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How Does AI Augment Entrepreneurial Opportunity Recognition: A Multiple Case Study from a Chinese Science Park

Xiaoping Wang*

Lijiang Tus-Holdings Incubator Industry Co., Ltd. Lijiang, China

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Corresponding Author
Xiaoping Wang*
Email: 490909669@qq.com

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Abstract

Despite growing scholarly interest in the intersection of artificial intelligence and entrepreneurship, the cognitive mechanisms through which AI tools shape entrepreneurial opportunity recognition remain empirically underexplored. This study addresses that gap through a qualitative multiple case study of eight early-stage ventures incubated at the Tsinghua University Science Park Yunnan Branch, a regional innovation hub in non-metropolitan China. Drawing on in-depth interviews, venture documents, and incubator records, and guided by cognitive load theory and the human-AI complementarity framework, we identify four themes that together describe how AI enters and reconfigures the opportunity recognition process. First, AI functions as cognitive scaffolding by reducing the extraneous informational load that crowds out deliberate judgment. Second, AI engagement transforms opportunity recognition from a moment of individual discovery into an iterative, dialogic construction process in which prompt quality serves as a critical mediating variable. Third, prior domain knowledge moderates the quality of human-AI engagement: founders with deeper expertise use AI critically and productively, while those with limited domain experience risk cognitive anchoring to AI-generated frames. Fourth, locally embedded tacit knowledge — knowledge of community dynamics, informal networks, and place-specific institutional logics — constitutes an irreducible human contribution that AI tools cannot replicate. These findings extend cognitive entrepreneurship theory into the human-AI era, specify the cognitive load mechanism through which AI augmentation operates, and theorize a form of human-AI boundary that is particularly salient in non-metropolitan and institutionally informal innovation contexts. Practical implications are drawn for entrepreneurs, incubator managers, and regional innovation policymakers.

Keywords
AI-augmented decision-making; Entrepreneurial opportunity recognition; Cognitive load; Human-AI complementarity; Multiple case study; Chinese science park

1. Introduction

The past three years have witnessed a fundamental shift in how entrepreneurs engage with information. Generative AI tools — from large language models to AI-powered market intelligence platforms — have moved rapidly from the periphery of business practice to the center of early-stage venture activity. A 2023 McKinsey survey found that half of organizations globally had integrated AI into at least one core function (McKinsey & Company, 2023), while in China's innovation ecosystem, AI-related enterprises now number approximately 2,200 in Beijing alone, representing nearly 40% of the national total (Beijing Municipal Commission of Development and Reform, 2024). Within this landscape, science parks have emerged as particularly fertile ground for observing AI adoption in real time: Zhongguancun Science Park, for instance, hosts nearly 22,000 high-tech companies, with an average of 90 new ventures launched daily (Zhongguancun Science Park, 2023). For the entrepreneurs navigating these environments, AI is no longer a distant abstraction — it is an active participant in the decisions they make, including one of the most consequential decisions of all: identifying which opportunities are worth pursuing.

Opportunity recognition has long occupied a privileged position in entrepreneurship scholarship. Since Shane and Venkataraman's (2000) foundational framing of entrepreneurship as the examination of how, by whom, and with what effects opportunities are discovered, evaluated, and exploited, researchers have made considerable progress in understanding the cognitive mechanisms behind this process. Prior knowledge shapes what entrepreneurs see (Shane, 2000), entrepreneurial alertness sensitizes individuals to value-creating possibilities others overlook (Kirzner, 1997), and pattern recognition allows experienced founders to read weak signals in noisy information environments (Baron, 2006). What this body of work largely assumed, however, is that the entrepreneur is the singular cognitive agent at work — scanning the environment, processing information, and ultimately arriving at a judgment through their own mental resources. That assumption is now being tested in the real world every day, as entrepreneurs increasingly offload portions of that cognitive work to AI.

