helps entrepreneurs explore counterintuitive solutions and craft plans that stand out in competitive markets.

AI integration enhances decision-making by offering real-time feedback and iterative adjustments, enabling entrepreneurs to rapidly refine their strategies (Shepherd & Majchrzak, 2022). For example, AI tools can synthesize extensive market and operational data, producing detailed execution strategies that improve operational precision. Research by Csazar et al. (2024) highlights how AI-generated business plans effectively identify go-to-market strategies and operational gaps, enhancing the execution phase through actionable recommendations.

However, as Grilli and Pedota (2024) cautioned, AI-driven exploitation strategies may prioritize feasibility over innovation and risk-taking, potentially discouraging entrepreneurs from pursuing bold, unconventional approaches. This trade-off can be explained by dual-process theories of cognition (Evans, 2008; Kahneman, 2011). AI primarily supports System 2 thinking, which emphasizes deliberative, analytical reasoning, but may suppress System 1 thinking, characterized by intuitive, rapid, and experience-based judgments. This is because System 2 enhances precision and structure, while reliance on AI may lead entrepreneurs to adopt more conservative strategies, limiting their ability to pursue innovative or high-risk initiatives. Therefore.

H5. *Entrepreneurs using AI will develop deeper exploitation plans but may overlook innovative approaches compared to those who do not use AI, as AI's data-driven approach fosters deliberative thinking over intuition.*

However, as Grilli and Pedota (2024) caution, AI-driven exploitation strategies often prioritize feasibility over innovation and risk-taking, potentially discouraging bold or unconventional approaches. This trade-off arises from the cognitive processes emphasized during AI usage. Dual-process theories of cognition (Evans, 2008; Kahneman, 2011) highlight that AI predominantly supports System 2 thinking, characterized by deliberative, analytical reasoning. While this fosters depth and precision, it can suppress System 1 thinking, which relies on intuition and experiential knowledge to explore innovative, high-risk opportunities.

AI tools optimize strategies by analyzing patterns and data, favoring approaches grounded in past trends and known variables. This process aligns with findings from Cockburn et al. (2018), who emphasize that AI improves incremental innovation but struggles to support disruptive, context-specific ideation. Similarly, Agrawal et al. (2022) suggest that reliance on AI can disincentivize risk-taking due to its focus on minimizing uncertainty and maximizing efficiency. Entrepreneurs leveraging AI may, therefore, default to conservative exploitation strategies that align with structured logic but lack the creativity and boldness required for groundbreaking ventures.

Furthermore, the interaction between intuition and deliberation shows this limitation. Entrepreneurs who rely on System 1 thinking often embrace ambiguity and explore unconventional paths, which is essential for identifying high-risk opportunities with transformative potential (Dane & Pratt, 2007). In contrast, System 2 thinking, which AI

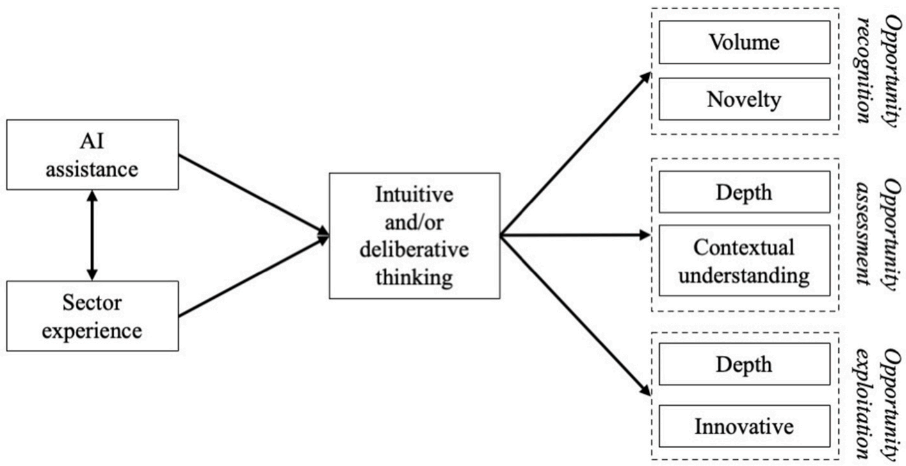

Fig. 1. Theoretical model.

amplifies, drives structured decision-making processes that constrain the exploration of novel possibilities, as highlighted by Shepherd and Patzelt (2018).

By reinforcing analytical reasoning, AI tools inadvertently narrow the scope of entrepreneurial experimentation, favoring exploitation strategies that optimize existing resources and market conditions rather than challenging them. Consequently, while AI facilitates more thorough exploitation plans, these strategies may lack the creativity or boldness to stand out. Therefore.

H6. *Entrepreneurs with prior sector knowledge integrate AI-driven deliberative insights with intuitive thinking during opportunity exploitation, resulting in innovative plans. Entrepreneurs without prior sector knowledge rely predominantly on AI-driven deliberative thinking, producing deep but less innovative plans.*

Fig. 1 illustrates the theoretical model tested in this study, highlighting the interaction between AI assistance, prior sector knowledge, and intuitive and/or deliberative thinking as a mediator, then influencing entrepreneurial decision outcomes.

3. Methodology

3.1. Experimental design

This study adopts a 2x2 between-groups experimental design to examine the effects of AI and sector knowledge on entrepreneurial decision-making processes, specifically focusing on opportunity recognition, assessment, and exploitation. This design aligns with the increasing reliance on experimental methodologies in entrepreneurship research (Schade & Burmeister-Lamp, 2009), allowing for a systematic examination of how these two factors interact to influence entrepreneurial cognition and outcomes. To ensure comparability and focus participants' cognitive efforts on the intended decision tasks, the study employed a standardized role-play prompt in which participants were asked to interpret the role of an entrepreneur evaluating a market opportunity. This procedure is commonly used in laboratory experiments to provide clear task boundaries ("guardrails") that reduce idiosyncratic interpretations, enhance the realism of decision contexts, and improve the consistency and validity of responses (e.g., Eisenbart et al., 2023). Moreover, in AI-assisted conditions, that role-play prompt helped constrain the scope of interaction with the model, thereby minimizing off-task exploration and mitigating risks of model hallucination or inconsistent advice. By manipulating AI usage and sector knowledge levels, this approach provides a robust framework to analyze their effects on entrepreneurial decisions while controlling for confounding variables. Participants were randomly assigned to one of four experimental conditions, representing varying combinations of AI usage and sector knowledge, with consumer electronics serving as the experimental context.

1. *No AI usage, no sector knowledge*: Entrepreneurs with no prior experience in the consumer electronics sector relied solely on their intuition to complete the task.
2. *AI usage, no sector knowledge*: Entrepreneurs with no sector experience interacted with an AI tool during the task.
3. *No AI usage, with sector knowledge*: Entrepreneurs with professional experience in the consumer electronics sector relied solely on their intuition and expertise.
4. *AI usage, with sector knowledge:* Entrepreneurs with sector experience interacted with AI to support their decision-making.

This factorial design enables an in-depth analysis of how varying levels of AI interaction and expertise shape recognizing, assessing, and exploiting entrepreneurial opportunities. It allows us to disentangle whether AI acts as a compensatory tool for non-experts or as an enhancement for those with domain-specific knowledge.

3.2. Participants and procedure

We initially recruited 135 entrepreneurs from professional networks, entrepreneurship incubators, and social media platforms, targeting individuals with diverse backgrounds. Participants were screened for their prior knowledge of the sector and categorized into two groups.

1. *Prior Sector Knowledge*: Participants with at least three years of entrepreneurial experience in the consumer electronics industry.
2. *No Sector Knowledge*: Participants with entrepreneurial experience but no direct exposure to consumer electronics.