Despite the speed at which practice has changed, scholarship has been slower to follow. Two notable gaps persist in the literature. First, the extensive body of work on entrepreneurial cognition — including seminal contributions on prior knowledge, alertness, and heuristic reasoning — has yet to seriously grapple with what happens when an AI system becomes an active interlocutor in the opportunity recognition process. The cognitive models relied on were developed to describe an individual mind working on an individual problem, and they do not straightforwardly extend to contexts where a significant portion of information retrieval, synthesis, and pattern generation is handled by a machine. Second, while a growing stream of research on human–AI collaboration has produced important insights into how AI augments decision-making in organizational settings (Brynjolfsson et al., 2023), this work has largely focused on structured, well-defined tasks — customer service interactions, coding assignments, medical diagnosis support — rather than the ambiguous, open-ended, high-stakes environment in which early-stage entrepreneurs operate. The specific question of how AI reshapes the cognitive process of recognizing a business opportunity has not, to date, been the subject of sustained empirical inquiry.

This study addresses these gaps through a qualitative multiple case study conducted within a Chinese science park incubator setting. Drawing on in-depth interviews with founders across eight early-stage ventures that vary in their depth of AI tool use and in the outcomes of their opportunity recognition efforts, two research questions were proposed. First: how do entrepreneurs use AI tools in the process of identifying and evaluating business opportunities? Second: through what cognitive mechanisms does AI engagement shape the quality and character of that recognition process? By examining these questions in a naturalistic setting — where founders are using AI not in a laboratory experiment but in the actual daily work of building a company — this study aims to offer a richer and more ecologically valid account than experimental or survey-based approaches could provide.

The study makes several contributions. Theoretically, it extends the cognitive entrepreneurship tradition into the domain of human–AI collaboration, proposing that AI tools function not merely as information sources but as active cognitive partners that alter the structure and experience of opportunity recognition itself. It also speaks to the cognitive load literature (Sweller, 1988) by exploring whether and how AI intervention reshapes the distribution of cognitive effort during the recognition process. Methodologically, it contributes a deeply contextual account of AI use in entrepreneurial cognition, grounded in a Chinese science park environment that is simultaneously globally significant and underrepresented in the scholarly literature. Practically, the findings carry implications for entrepreneurs seeking to use AI without becoming dependent on it, for incubator managers designing AI literacy programs, and for policymakers working to ensure that China's AI entrepreneurship ecosystem develops in ways that enhance rather than erode human judgment.

2. Literature Review

2.1 Opportunity Recognition Through a Cognitive Lens

The question of why some individuals recognize business opportunities while others, facing identical information environments, do not has occupied entrepreneurship scholars for decades. The most influential answer to this question traces back to Shane and Venkataraman's (2000) foundational framing, which positioned entrepreneurship as the study of how opportunities to create goods and services are discovered, evaluated, and exploited — and more specifically, why that process unfolds differently across individuals. Their work, and Shane's (2000) companion piece on prior knowledge, established a durable consensus: what a person already knows shapes what they are able to see. Individuals carry idiosyncratic information corridors — accumulated experience in particular industries, technologies, or markets — that sensitize them to value-creating possibilities others simply cannot perceive. The practical implication is that opportunity recognition is never random; it is systematically structured by the cognitive resources a person brings to a given situation.

The cognitive tradition that followed this foundational work has progressively elaborated the mechanisms through which recognition actually occurs. Baron (2006) proposed that experienced entrepreneurs engage in pattern recognition, connecting disparate signals in their environment into coherent configurations that resemble previously encountered opportunity structures. This process draws on mental schemas built through prior experience and does not require systematic deliberation: entrepreneurs often describe recognizing an opportunity as a moment of sudden clarity rather than the outcome of methodical analysis. Kirzner's (1997) earlier concept of entrepreneurial alertness speaks to the same phenomenon from a different angle, emphasizing a heightened sensitivity to previously unnoticed profit possibilities — a cognitive stance of active readiness to notice what others overlook.

Grégoire et al. (2010) pushed the cognitive account further by examining not just what factors facilitate recognition, but the specific cognitive process through which it occurs. Using think-aloud protocols with executive entrepreneurs, they found that recognizing an opportunity involves structural alignment — a process of identifying deep relational similarities between a new technology or context and familiar domains, rather than merely matching surface features. This work was significant because it opened the black box of the recognition process itself, revealing that the cognitive work involved is considerably more effortful and structurally complex than the alertness or pattern recognition accounts had implied. Opportunity recognition, in this view, is less a matter of passive noticing and more a form of active analogical reasoning that requires substantial cognitive engagement.

More recent scholarship has continued to enrich this picture, particularly by taking seriously the role of affect, social context, and environmental dynamism. Zhu et al. (2025) demonstrate that entrepreneurial passion influences recognition through its effects on alertness, and that this relationship is modulated by environmental conditions — entrepreneurs operating in more dynamic environments derive greater recognition benefits from passion for inventing and founding. Research on Chinese university entrepreneurs has similarly highlighted the interplay between implicit cognitive capacities, such as environmental intelligence and entrepreneurial drive, and explicitly developed skills in structuring and evaluating emerging opportunities (Fang et al., 2024). These more recent contributions underscore a growing consensus that opportunity recognition is neither purely individual nor purely rational — it is an affective-cognitive process embedded in a specific context and shaped by the resources, experience, and situational demands the entrepreneur brings to bear.

Taken together, this literature rests on a premise that, while rarely stated explicitly, runs through virtually every contribution: the entrepreneur is the singular cognitive agent at work. The mental schemas, prior knowledge, alertness, and analogical reasoning capacities that drive opportunity recognition are all properties of an individual mind. What happens when a significant portion of that cognitive work is offloaded to, or co-produced with, an AI system? The frameworks developed over three decades of cognitive entrepreneurship research do not readily answer that question, and it is precisely this gap that motivates the present study.

2.2 Cognitive Load Theory and Entrepreneurial Decision-making

Understanding why AI might matter for opportunity recognition requires a theoretical account of the cognitive demands the process imposes. Cognitive load theory, originally developed by Sweller (1988) in the context of instructional design, provides exactly that. The theory begins from a straightforward premise: the human working memory system has a fixed and relatively small capacity. When the demands of a task exceed that capacity, cognitive performance degrades — people make more errors, rely more heavily on heuristics, and struggle to integrate new information with existing knowledge. The theory distinguishes three types of cognitive load: intrinsic load, which reflects the inherent complexity of the task itself; extraneous load, which arises from the way information is presented or the context in which processing occurs; and germane load, which reflects the cognitive effort productively invested in schema formation and deep understanding. Crucially, these three types of load compete for the same limited working memory resource, meaning that reductions in extraneous load free up capacity for the germane cognitive work that actually drives learning and judgment quality.

The early entrepreneurship decision-making environment is a particularly demanding one from a cognitive load perspective. Founders operating in the early stages of venture development must simultaneously monitor market signals, evaluate competitive dynamics, assess customer needs, and form judgments about feasibility — often under severe time pressure and with limited access to reliable information. The volume and complexity of market information alone would substantially elevate extraneous load, crowding out the higher-order cognitive processing needed to make sound opportunity assessments. Consistent with this view, research on managerial and entrepreneurial decision-making has documented a reliable pattern: when cognitive demands are high, decision-makers default to simpler, more heuristic-based reasoning strategies that reduce deliberative effort but also reduce judgment accuracy (Sweller et al., 1998). In entrepreneurial contexts specifically, this manifests in overconfidence, confirmation bias, and premature commitment to opportunity assessments that later prove unsound.

Two more recent developments are particularly relevant here. First, Arnold et al. (2023) conducted a comprehensive review of information overload research across disciplines, documenting that the cognitive and affective consequences of excessive information — including anxiety, mental fatigue, and avoidance behaviors — are now substantially amplified by the digital information environment in which most decision-makers operate. Entrepreneurs embedded in fast-moving technology ecosystems, where the volume and velocity of relevant market information has grown dramatically, face precisely this kind of structural overload. Second, Fossen et al. (2024), in a major survey of the AI-entrepreneurship nexus published in Foundations and Trends in Entrepreneurship, identify AI's capacity to reduce uncertainty through prediction as one of its most significant potential contributions to entrepreneurial decision-making. AI systems can process information at scales and speeds that far exceed human working memory capacity, potentially absorbing a large portion of the extraneous load that currently burdens entrepreneurs during the opportunity recognition process.

The theoretical connection between cognitive load theory and AI-augmented opportunity recognition is therefore relatively direct: if AI tools can effectively handle the information-intensive, low-judgment components of market scanning and opportunity screening, they may free up working memory resources for the deeper, schema-building cognitive work that genuine opportunity evaluation requires. Whether this theoretical possibility materializes in practice — and under what conditions — is an empirical question that existing research has not yet answered. The present study takes up that question directly, embedding it in the real-world context of early-stage ventures operating within a Chinese science park incubator setting where AI tools are already in active use.