Following exclusions for incomplete responses or deviations from task instructions, the final sample comprised 124 participants, evenly distributed across the four experimental conditions (31 each). We determined our sample size using an a priori power analysis in G*Power 3.1 (Faul et al., 2007) for a 2×2 between-subjects factorial ANOVA. To detect a medium effect size ($f = 0.25$) with power ($1–\beta$) of 0.80 at $\alpha = .05$, the required sample size was 128 participants (32 per cell). Our final sample of 124 participants (31 per cell after exclusions) thus afforded a power of 0.78 for detecting medium-sized interaction effects. As a robustness check, we conducted a sensitivity analysis to determine the minimum effect size detectable with our actual sample (N = 124). Results indicated that the study was sufficiently powered ($1-\beta = 0.80$, $\alpha = .05$) to detect effects of $f \geq 0.255$ ($\eta^2 p \approx .061$).

Participants were tasked with assuming the role of entrepreneurs evaluating a strategic opportunity to enter the Asian consumer electronics market. Participants in the no AI usage condition executed the task manually, while participants in the AI conditions completed the task using a laptop with no access to other resources on the web. Researchers monitored the experiment. The experimental scenario involved a fictitious technology startup considering this market entry, supported by preliminary data on industry growth rates, competitor analysis, and macro trends (Appendix B).

The study was conducted online through a controlled experimental platform, which tracked participants' interactions with the AI tool where applicable. In AI conditions, participants received detailed instructions on using ChatGPT (GPT-4; model snapshot November 2023; data collected December 10, 2024), with AI usage operationalized as the number of input-output interactions. Each participant accessed the system via a standardized web interface and was informed that no other online resources could be used. To ensure consistency and prevent misuse, participants were monitored for compliance, and those who deviated from the guidelines (e.g., using AI for unrelated tasks) were excluded from the final analysis. While prompts were generated freely by participants, this variability was bounded by the standardized task instructions, and all interactions with the system were automatically logged to ensure transparency and enable replication.

The experimental procedure was pilot tested with 16 doctoral students and two lecturers from an Italian university, leading to refinements based on their feedback. The pilot study also assessed instruction clarity and helped researchers refine their evaluation of strategic decision-making processes. It provided a valuable opportunity to practice applying criteria, clarify uncertainties, and ensure a robust experimental design.

3.3. Experimental task

The experimental task lasted 90 min, during which participants developed strategic recommendations regarding whether to proceed with market entry. They were required to submit their final decision (support, oppose, or neutral), a rationale for their decision, and any AI-generated content if applicable. This task was designed to simulate a realistic entrepreneurial decision-making scenario while isolating the effects of AI interaction and sector knowledge on participants' cognitive processes.

ChatGPT 4 was chosen for its state-of-the-art capabilities in generating strategic insights, ease of use, and widespread adoption (Statista, 2023). Participants in AI conditions were provided with specific guidelines, including definitions of a single interaction (input-output sequence). Researchers monitored compliance and clarified participant questions to ensure consistency.

This scenario was proposed to participants: *You are part of an entrepreneurial team for a European technology startup, InnoTech, that specializes in developing innovative wearable devices. The company has identified a potential entrepreneurial opportunity to enter the Asian wearable technology market. Your task is to evaluate this opportunity through the stages of opportunity recognition, assessment, and exploitation to determine its viability and strategic fit for InnoTech. In the opportunity recognition phase, you must identify key opportunities within the Asian wearable tech market based on the provided market data and trends, highlighting what makes this opportunity unique or attractive. During opportunity assessment, you will evaluate the identified opportunity based on its feasibility, strategic fit, and potential risks, considering factors such as market demand, the competitive landscape, and resource alignment. Finally, in the opportunity exploitation stage, you will develop a high-level strategy for entering the market, including potential business models, resource allocation, and partnerships, while discussing how to maximize the opportunity's potential and mitigate associated risks.*

In addition to the standardized session preamble that constrained capabilities (no web browsing/external paste), scope (task-relevant, no real-world claims), and time, Appendix C provides a six-turn, anonymized prompt/response trail illustrating how participants engaged the AI within these bounds during recognition, assessment, and exploitation. The next section elaborates on the measurements adopted to evaluate cognitive processes and biases in the strategic decision-making task.

3.4. Measurement

This section introduces the measurements employed to assess the impact of AI adoption on entrepreneurial decision-making, considering prior sector knowledge.

Opportunity recognition: participants were required to identify and submit a series of opportunities in the Asian wearable technology market. Apart from the number of recognized opportunities, these were evaluated based on novelty. Novelty was assessed as the degree to which the identified opportunities introduced innovative products or services, diverging from existing solutions in the market. This operationalization is consistent with prior entrepreneurship research that conceptualizes novelty as an actor-independent attribute of venture ideas, typically considered alongside feasibility and value in opportunity evaluation. For example, a participant identified the development of a smartwatch with integrated hydration monitoring based on sweat analysis – an innovation not widely available in the current market. This was scored highly on novelty for addressing a unique health need. Three independent evaluators, experienced investors (five years of experience each) in the consumer electronics industry, scored each submission on the above parameter using a 7-point Likert scale (1 = low, 7 = high).

Opportunity assessment: Participants submitted detailed evaluations of the opportunities they identified, focusing on the following dimensions.

Depth: In opportunity assessment, depth concerns how extensively and systematically a person analyzes the internal dimensions of an idea. It reflects the ability to break the opportunity down into its key components (e.g., market alignment, strategic fit, cost structure, and long-term viability) and to connect them in a coherent evaluation. For example, a participant assessing an eco-friendly fitness band examined production costs, expected demand for sustainable technology, and possible government incentives. This shows depth because it demonstrates a detailed, multi-angle analysis of the opportunity itself, regardless of the specific setting in which it might operate.

Contextual Understanding: Unlike depth, which emphasizes comprehensiveness across various dimensions, focuses on how well a person recognizes and integrates external circumstances that affect the opportunity's success. It is not about the internal logic of the idea, but about how that idea fits the surrounding environment (e.g., cultural norms, infrastructure, legal constraints, or local market conditions). For instance, a participant evaluating a subscription-based educational platform discussed regional differences in internet access and cultural preferences for personalized learning. This reflects contextual understanding because it shows awareness of how external realities shape feasibility and adoption.

Submissions included structured assessments of opportunities, which expert investors reviewed using a 7-point Likert scale. Textual analysis, see the intuitive versus deliberative thinking measurement, further validated the evaluations.

Opportunity exploitation: Participants provided strategic plans detailing capitalizing on one recognized and assessed opportunity. Plans were evaluated based on the following criteria:

Depth for opportunity exploitation: For opportunity exploitation, depth emphasizes the comprehensiveness of strategic plans in addressing implementation aspects, including market alignment, scalability, and resource allocation. For example, a participant proposing the launch of an eco-friendly fitness band detailed a go-to-market strategy involving production costs, demand for sustainable products, and leveraging government incentives. This structured strategy demonstrated depth by thoroughly addressing the execution's financial, operational, and strategic components.

Innovation: Assessed by the originality of the proposed exploitation strategies, such as product differentiation or unique business models. A strategy proposing subscription-based wearable devices with AI-driven personalized health recommendations scored highly on innovation for its creative approach to consumer engagement. Expert investors rated the submissions using a 7-point Likert scale. Additionally, qualitative analysis – specifically, the measurement of intuitive and deliberative thinking– identified whether participants prioritized high-risk, high-reward approaches over more conservative strategies.

Intuitive and deliberative thinking: To evaluate participants' cognitive processes during the decision-making task, we applied the think-aloud method (Wolcott & Lobczowski, 2021), requiring participants to verbalize their thought processes in real-time. These verbalizations were analyzed through the lens of dual-process theory (Kahneman, 2011), which differentiates between two modes of cognitive functioning: intuitive thinking (fast, automatic, and heuristic-driven) and deliberative thinking (slow, structured, and analytical). For instance, statements such as "The demand for AI-integrated wearables seems high, so entering the market is a good idea" were considered intuitive. In contrast, "The demand for AI-integrated wearables is growing, but we need to evaluate the competition, cost structures, and potential partnerships before deciding" were categorized as deliberative. We developed the Cognitive Thinking Index (CTI) to measure the balance between these cognitive processes. Intuitive thoughts were assigned a weight of 1, and deliberative thoughts a weight of 2, reflecting their respective levels of cognitive effort and complexity. For example, a participant producing 14 intuitive and nine deliberative thoughts would achieve a CTI score of 32. The CTI was treated as a continuous variable, providing insight into participants' reliance on intuitive versus deliberative thinking during opportunity recognition, assessment, and exploitation. A post hoc analysis also decomposed CTI scores into their intuitive and deliberative components to better understand the respective contributions of these components to biases in strategic decision-making. Inter-rater reliability was high (ICC(2,k) = 0.82), indicating excellent agreement. Minor discrepancies were resolved through discussion.