2.3 AI-augmented Decision-making: From Automation to Augmentation

The literature on human–AI collaboration has developed rapidly over the past decade, largely in response to a persistent debate about whether AI replaces or enhances human judgment. An early and still influential contribution by Jarrahi (2018) reframed this debate by arguing for the essential complementarity of humans and AI in organizational decision-making. Drawing on the distinction between analytical and intuitive reasoning, Jarrahi proposed that AI's computational superiority makes it well-suited to managing complexity — processing large volumes of structured information and identifying patterns within it — while humans retain a comparative advantage in navigating uncertainty and equivocality, where data is incomplete, contextually ambiguous, or emotionally laden. The implication is that the most effective arrangements are not those that maximize AI's role, but those that deploy humans and AI in the tasks each handles best.

This augmentation framing gained considerable traction in entrepreneurship scholarship with Shepherd and Majchrzak's (2022) influential Journal of Business Venturing paper, which proposed that AI and entrepreneurship together constitute a "super tool" whose potential has barely been explored. The paper identifies a range of entrepreneurship topics — including opportunity recognition, pattern detection, and uncertainty reduction — where AI's augmentation potential is particularly significant. Critically, Shepherd and Majchrzak conceptualize AI not as an autonomous decision-maker but as a capability amplifier, extending what entrepreneurs are able to perceive and process without displacing the fundamentally human acts of judgment, commitment, and action. This framing aligned closely with broader developments in the human–AI collaboration literature, which has increasingly emphasized that complementary team performance — a level of combined output that neither humans nor AI could achieve independently — is the appropriate benchmark for evaluating human–AI systems, even as it acknowledges how rarely such complementarity is achieved in practice (Hemmer et al., 2023).

Generative AI has added a new dimension to this picture. Unlike earlier AI systems that primarily retrieved, sorted, or classified existing information, large language models can generate novel content, synthesize across disparate domains, and engage in extended dialogue — capabilities that are directly relevant to the kind of open-ended, speculative reasoning that characterizes early-stage opportunity identification. Brynjolfsson et al.'s (2023) empirical work documents that generative AI tools substantially raise the performance floor of less experienced workers by giving them access to capabilities previously available only to more skilled colleagues. This finding has direct implications for entrepreneurial contexts: it suggests that AI may be especially consequential for early-stage founders who lack deep domain expertise, potentially enabling them to engage in more sophisticated opportunity analysis than their prior knowledge alone would allow.

What remains underexplored, however, is the process by which this augmentation unfolds in real entrepreneurial practice. Existing empirical work has largely been conducted in structured, well-defined task environments — customer service, professional writing, software coding — that differ substantially from the ambiguous, self-directed, judgment-intensive conditions under which entrepreneurs seek to identify opportunities. Giuggioli and Pellegrini (2023), in a systematic review of AI as an entrepreneurial enabler, identify opportunity recognition as a domain of high potential AI impact, yet note that the actual cognitive mechanisms through which AI reshapes this process remain empirically unexamined. This gap is the departure point for the present study.

2.4 Theoretical Gap and Analytical Framework

Drawing together the three streams reviewed above, a coherent theoretical story begins to emerge — but with a critical missing chapter. Cognitive entrepreneurship scholarship establishes that opportunity recognition is a cognitively demanding process, shaped by prior knowledge, alertness, pattern recognition, and structural alignment, and that it places substantial demands on a working memory system with finite capacity. Cognitive load theory proposes that when extraneous cognitive burdens are reduced, higher-quality germane processing becomes possible. And the human–AI collaboration literature suggests that AI systems are increasingly capable of absorbing precisely those information-intensive, pattern-matching tasks that generate the highest extraneous load in information-rich environments. Together, these three bodies of work point toward a coherent hypothesis: that AI tools, deployed well, should enhance the quality of entrepreneurial opportunity recognition by relieving cognitive burden and enabling deeper, more reflective judgment.

What is missing is empirical evidence of whether and how this process actually unfolds. The studies reviewed here were built on assumptions of individual cognition, task-defined AI environments, and organizational rather than entrepreneurial settings. None situates the question in the naturalistic context of early-stage ventures operating within a real entrepreneurship support ecosystem. The analytical framework guiding this study therefore maps three interacting elements: the information environment facing early-stage entrepreneurs (characterized by high complexity and uncertainty); AI tool use as a moderating cognitive mechanism (potentially reducing extraneous load and enabling iterative opportunity construction); and the entrepreneur's prior knowledge as a filter that shapes both the quality of AI engagement and the ultimate character of the opportunity recognition process. This framework is depicted in Figure 1, and the following methodology section describes how it was empirically investigated.

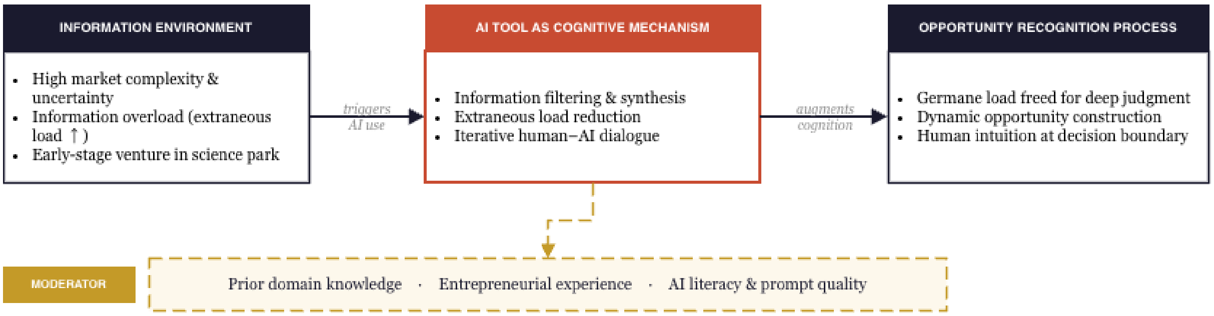

Figure 1. Analytical framework: AI-augmented entrepreneurial opportunity recognition

3. Methodology

3.1 Research Design

This study employs a qualitative multiple case study design. The choice of case study as the primary research strategy is driven by three interlocking considerations that together make it the most appropriate design for the questions at hand.

First, both research questions are process-oriented and ask "how" rather than "how many." RQ1 asks how entrepreneurs use AI tools in the opportunity recognition process; RQ2 asks how AI engagement affects the cognitive experience of that process. Yin (2018) is explicit that case study logic is best suited to "how" and "why" questions about contemporary phenomena unfolding in real-world contexts — precisely the conditions that define this study. Survey or experimental designs could tell us whether AI use is associated with better outcomes, but they cannot reveal the cognitive mechanisms connecting the two.

Second, AI-augmented opportunity recognition is a phenomenon that is both recent and theoretically underspecified. When the goal is to develop theory rather than test it, Eisenhardt (1989) argues that case comparison is among the most productive strategies available: by systematically examining variation across cases, researchers can identify patterns that suggest theoretical propositions and begin to specify the conditions under which they hold. The present study is explicitly exploratory and theory-building in orientation.

Third, opportunity recognition is a cognitively and contextually embedded process that cannot be adequately understood in abstraction from the specific organizational, relational, and cultural environment in which it occurs. The case study's defining strength — its capacity to preserve contextual richness while still enabling cross-case comparison — is therefore not incidental to the research design but central to it. Qualitative depth is not a concession to data constraints; it is a methodological requirement given what the study is trying to learn.

The study draws on semi-structured interviews as its primary data source, supplemented by internal incubator documents and the first author's direct observational knowledge as the Yunnan Branch director. This triangulated approach follows Miles et al.'s (2020) recommendation that qualitative case research draw on multiple evidence streams to strengthen construct validity. Data collection and preliminary analysis proceeded iteratively across a five-month fieldwork window, with emerging insights informing refinements to the interview protocol in later rounds.

3.2 Research Setting

The empirical setting is the Tsinghua University Science Park Yunnan Branch, a regional division of the K-Stack incubator network operating across multiple sites in Yunnan Province. Established to extend innovation infrastructure into non-metropolitan regions, the Yunnan Branch supports early-stage ventures in technology-intensive sectors, providing mentorship, workspace, and access to the broader Tsinghua network.