Novelty, assessment depth, exploitation depth, and exploitation innovation were rated on 7-point scales by three professional investors who were blind to participants' condition. Inter-rater reliability was satisfactory across all dimensions, with ICC(2,k) values ranging from 0.76 to 0.84. Because of the strong agreement, ratings were averaged across raters to form composite measures used in subsequent analyses.

3.5. Group parity verification and control variables

We implemented random assignment, assessed cognitive abilities, and evaluated AI literacy to ensure group comparability. Participants were randomly allocated to experimental conditions, reducing extraneous variables and ensuring similar baseline characteristics among groups (Wickens & Keppel, 1991). This approach strengthened internal validity by isolating the causal effects of AI usage on entrepreneurial decision making (Eisenbart et al., 2023).

Participants also completed the Cognitive Reflection Test (CRT), measuring their tendency for reflective thinking and causal reasoning (Frederick, 2005). This test helped distinguish participants who engaged in deeper cognitive processing from those who relied more on intuition, ensuring uniformity in reasoning abilities across the experimental groups (Pennycook et al., 2016). Additionally, participants's familiarity with AI was measured using a 12-item AI literacy scale (Wang et al., 2022; Cronbach's alpha = 0.83), which employed a 7-point Likert scale.

4. Results

4.1. Descriptive statistics

Of the total sample, 50 % (62 participants) of entrepreneurs self-categorized as having prior knowledge in the consumer electronics sector. The remaining 50 % lacked sector knowledge, representing other entrepreneurial industries: technology: 18 %; manufacturing: 17 %; consumer goods: 10 %; healthcare: 5 % – all excluding consumer electronics. Participants ranged in age from 28 to 44 years, with an average age of 38.2 years (SD = 4.5). Entrepreneurial experience ranged from 3 to 18 years, with a mean of 7.8 years (SD = 3.1). The gender distribution was balanced, with 53 % male and 47 % female participants.

Table 1 provides the variables' means, standard deviations, and correlations. Significant correlations are observed between novelty in opportunity recognition and innovation in exploitation ($r = 0.66$, $p < .01$), as well as assessment depth and exploitation depth ($r = 0.80$, $p < .01$). Additionally, the CTI shows a strong positive correlation with the CRT score ($r = 0.83$, $p < .01$), suggesting alignment between reflective and deliberative cognitive processes, and, more interestingly, with novelty of recognized opportunity ($r = 0.67$, $p < .01$), contextual understanding ($r = 0.78$, $p < .01$), and innovation in exploitation ($r = 0.74$, $p < .01$).

4.2. Main effects of AI assistance

To test H1, we analyzed the effects of AI usage on the number and novelty of opportunities recognized by entrepreneurs assisted or no AI (considering the average of groups with and without sector knowledge), see Table 2 and Fig. 2.

AI-assisted entrepreneurs identified significantly more opportunities (M = 6.1, SD = 1.0) compared to those who were not assisted by AI (M = 4.0, SD = 1.2), $F(1, 122) = 12.56$, $p < .001$. These results confirm that AI assistance enhances the volume of identified opportunities, likely due to their ability to process large datasets.

However, a different pattern emerged for the novelty of the opportunities identified. In line with H2, AI-assisted entrepreneurs scored significantly lower on novelty (M = 4.8, SD = 1.2) compared to non-AI-assisted entrepreneurs (M = 6.7, SD = 1.0), $F(1, 122) = 8.43$, $p < .01$. This suggests that while AI enhances the number of opportunities recognized, its reliance on structured, data-driven processes may inhibit the identification of more innovative or unconventional opportunities. These findings highlight a trade-off between quantity and novelty in AI-assisted opportunity recognition.

H3 posited that AI usage enhances the depth of opportunity assessments. The results support this hypothesis, with AI-assisted entrepreneurs demonstrating significantly greater depth in their evaluations (M = 6.1, SD = 1.0) compared to non-AI-assisted entrepreneurs (M = 3.9, SD = 1.1), $F(1, 122) = 15.67$, $p < .001$.

Finally, H5 examined the effects of AI usage on the depth of exploitation plans. Results indicate that AI-assisted entrepreneurs produced deeper exploitation plans (M = 5.6, SD = 1.0) compared to non-AI-assisted entrepreneurs (M = 3.6, SD = 1.2), $F(1, 122) = 6.32$, $p < .05$, supporting the hypothesis that AI enhances the thoroughness of strategic planning.

However, consistent with H6, AI-assisted entrepreneurs scored lower on innovation in their exploitation plans (M = 3.9, SD = 1.3) compared to non-AI-assisted entrepreneurs (M = 5.4, SD = 1.2), $F(1, 122) = 5.89$, $p < .05$. While adept at optimizing execution strategies, AI may inadvertently constrain creativity by prioritizing feasibility and efficiency

Table 1
Means, standard deviations, and correlations among key variables.

Variable	Mean (M)	Standard Deviation (SD)	1	2	3	4	5	6	7	8	9
1. Opportunities Recognized	3.7	1.2	1								
2. Novelty (recognition)	5.4	1.1	0.34	1							
3. Depth (assessment)	5.3	1.1	0.30	0.42	1						
4. Contextual Understanding	5.0	1.2	0.27	0.38*	0.25*	1					
5. Depth (exploitation)	5.4	1.1	0.35	0.40	0.80**	0.40*	1				
6. Innovation (exploitation)	5.1	1.3	0.30	0.66**	0.39	0.42	0.43	1			
7. CTI	27.8	6.5	0.25	0.67**	0.35	0.78**	0.36	0.74**	1		
8. CRT	1.54	0.67	0.20	0.22	0.28	0.30	0.25	0.20	0.83**	1	
9. AI Literacy	7.18	0.74	0.25	0.28	0.25	0.20	0.30	0.22	0.38	0.18	1

Note: *p < .05; **p < .01.

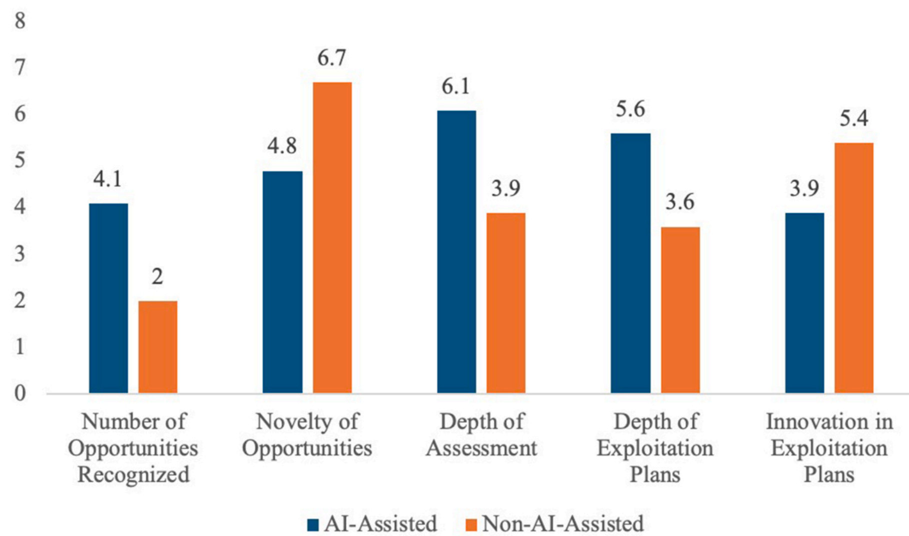

Fig. 2. Comparison of AI-assisted vs. non-AI-assisted entrepreneurial decision-making outcomes.