This setting is theoretically appropriate for three reasons. First, it concentrates early-stage ventures at the precise stage of development — pre-product-market-fit, pre-Series A — where opportunity recognition is most consequential and most cognitively demanding. Second, the Yunnan Branch hosts ventures operating in a distinctive regional environment characterized by ethnic minority communities, cross-border trade with Southeast Asia, and informal economic networks that are not well captured by national-level market data. This creates conditions under which the limits as well as the capabilities of AI tools become visible — a theoretically productive feature, not a limitation. Third, the first author's role as Branch director provides privileged access to founders, internal records, and the daily dynamics of incubated ventures, enabling the kind of deep contextual familiarity that qualitative case research requires.

The insider position carries potential risks as well as advantages. Founders may have moderated their accounts in light of the relationship, and the first author may have brought prior interpretive commitments to the data. These risks were managed through a reflexivity journal maintained throughout fieldwork, independent coding by a second researcher, and member checking with four informants, as described in Section 3.4.

3.3 Case Selection and Sample Composition

Cases were selected through theoretical sampling — a purposive strategy in which cases are chosen not for statistical representativeness but for their capacity to illuminate the theoretical question (Eisenhardt, 1989; Yin, 2018). The sampling logic followed a 2×2 matrix defined by two dimensions: depth of AI tool use (high versus low) and opportunity recognition outcome (successfully commercialized versus stalled or abandoned). This design was chosen deliberately to ensure both within-cell replication — multiple cases making similar theoretical arguments — and cross-cell contrast — cases that challenge, complicate, or bound the emerging theory. The resulting matrix is shown in Table 1.

Table 1. Theoretical sampling matrix

	Opportunity Recognition: Success	Opportunity Recognition: Stalled
High AI Use Depth	Case A, Case B, Case C (n = 3)	Case D (n = 1)
Low AI Use Depth	Case E, Case F (n = 2)	Case G, Case H (n = 2)

The asymmetric distribution across cells is intentional. The high-AI-use/success cell contains three cases because it is the primary site of theoretical interest: it is here that the mechanisms of AI-augmented opportunity recognition are most fully expressed and most varied across individuals. The high-AI-use/stalled cell contains only one case, but that case — the hospitality tech venture (Case D) — plays a critical analytical role as a "negative case" (Miles et al., 2020): its failure, despite heavy AI use, reveals the conditions under which AI engagement does not produce effective opportunity recognition, thereby bounding the theory.

The two low-AI-use cells provide the essential comparative baseline. Cases E and F demonstrate that successful opportunity recognition is possible without AI — preserving the theoretical space for prior knowledge and local relational networks as independent drivers — while Cases G and H illustrate the cognitive costs of operating in information-dense environments without either AI assistance or substantial domain expertise.

An initial pool of ventures was screened against three entry criteria: established within three years at the time of data collection; documented evidence of an AI tool use decision (either to use or to consciously not use AI in business development); and founding team willing to participate in multi-session interviews with audio recording consent. AI use depth was assessed through an initial screening interview and, where available, usage logs or shared chat histories. Opportunity recognition outcome was assessed through incubator milestone records and, where applicable, independent verification of reported commercialization. All ventures were anonymized; cases are referred to by letter codes throughout the paper to protect participant confidentiality. The final sample of eight ventures is described in Table 2.

Table 2. Case characteristics

Case	Sector	Founder Type	AI Use	Domain Exp.	Outcome
Case A	Cross-border agri-trade	Serial	High	5 yrs+	Success
Case B	Cultural content SaaS	First-time	High	3 yrs	Success
Case C	Intangible heritage	First-time	High	N/A*	Success
Case D	Hospitality tech SaaS	First-time	High	<1 yr	Stalled
Case E	Regional food brand	Serial	Low	15 yrs	Success
Case F	Cross-border logistics	Serial	Low	7 yrs	Success
Case G	Agri-tech traceability	First-time	Low	<1 yr	Stalled
Case H	Health tourism platform	First-time	Low	<1 yr	Stalled

Note: Case C founder's relevant prior knowledge is cultural and community-based rather than commercial domain experience.

3.4 Data Collection and Analysis

Data were gathered from three complementary sources. The primary source was semi-structured interviews with each venture's founding entrepreneur and, where applicable, one additional core team member, yielding sixteen interviews in total. Interviews lasted between 60 and 90 minutes, were conducted in Mandarin, and followed a four-module protocol: AI tool adoption history and habitual usage patterns; retrospective accounts of specific opportunity recognition episodes; phenomenological descriptions of the cognitive experience during those episodes; and founders' own assessments of decision quality and subsequent outcomes. All interviews were audio-recorded and professionally transcribed.

The secondary source comprised internal venture documents — business plans, meeting records, product iteration logs, and AI-generated outputs that informants retained and consented to share. These served both as corroborating evidence and as interview prompts, anchoring abstract cognitive accounts in concrete textual artifacts. The third source drew on the first author's insider access to incubator records: intake assessments, mentoring session notes, and milestone evaluation reports provided an independent check on founders' self-reported accounts.

Analysis followed Eisenhardt's (1989) two-stage procedure. Within-case analysis was conducted first, producing a standalone narrative for each venture that preserved contextual richness and traced the sequence of AI engagement across the opportunity recognition process. Cross-case analysis followed only after all eight narratives were complete, with the goal of identifying patterns that recurred across cases and divergences that demanded theoretical explanation. NVivo 14 supported systematic coding across the full corpus through three iterative rounds: open coding to surface descriptive categories, focused coding to consolidate categories against the theoretical framework, and theoretical coding to map relationships between categories.

To safeguard analytical rigor, a second researcher coded a 20% subsample of transcripts independently, achieving a Cohen's Kappa of 0.84 — exceeding the 0.80 threshold conventionally treated as indicative of adequate reliability (Landis & Koch, 1977). Member checking was conducted with four informants, who reviewed summary case narratives and confirmed the interpretations. The first author's reflexivity journal, maintained throughout fieldwork and analysis, documented observational influences and emerging assumptions, and was reviewed jointly with the second researcher at key analytical junctures. All participants provided informed consent and were assured of anonymity prior to data collection.

4. Findings

Cross-case analysis of the eight ventures yielded four themes that together describe the cognitive landscape of AI-augmented opportunity recognition in an early-stage incubator setting. These themes emerged inductively from the data rather than being imposed from the theoretical framework, though their resonance with prior theory is noted where relevant. The four themes follow a logical progression: how AI is used to manage information (Theme 1), how that use reshapes the nature of the recognition process itself (Theme 2), what moderates the quality of AI engagement (Theme 3), and where the boundary of AI contribution lies (Theme 4).

4.1 AI as Cognitive Scaffolding: Reducing the Burden of Information Overload

Across the high-AI-use cases, a consistent pattern emerged in which founders systematically delegated information-intensive tasks to AI tools, freeing cognitive resources for higher-order judgment. Rather than using AI sporadically or experimentally, Cases A, B, and C had each developed stable routines in which AI handled the early-stage work of market scanning, competitive mapping, and demand estimation — tasks that founders in the low-AI-use group described as cognitively exhausting.

The founder of the cross-border agri-trade venture (Case A) articulated this most directly:

"Before I started using AI properly, just reading through competitor pricing data and export reports would take me a week. Now I get a structured picture in a day, and I can spend the rest of the week actually thinking about what it means."

This account captures the essential mechanism: the reduction of extraneous cognitive load does not itself produce insight, but it creates the conditions under which deeper processing becomes possible.

The contrast with the low-AI-use stalled cases was sharp. The founder of the agri-tech traceability venture (Case G) described a qualitatively different experience of the same information environment:

"There was so much to read — policy documents, industry reports, what competitors were doing overseas. I never felt like I had a full picture. I was always reacting to the last thing I

read."

This account is consistent with the information overload dynamic identified by Arnold et al. (2023): when extraneous load is not managed, decision-makers default to reactive, heuristic-based processing rather than deliberate evaluation.

Notably, the two low-AI-use success cases (E and F) do not undermine this pattern — they complicate it productively. Both founders drew on deep prior knowledge to perform their own cognitive filtering, effectively substituting domain expertise for AI-assisted information management. The founder of the regional food brand (Case E) acknowledged the cost of this approach:

"I eventually got to the right answer, but it took me almost eight months of going back and forth before I felt confident. Someone with the right tools probably could have gotten there in two."

This retrospective suggests that AI scaffolding and prior knowledge are partially substitutable mechanisms for managing cognitive load, but that the former offers significant efficiency advantages when available and used well.

The exception within the high-AI-use group, the hospitality tech venture (Case D), illustrates that volume of AI use does not equate to effective cognitive scaffolding. This founder used AI tools frequently but did not use them to systematically structure the information environment; instead, AI outputs were consumed in isolated queries without synthesis or iteration. The result was not reduced cognitive load but a different form of overload — an accumulation of unintegrated data points that gave the appearance of comprehensive research without its substance.