Table 2
ANOVA results for hypotheses H1, H3, and H5.

Dependent Variable	AI Usage (M ± SD)	No AI Usage (M ± SD)	F-statistic	p-value
Number of Opportunities Recognized	6.1 ± 1.0	4.0 ± 1.2	12.56	0.0004
Novelty of Opportunities	4.8 ± 1.2	6.7 ± 1.0	8.43	0.0045
Depth of Assessment	6.1 ± 1.0	3.9 ± 1.1	15.67	0.0001
Depth of Exploitation Plans	5.6 ± 1.0	3.6 ± 1.2	6.32	0.0131
Innovation in Exploitation Plans	3.9 ± 1.3	5.4 ± 1.2	5.89	0.0173

over bold, unconventional approaches.

4.3. Interaction effects of AI assistance and sector knowledge

The analysis of the interaction effects between AI assistance and sector knowledge revealed significant patterns in entrepreneurial decision-making outcomes, as shown in Table 3 and Fig. 4. The results demonstrate the differential impact of AI and sector knowledge across several dimensions of opportunity recognition, assessment, and exploitation.

Number and novelty of opportunities (H1 and H2). Entrepreneurs with both AI assistance and sector knowledge identified the highest number of opportunities (M = 6.8, SD = 0.3), significantly outperforming other groups (F = 22.56, p < .001). AI assistance alone also led to more opportunities (M = 4.1, SD = 1.0) than those without AI and no sector knowledge (M = 3.0, SD = 1.0). However, while AI boosted the number of recognized opportunities, the novelty of these opportunities was significantly lower unless sector knowledge was also present. Entrepreneurs with both AI and sector knowledge achieved the highest novelty scores (M = 6.8, SD = 0.2). These results support H1 and H2, showing that AI increases the number of opportunities but its effect on novelty depends on sector knowledge.

Depth of opportunity assessments and contextual understanding (H3 and H4). In terms of the depth of opportunity assessments and contextual understanding, entrepreneurs with both AI assistance and sector knowledge scored the highest (M = 6.9, SD = 0.1), significantly outperforming all other groups (F = 25.67, p < .001). Entrepreneurs with sector knowledge alone (M = 6.0, SD = 0.7) also scored higher in depth of assessment compared to those relying solely on AI (M = 5.5, SD = 0.9; see Fig. 5). These results support H3 and H4, emphasizing that while AI promotes depth through structured deliberation, integrating intuitive thinking enabled by sector knowledge adds contextual nuance.

Depth of exploitation plans and innovation of exploitation plans (H5 and H6). Entrepreneurs with both AI assistance and sector knowledge produced the most comprehensive exploitation plans (M = 6.9, SD = 0.1), significantly outperforming other groups (F = 24.12, p < .001). Those relying solely on AI (M = 5.6, SD = 1.0) also developed deeper plans than those without AI and sector knowledge (M = 3.6, SD = 1.1). However, the results showed a clear trade-off for innovation. Entrepreneurs with both AI and sector knowledge achieved the highest innovation scores (M = 6.7, SD = 0.3), while those relying solely on AI or with neither AI nor sector knowledge scored lower (see Fig. 6). These findings support H5 and H6, illustrating that while AI enhances the

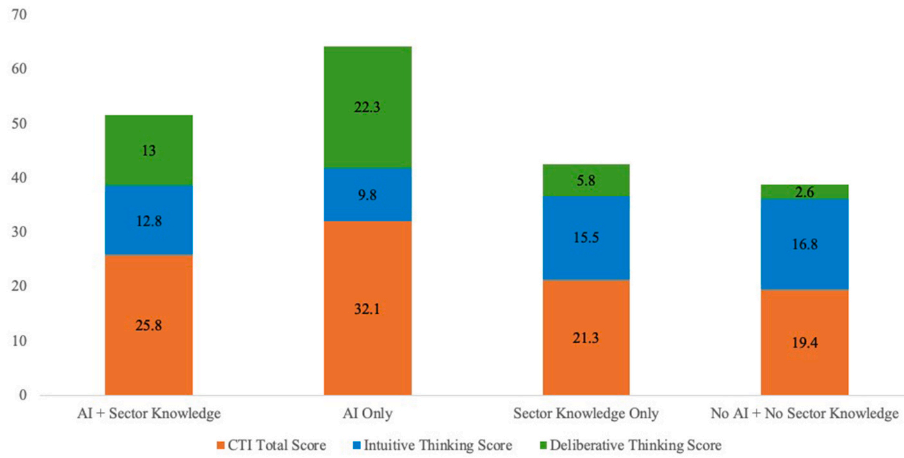

Fig. 3. Comparison of cognitive thinking Index (CTI) scores across experimental groups.

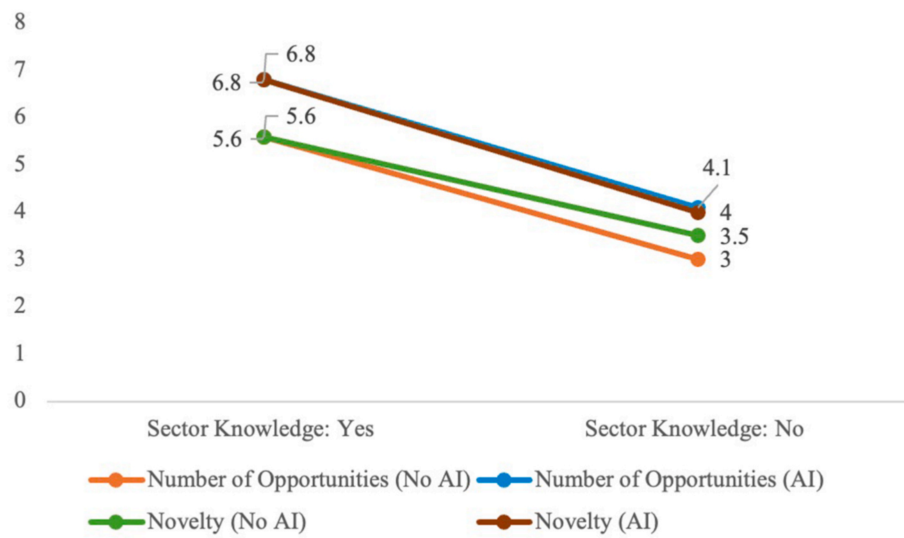

Fig. 4. Interaction effects of AI assistance and sector knowledge on the volume and novelty of opportunity recognition.

Table 3
Interaction effects of AI assistance and sector knowledge on entrepreneurial decision-making outcomes.

Dependent Variable	AI + Sector Knowledge (M ± SD)	AI Only (M ± SD)	No AI + Sector Knowledge (M ± SD)	No AI + No Sector Knowledge (M ± SD)	F-statistic	p-value
Number of Opportunities	6.8 ± 0.3	4.1 ± 1.0	5.6 ± 0.8	3.0 ± 1.0	22.56	<0.001
Novelty of Opportunities	6.8 ± 0.2	4.0 ± 1.2	5.6 ± 0.8	3.5 ± 1.0	20.45	<0.001
Depth of Assessments	6.9 ± 0.1	5.5 ± 0.9	6.0 ± 0.7	4.0 ± 1.0	25.67	<0.001
Contextual Understanding	6.8 ± 0.2	5.3 ± 1.0	5.8 ± 0.8	3.9 ± 1.0	23.34	<0.001
Depth of Exploitation Plans	6.9 ± 0.1	5.6 ± 1.0	5.3 ± 0.8	3.6 ± 1.1	24.12	<0.001
Innovation of Exploitation Plans	6.7 ± 0.3	4.2 ± 1.0	5.9 ± 0.6	3.6 ± 1.1	18.34	<0.001

depth of exploitation plans, its effect on innovation depends critically on the presence of sector knowledge.

4.4. Mediation analyses of cognitive processes

To examine whether cognitive processes, as measured by the CTI, drive differences in entrepreneurial decision-making outcomes, results were analyzed with a focus on how AI assistance and sector knowledge influence the balance of intuitive and deliberative thinking. A formal two-way ANOVA was conducted to test group-level differences in CTI scores, with AI usage (Yes/No) and sector knowledge (Yes/No) as independent variables. Post hoc comparisons (Tukey's HSD) were applied to identify specific group differences.

The two-way ANOVA revealed significant main effects for both AI assistance ($F(1, 120) = 25.32$, $p < .001$) and sector knowledge ($F(1, 120) = 18.47$, $p < .001$) on CTI scores, as well as a significant interaction effect ($F(1, 120) = 16.78$, $p < .001$). These results confirm that cognitive processes, as measured by CTI, differ significantly across groups depending on the presence of AI and sector knowledge. Post hoc comparisons (Tukey's HSD) revealed the following patterns.

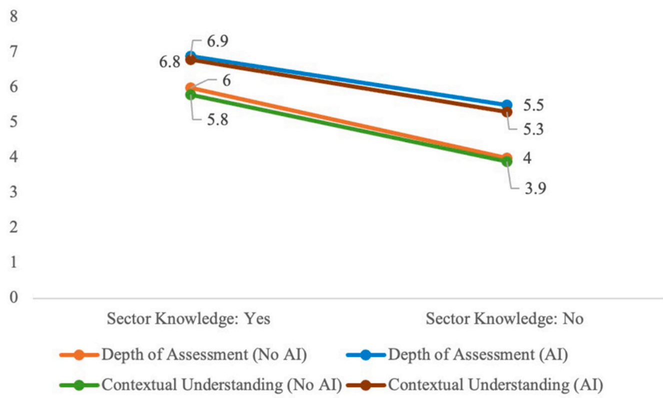

Fig. 5. Interaction effects of AI assistance and sector knowledge on the depth and contextual understanding of opportunity assessment.

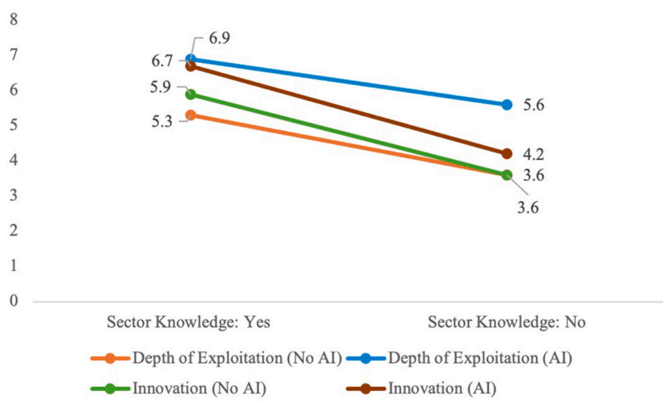

Fig. 6. Interaction effects of AI assistance and sector knowledge on the innovation of opportunity exploitation.

1. Entrepreneurs assisted by AI and possessing sector knowledge demonstrated the most balanced cognitive approach, with a CTI Total Score of 25.8 (SD = 3.2). This balance was evident in the near-equal contributions of intuitive thinking (M = 12.8, SD = 1.9) and deliberative thinking (M = 13.0, SD = 1.7). This balance supported high scores in novelty, contextual understanding, and innovation.
2. Entrepreneurs without sector knowledge but assisted by AI strongly relied on deliberative thinking. Their CTI Total Score was significantly higher at 32.1 (SD = 4.0, $p < .001$), with deliberative thinking contributing disproportionately (M = 22.3, SD = 2.5) compared to intuitive thinking (M = 9.8, SD = 2.0). This group excelled in the number of recognized opportunities and depth of assessment and exploitation, driven by AI-stimulated analytical processes, but struggled with novelty and innovation due to limited intuitive input.
3. Entrepreneurs without AI assistance but possessing sector knowledge relied more heavily on intuitive thinking. Their CTI Total Score was 21.3 (SD = 3.7, $p < .001$), composed of intuitive thinking (M = 15.5, SD = 2.3) and deliberative thinking (M = 5.8, SD = 1.6). This group leveraged domain expertise to guide intuitive processes but lacked the analytical support of AI, resulting in limited depth of assessment and exploitation.
4. Entrepreneurs without AI assistance and sector knowledge had the lowest CTI Total Score at 19.4 (SD = 3.6, $p < .001$), dominated by intuitive thinking (M = 16.8, SD = 2.2) with minimal contribution from deliberative thinking (M = 2.6, SD = 1.4). Their heavy reliance on heuristics and rapid judgments constrained their ability to perform in entrepreneurial decision making.

The significant group differences in CTI scores demonstrated through ANOVA provide a foundation for testing moderation. See also Fig. 3

To explore whether CTI mediates the effects of AI usage and sector knowledge on decision-making outcomes, the PROCESS macro (Model 4) was applied (see Fig. 4). Separate models were tested for each outcome variable: number of opportunities, novelty, depth (assessment), contextual understanding, depth (exploitation), and innovation. The results are summarized in Table 4.

Separate models were tested. Regarding the number of opportunities, CTI significantly mediated the relationship between AI usage and the number of opportunities recognized (indirect effect = 0.22, SE = 0.06, 95 % CI [0.10, 0.34]). These results highlight the role of AI-driven deliberative thinking in enabling entrepreneurs to identify more opportunities through enhanced data processing and structured analysis.

For novelty, sector knowledge significantly influenced CTI, which enhanced creativity in recognizing opportunities (indirect effect = 0.18, SE = 0.05, 95 % CI [0.09, 0.29]). Intuitive thinking, stimulated by prior sector knowledge, fostered innovation during opportunity recognition. CTI mediated the relationship between AI usage and the depth of opportunity assessments (indirect effect = 0.30, SE = 0.07, 95 % CI [0.16, 0.45]). Deliberative thinking supported by AI led to more comprehensive evaluations, addressing dimensions such as feasibility, strategic fit, and long-term viability. AI usage significantly mediated contextual understanding through CTI (indirect effect = 0.27, SE = 0.06, 95 % CI [0.14, 0.39]). While deliberative thinking contributed to structured evaluations, contextual understanding depended on intuitive thinking enriched by sector knowledge. CTI also mediated the relationship between AI usage and the depth of exploitation plans (indirect effect = 0.25, SE = 0.06, 95 % CI [0.12, 0.38]). Entrepreneurs using AI produced more structured and actionable strategies, reflecting the strength of deliberative thinking in fostering detailed planning. For innovation, the combined effects of AI usage and sector knowledge were mediated by CTI (indirect effect = 0.21, SE = 0.07, 95 % CI [0.08, 0.36]). The balance between intuitive and deliberative thinking was critical in enabling entrepreneurs to develop original and creative exploitation strategies.

5. Discussion

Entrepreneurial decision-making is fundamentally shaped by bounded rationality (Sarasvathy & Berglund, 2010; Simon, 1947). Entrepreneurs rarely operate with complete information, unlimited time, or unconstrained cognitive capacity (Pollack et al., 2023). Instead, they must navigate uncertainty by combining heuristics, intuition, and analysis (Cristofaro & Giannetti, 2021). In this study, we examined how AI and prior sector knowledge interact to reshape this balance across the three core phases of entrepreneurial decision-making: opportunity

Table 4
Mediation effects summary.

Outcome Variable	Mediator	Indirect Effect	SE	95 % Confidence Interval (Lower)	95 % Confidence Interval (Upper)
Number of Opportunities	CTI	0.22	0.06	0.10	0.34
Novelty	CTI	0.18	0.05	0.09	0.29
Depth (Assessment)	CTI	0.30	0.07	0.16	0.45
Contextual Understanding	CTI	0.27	0.06	0.14	0.39
Depth (Exploitation)	CTI	0.25	0.06	0.12	0.38
Innovation	CTI	0.21	0.07	0.08	0.36

recognition, opportunity assessment, and opportunity exploitation. Our findings extend dual-process accounts of entrepreneurial cognition by showing how AI systematically tilts decisions toward deliberative, System 2 reasoning (Evans, 2008; Kahneman, 2011), while prior knowledge reactivates intuitive, System 1 reasoning (Dane & Pratt, 2007), thereby conditioning creativity and originality.

Our results reveal a trade-off between the quantity and novelty of opportunities identified. Entrepreneurs supported by AI recognized significantly more opportunities, reflecting AI's strength in processing large datasets and surfacing patterns (Chalmers et al., 2021; Kraus et al., 2020). Yet these opportunities were less novel, consistent with the structured, deliberative orientation of AI outputs (Dellermann et al., 2021; Shepherd & Majchrzak, 2022). From a dual-process perspective, AI amplifies System 2 search but dampens the flexibility of System 1 intuition, which is often central to originality (Evans, 2008; Kahneman, 2011). Opportunity theories provide interpretive traction here. Within recognition views (Shane & Venkataraman, 2000), AI accelerates search but surfaces largely conventional opportunities. Within creation views (Alvarez & Barney, 2007), novelty emerges when intuition and imagination recombine resources in unexpected ways. Crucially, we find that prior sector knowledge restores novelty by reactivating intuitive pattern recognition, enabling entrepreneurs to integrate AI's systematic exploration with contextual insights (Fuentes Fuentes et al., 2010; Shane, 2000). In line with Klein's (1998) notion of expertise as a "pattern library," knowledge allows entrepreneurs to perceive the significance of patterns that AI alone cannot interpret, producing opportunities that are both numerous and original.

AI also significantly enhanced the depth of opportunity assessments, enabling entrepreneurs to evaluate opportunities comprehensively across dimensions such as feasibility, strategic fit, and market alignment (Shepherd & Majchrzak, 2022). This aligns with System 2 reasoning: slow, effortful, and analytical processes that reduce uncertainty and improve structured evaluation (Csaszar et al., 2024; Dellermann et al., 2021). Yet such deliberation alone risks overlooking the contextual understanding that often determines strategic relevance. While AI extends analytical capacity, it does not relax the entrepreneur's interpretive limits. Entrepreneurs with prior sector knowledge bridged this gap, enriching AI's deliberative outputs with intuitive judgments rooted in context (Shane, 2000; Fuentes Fuentes et al., 2010). In theoretical terms, knowledge enabled System 1 intuition to complement System 2 deliberation, yielding evaluations that were both comprehensive and contextually grounded (Evans, 2008; Kahneman, 2011). This dynamic also resonates with causation–effectuation theory. AI strengthens causation logics by enabling structured, goal-oriented evaluations, while prior knowledge sustains effectual reasoning by allowing entrepreneurs to flexibly interpret resources and improvise under uncertainty (Sarasvathy, 2001). Thus, the balance between causation and effectuation depends not only on the presence of AI but also on the entrepreneur's experiential repertoire.

The exploitation phase exhibited similar dynamics. AI improved the depth and precision of exploitation plans, fostering structured strategies optimized for feasibility and risk minimization (Csaszar et al., 2024; Shepherd & Majchrzak, 2022). Yet these plans were less innovative, underscoring AI's tendency to privilege deliberative risk-aversion over bold exploration (Cockburn et al., 2018; Grilli & Pedota, 2024). In dual-process terms, AI promotes System 2 exploitation, but at the cost of suppressing System 1 improvisation. Entrepreneurs with prior sector knowledge were better able to combine AI's structured deliberation with intuitive insights, producing exploitation plans that were both strategically rigorous and creatively differentiated (Dane & Pratt, 2007; Shane, 2000). This integration again highlights expertise as a "pattern library": knowledge enables entrepreneurs to use AI's outputs as inputs into established cognitive repertoires, recombining them into novel strategies (Klein, 1998). By contrast, entrepreneurs without sector knowledge relied almost exclusively on AI-driven deliberation, achieving operational depth but missing the originality required for competitive advantage (Agrawal et al., 2022).

Taken together, these findings suggest that AI does not simply supplement entrepreneurial cognition but reconfigures how bounded rationality is managed. Prior research describes entrepreneurial decision-making as a dynamic balance between intuition (System 1) and deliberation (System 2) (Grégoire et al., 2011; Mitchell et al., 2002). Our results refine this account: AI systematically tilts cognition toward System 2, enhancing efficiency in recognition and depth in assessment and exploitation, but often constraining originality. Crucially, this trade-off is moderated by prior sector knowledge, which reactivates System 1 intuition and restores creativity. This knowledge-conditioned creativity reframes the relation between AI and entrepreneurship. AI facilitates opportunity recognition by accelerating search but primarily surfaces conventional options; knowledge allows entrepreneurs to create opportunities by reintroducing intuition and imagination. AI strengthens causation logics by promoting structured planning, while sector knowledge sustains effectual logics by enabling improvisation and resource recombination. Finally, AI enhances deliberative analysis, but knowledge ensures that outputs are filtered through the entrepreneur's experiential "pattern library", balancing depth with originality (Dane & Pratt, 2007; Klein, 1998).

In sum, our study theorizes that the future of entrepreneurial decision-making lies not in AI replacing intuition, but in the co-evolution of machine intelligence and human expertise. Entrepreneurs who strategically integrate AI with sector knowledge are best positioned to transcend bounded rationality: they can exploit AI's analytical precision without sacrificing the intuitive leaps that drive innovation.

6. Implications

6.1. Implications for theory

This study advances entrepreneurial cognition research by clarifying how AI and sector knowledge jointly shape decision-making outcomes. We highlight three main implications.

First, we reconceptualize the role of AI in entrepreneurship. Rather than functioning solely as an information-processing tool (Dellermann et al., 2021; Shepherd & Majchrzak, 2022), our findings suggest that entrepreneurs assisted by AI identified more opportunities and developed deeper assessments and exploitation strategies, demonstrating AI's capacity to expand analytical reach and reduce uncertainty (Chalmers et al., 2021; Kraus et al., 2020). However, this shift comes at a cost: opportunities identified with AI were less novel, and exploitation strategies less innovative, highlighting AI's structured, risk-averse orientation (Cockburn et al., 2018; Csaszar et al., 2024). This duality positions AI as a double-edged cognitive input – enhancing structured evaluation while constraining heuristic novelty – thereby extending theories of entrepreneurial judgment beyond human-centric accounts of bounded rationality (Simon, 1947; Townsend & Hunt, 2019).

Second, the findings enrich dual-process and opportunity theories by showing how sector knowledge conditions the cognitive effects of AI. Entrepreneurs without sector knowledge relied heavily on AI-driven deliberation, achieving analytical depth but struggling with originality. By contrast, those with prior knowledge reactivated System 1 intuition, enabling them to interpret AI's outputs contextually and recombine them into novel opportunities. This demonstrates that entrepreneurial cognition in the AI era is best understood as a hybrid system in which knowledge-based intuition balances technology-driven deliberation. Theoretically, this reframes opportunity recognition as optimized by AI's deliberative reach but limited in novelty, while opportunity creation remains rooted in the intuitive recombination of resources enabled by expertise (Shane & Venkataraman, 2000; Alvarez & Barney, 2007; Fuentes Fuentes et al., 2010). Dual-process theory is thereby extended: AI amplifies System 2 search, but sector knowledge safeguards the generative capacity of System 1 (Evans, 2008; Kahneman, 2011).

Third, the results extend theories of expertise and entrepreneurial logic by highlighting the interactive role of knowledge in AI-supported contexts. Expertise operates as a "pattern library" that facilitates recognition (Klein, 1998; Shane, 2000) and as the interpretive lens through which AI outputs are evaluated and applied. Knowledge allows entrepreneurs to embed AI-generated insights into strategic judgment, achieving analytically rigorous and contextually meaningful decisions. This integration also redefines the interplay between causation and effectuation: while AI strengthens causation logics of structured, goal-oriented planning (Csaszar et al., 2024; Dellermann et al., 2021), sector knowledge sustains effectual logics by enabling improvisation and flexibility under uncertainty (Sarasvathy, 2001). Thus, the balance between causation and effectuation depends not merely on the presence of AI but on the interaction between AI and sector knowledge, positioning sector expertise as a critical boundary condition for theorizing entrepreneurial cognition in technology-augmented environments (Grilli & Pedota, 2024).

These implications suggest that entrepreneurial decision-making should be modeled as a triadic system: AI-driven deliberation, knowledge-driven intuition, and their interaction. This reframing extends dual-process, opportunity, and expertise theories by situating entrepreneurial judgment in human–AI complementarity dynamics.

6.2. Implications for practice

The results of this study have some relevant implications for practice. *First*, entrepreneurs should pursue a balanced approach to decision-making by deliberately integrating AI-driven deliberation with intuitive reasoning. Our results show that while AI significantly improves the number and depth of opportunities and exploitation strategies, it constrains novelty and innovation when used in isolation. The CTI findings further demonstrate that the highest-performing entrepreneurs balanced System 1 (intuition) and System 2 (deliberation), rather than relying on one mode exclusively. In practice, this means entrepreneurs should treat AI as a first-layer filter for surfacing patterns and opportunities, but then engage their intuition and contextual judgment to refine, adapt, and challenge these outputs (Kraus et al., 2020; Shepherd & Majchrzak, 2022). Training entrepreneurs to switch dynamically between intuitive and deliberative modes could strengthen their ability to maximize AI's benefits while preserving creativity.

Second, developers and organizations deploying AI tools must address the observed trade-off between depth and innovation. While AI enhanced the comprehensiveness of assessments and exploitation plans, it produced risk-averse, less creative outcomes. To mitigate this, AI systems should be designed to stimulate exploratory thinking, for instance by generating counterintuitive suggestions, running "what-if" scenarios, or offering diverse alternative recommendations rather than converging on a single optimal solution (Cockburn et al., 2018; Grilli & Pedota, 2024). Organizations implementing these tools should create processes that pair AI insights with collective ideation, such as workshops where AI-generated outputs are critically debated and recombined by teams. This ensures that strategic decisions preserve analytical depth and novelty, allowing AI to act as a creative partner rather than a purely data-driven aid.

Third, organizations and entrepreneurial teams should recognize sector knowledge as a critical enabler of effective AI use. Entrepreneurs with prior sector expertise were consistently better at interpreting AI outputs, enriching them with intuitive judgments to generate outcomes that were not only rigorous but also original. This finding highlights the importance of cultivating domain-specific expertise through mentorship programs, industry immersions, and targeted experiential learning (Fuentes Fuentes et al., 2010; Shane, 2000). Organizations should combine AI proficiency with domain expertise at the team level by assembling cross-functional groups that integrate technical specialists and industry veterans. Such configurations replicate the conditions in which our study observed superior performance – where AI's structured outputs were filtered through contextual understanding to produce feasible and innovative strategies.

6.3. Limitations and future research

While offering valuable insights into the interplay of AI, prior sector knowledge, and entrepreneurial decision-making, this study faces several limitations that also open avenues for future research. First, the experimental design, though controlled, cannot fully capture the complexity of real-world contexts where team interactions, market pressures, and regulation shape decision-making (Schade & Burmeister-Lamp, 2009). Second, the sample, while balanced in gender and experience, lacked cultural and geographic diversity. Since cultural and institutional conditions influence how entrepreneurs use AI under uncertainty (Shepherd et al., 2015; Townsend & Hunt, 2019), future studies should adopt cross-cultural or longitudinal designs. Third, focusing on the consumer electronics sector provided consistency but may limit generalizability. Extending analyses to industries with different knowledge bases or innovation logics (e.g., healthcare, manufacturing, creative industries) would test the robustness of the findings.

Fourth, AI support was operationalized through ChatGPT-4. While this ensured a clean and consistent experimental design, the generative AI landscape has advanced substantially since data collection on December 10, 2024. In less than a year, more capable and agentic systems (e.g., Gemini, Perplexity Deep Research, and GPT-5) have introduced markedly greater reasoning depth, multimodal integration, and autonomy in research and decision-support tasks. These developments are likely to expand both the scope and complexity of AI–human collaboration. Nevertheless, the core mechanism identified here – the interaction between AI-driven deliberation and knowledge-driven intuition – should remain generalizable across platforms. Future research could systematically compare newer models, prompt designs, or agentic frameworks to assess how evolving architectures reshape collaborative cognition (Dorigoni & Giardino, 2025; Haase et al., 2025; Yao et al., 2023). Fifth, we measured baseline AI literacy but not AI proficiency. Prompt-engineering skill is a more specific construct that shapes output quality (Korzynski et al., 2023). Future research should systematically examine proficiency as a moderator, perhaps via training interventions or experimental manipulations. Sixth, dispositional factors such as creativity, tolerance for ambiguity, and entrepreneurial self-efficacy were not directly modeled, though they likely shape how entrepreneurs engage with AI (Duong, 2025; Xie & Wang, 2025).

Future work could therefore examine the integration of AI in longitudinal, team-based, or cross-cultural settings, explore the role of AI proficiency in shaping outcomes, and incorporate neurocognitive measures (e.g., EEG, fMRI) to directly capture how AI shifts the balance between intuition and deliberation (Dane & Pratt, 2007; Evans, 2008).

7. Conclusion

This study shows that entrepreneurship in the age of AI is not defined by technology alone, but by how human knowledge and machine intelligence are woven together. AI assistance sharpens deliberation, expands the depth of assessments, and enriches exploitation strategies, yet its structured logic can mute the originality that springs from intuition. Sector knowledge reintroduces this creative spark, enabling entrepreneurs to balance fast and slow thinking in ways that make opportunity recognition bold and precise. In doing so, it reframes AI not as a replacement for judgment but as a catalyst whose value depends on the expertise it meets. The implication is clear: the future of entrepreneurial decision-making lies in cultivating the capacity to integrate, not substitute – where machines provide scale and depth, and humans sustain imagination and vision. In this balance, entrepreneurship retains its essence as the art of turning uncertainty into opportunity, now amplified by the intelligence of algorithms but still guided by the wisdom of experience.

CRediT authorship contribution statement

Matteo Cristofaro: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pier Luigi Giardino:** Writing – review & editing, Writing – original draft. **Jeffrey Muldoon:** Writing – review & editing, Writing – original draft.

Statement AI

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

Declaration of interest statement

The authors do not have any conflict of interest to declare.

Appendix A. Investigated variables.

Construct	Definition	Key processes	Examples	Outcomes	References
Novelty	The distinctiveness or uniqueness of an entrepreneurial opportunity relative to existing products, services, or practices, reflecting the extent to which the idea departs from prevailing solutions while maintaining coherence and potential value.	Identifying discontinuities from existing offerings, reframing problems in unconventional ways, and combining resources or technologies in novel configurations.	Conceptualizing offerings that challenge dominant designs; applying decision rules that weigh novelty alongside feasibility and value; generating ideas that differentiate ventures in competitive markets.	Increases opportunity attractiveness when combined with feasibility and value; enhances differentiation in crowded markets; signals originality to investors and stakeholders.	Frederiks et al. (2019); Scheaf et al. (2020); Davidsson et al. (2021)
Depth	The degree of elaboration and cognitive sophistication with which an entrepreneurial opportunity is evaluated, reflected in the integration of multiple dimensions (e.g., feasibility, market alignment, strategic fit, long-term viability) and grounded in a coherent understanding of assumptions and implications.	Progressive refinement of opportunity concepts through testing assumptions, exploring contingencies, linking resources, markets, and value propositions, and pooling knowledge in team settings.	Iterative belief updating during planning; integrating gain–loss estimation, feasibility, and desirability into sophisticated mental models; enhancing robustness through team debate and shared sensemaking.	More comprehensive, balanced, and robust opportunity evaluations that anticipate long-term implications and increase the persuasiveness of strategic plans to stakeholders.	McCann and Vroom (2015); Scheaf et al. (2020); Healey et al. (2021)
Contextual understanding	The ability to situate an entrepreneurial opportunity within its broader technological, market, and environmental conditions, reflecting how well entrepreneurs align internal features of an idea with external contingencies such as demand, competition, and institutional logics.	Using analogical reasoning and structural alignment to connect new technologies with viable markets; interpreting contextual signals such as resource requirements, customer demand, and competitive intensity; mapping supply-side attributes to market-side needs.	Identifying technology–market combinations; discerning structural fit between ideas and environmental conditions; refining opportunity beliefs under risky or uncertain conditions.	Enhances feasibility and desirability judgments; improves accuracy of risk assessment; strengthens alignment between ideas and external conditions, supporting long-term viability.	Grégoire and Shepherd (2012); Grégoire et al. (2010); Keh et al. (2002)

Appendix B. Company, market, and macro information for the experimental task

Company info

InnoTech is widely recognized for its cutting-edge technology and sleek designs, catering primarily to the European market. The company has built a reputation for delivering premium products with advanced AI features, making it a strong contender in the wearable technology industry. InnoTech is considering expanding its reach into the Asian wearable technology market, a move that represents a significant strategic opportunity for growth.

Market and Macro info

The Asian wearable technology market is experiencing rapid growth, with a projected annual growth rate of 18 %. This expansion is driven by increasing consumer demand for health insights, real-time fitness tracking, and smart connectivity devices. Additionally, macroeconomic trends such as rising disposable incomes and urbanization fuel the adoption of wearable technology, particularly among tech-savvy urban populations. These factors make the Asian market a lucrative prospect for technology companies like InnoTech looking to expand their global footprint.

Despite the market's potential, the competitive landscape poses significant challenges. The sector is dominated by global giants that offer a wide range of cost-competitive products, creating high barriers to entry for new players. Competitors include established brands that have secured substantial market shares through aggressive pricing, strong distribution networks, and localized marketing strategies. Furthermore, regulatory requirements in the region are complex, including high tariffs and certification standards that must be met to enter the market successfully. The limited availability of local partnerships for distribution and after-sales support adds another layer of complexity to market entry.

Appendix C. A six-turn, anonymized prompt/response trail.

Participant #022

Turn 1 – Opportunity Recognition

Prompt:

"Using only the Market Pack, list five distinct opportunity spaces for InnoTech in Asian wearables. For each, add a one-line rationale and reference the data card(s) (e.g., D2, D5). No real brands, no external stats."

AI Response:

1. Commute-aware posture clip – micro-nudges for slouch/neck tilt during transit; daily trigger frequency supports habit formation (D1 urban commute density, D3 posture/pain complaints).
2. Modular hearables for focus/ambient switching – swap inserts for deep work vs. awareness; aligns with fragmented workday patterns (D2 hybrid work routines, D4 audio accessory attachment).
3. Contactless vitals badge for workplace entry – passive temp/HRV screening where acceptable; B2B2E wedge (D5 enterprise well-being pilots, – D6 privacy sensitivity gradient).
4. Hydration + micro-movement band – sedentary risk prompts tuned to office hours (D2, D3).
5. Lightweight parental safety tag – proximity + gentle alerts in dense public spaces (D1 crowding, D6 consent norms).

Note: Concepts remain brand-agnostic and derive only from Market Pack patterns.

Participant reaction/steer:

"Prioritize #1 posture clip and #2 modular hearables for depth. #3 feels policy-sensitive; parking it."

Turn 2 – Recognition Refinement

Prompt:

"For #1 and #2, list three user pains each that are evidenced or implied by the Market Pack, plus two behavioral success metrics per idea. No market claims."

AI response:

1. Posture clip
   a. *Pains:* neck/shoulder strain on crowded lines (D3), desk slouch after commute (D2), low self-awareness until pain (D3).
   b. *Metrics:* posture-nudge adherence %; weekly commute-mode sessions.
2. Modular hearables
   a. *Pains:* context-switch fatigue (D2), missed notifications in isolation mode (D4), ear fatigue from long wear (D4).
   b. *Metrics:* module-swap rate/user/week; weekly active users (WAU).

Why behavioral? They're observable within product telemetry and don't require external stats.

Participant reaction/steer:

"Good. I want a compact fit–feasibility–risk view against InnoTech's strengths (sensors, low-power firmware, EU-grade privacy posture per brief)."

Turn 3 – Opportunity assessment

Prompt:

"Build a ≤70-word table comparing #1 vs #2 on strategic fit, feasibility (near-term), key complements, and main adoption risk. Base it only on the Market Pack + InnoTech capabilities from the brief."

AI response:

1. Fit – #1: leverages motion + posture sensing; #2: audio DSP path less proven.
2. Feasibility (near-term) – #1: clip form + nudge engine align with low-power stack; #2: modular HW adds supply risk.
3. Complements – #1: desk app, commute mode; #2: calendars/calls.
4. Adoption risk – #1: nudge fatigue; #2: parity with existing hearables.
5. Signals – #1 adherence >35 %; #2 swaps >1.5/week.

Participant reaction/steer:

"Favor #1 posture clip. Propose a go with a falsifiable kill criterion."

Turn 4 – Go/No-go

Prompt:

"Recommend GO or NO-GO for #1, in <40 words, with one kill-criterion and a single leading indicator we can measure in a 2-week alpha. Keep within Market Pack constraints."

AI response:

1. GO: Posture clip. Daily commute + desk triggers, clear pain evidence (D2, D3), strong capability fit.
2. Kill if adherence <35 % by week-2 despite ≤3 nudges/day and a 1-min calibration.

Leading indicator: onboarding completion ≥70 % within 48 h.

Participant reaction/steer:

"Proceed. I need a high-level entry strategy: model, partnerships (types only), resource focus, and risk mitigations."

Turn 5 – Opportunity exploitation (strategy)

Prompt:

"Draft a high-level market entry for Tier-1 Asian cities: business model, resource allocation focus, partnership types, and risk mitigations. No real brands, no external claims."

AI response:

1. Model: DTC starter kit + B2B2E workplace cohorts (opt-in).
2. Resource focus: posture sensing firmware; haptic nudge ladder; localization for commute patterns (from D1/D2).
3. Partnership types: mobility operators (pilot access), corporate wellness programs, privacy counsel (D6 alignment).
4. Mitigations: nudge fatigue → cap ≤3/day + adaptive scheduling; privacy sensitivity → on-device processing + transparent consent flow; supply risk → clip form with standard fasteners.

Participant reaction/steer:

"Good. Specify week-1 differentiators we can A/B in alpha, and how to judge them."

Turn 6 – Exploitation (Week-1 differentiators)

(*continued on next page*)

(*continued*)

Participant #022
Prompt:
"List three differentiators for alpha and how to test each in week 1. Metrics must be in-product behavioral (no surveys beyond a single in-app Likert). Test design stays internal to product."
AI response:
1. Silent haptic 'nudge ladder' (pulse → buzz): *Test:* ladder vs single-pulse cohorts; track adherence % and nudge dismiss-rate. 2. Commute-mode detection (standing/vehicle cues): *Test:* on vs off; compare session starts/commute hour and nudges/hour. 3. Desk-angle check (on-device): *Test:* enabled vs disabled; capture relevance taps (Likert 1–5) and manual snoozes.
Alpha success gate: 2/3 differentiators improve their primary metric by ≥ 10 % over control within week 1.
Participant reaction/steer:
"Lock these. If week-1 gates clear, we'll expand pilots to a second Tier-1 city per D1 transit patterns."

Data availability

Data will be made available on request.

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