4.2 Opportunity as Construction: Iterative Human-AI Dialogue and the Role of Prompt Quality

A second and theoretically significant pattern concerned the nature of the opportunity recognition process itself. In the successful high-AI-use cases, opportunity recognition was not experienced as a moment of discovery — a sudden perception of a pre-existing gap — but as an iterative construction that unfolded across multiple rounds of human-AI dialogue. This distinction has direct implications for how the field theorizes the process.

The cultural content SaaS venture (Case B) provided the most detailed account of this iterative dynamic. The founder described a sequence that began with broad market queries and progressively narrowed through a series of increasingly specific prompts:

"The first answer AI gave me was about as useful as a textbook chapter — accurate but generic. It was only when I started pushing back, asking it to assume different customer profiles, to compare scenarios, that things got interesting. The opportunity I ended up pursuing was probably the fifteenth version of the idea, not the first."

This account resonates with Shepherd and Majchrzak's (2022) characterization of AI as a capability amplifier: the amplification is not automatic but requires deliberate human direction.

Prompt quality emerged across these cases as the critical variable mediating the relationship between AI tool use and recognition quality. Founders who entered interactions with a clear conceptual frame — informed by domain knowledge, prior experience, or a specific hypothesis to be tested — consistently elicited more useful outputs and engaged in more productive iteration. The intangible heritage digitization founder (Case C) reflected:

"I know what questions matter in this space. So I know how to ask. If I didn't know the field, I don't think AI would help me that much — I'd just be asking the wrong things in more sophisticated ways."

This observation points to a recursive relationship between prompt quality and prior knowledge that is elaborated further in Theme 3. For the present purposes, it establishes that the iterative construction of opportunity is not a property of AI tools per se, but of a specific mode of human-AI engagement characterized by goal-directed, reflective dialogue.

The stalled hospitality tech case (Case D) again provides the critical contrast. This founder's AI interactions were characterized by single-shot queries — questions asked once, answers accepted without challenge. There was no iteration, no scenario comparison, no deliberate refinement of the question in light of the answer received:

"I asked whether there was a market for smart property management in Yunnan's guesthouse sector. The AI said yes, the market was growing. That felt like enough."

The opportunity that emerged from this interaction was not constructed through dialogue but imported wholesale from an AI output — a fundamentally different cognitive process with fundamentally different epistemic status.

4.3 Prior Knowledge as Cognitive Filter: Moderating the Quality of AI Engagement

The third theme concerns the conditions under which AI engagement produces high-quality opportunity recognition. Across the eight cases, prior domain knowledge emerged as the central moderating variable — shaping not only whether founders used AI effectively, but what kind of cognitive relationship they formed with AI outputs.

Founders with deep domain expertise consistently approached AI as a hypothesis-testing tool rather than an authority. The cross-border agri-trade founder (Case A), drawing on five years of direct market experience, described a reflexive skepticism toward AI-generated market data:

"When AI gives me a number, my first question is: where does that come from? I've been in this industry long enough to know when something doesn't add up. I use AI to challenge my assumptions, not to replace them."

This critical stance transformed AI from an information source into a cognitive sparring partner — an interlocutor that generates positions to be evaluated rather than conclusions to be adopted.

The pattern was markedly different among first-time founders with limited domain experience. The health tourism platform founder (Case H), entering a sector they knew primarily through secondary research, described a relationship with AI outputs characterized by acceptance rather than interrogation:

"I didn't really have a basis to question what it was telling me. It seemed well-reasoned. I trusted it."

The consequence — a fundamental misreading of the target customer's digital behavior and willingness to pay — illustrates what might be termed cognitive anchoring: the uncritical adoption of AI-generated frames that then constrain subsequent thinking.

The intangible heritage case (Case C) introduces a productive complication. This founder lacked formal business training but possessed an unusually deep store of local cultural knowledge — an implicit understanding of community dynamics, craft traditions, and the informal protocols governing access to indigenous design assets. This form of prior knowledge, while domain-specific rather than commercially oriented, proved highly effective as a filter for AI outputs:

"AI can tell me that the market for ethnic design licensing is growing. But it can't tell me whether a particular community will agree to have their patterns used commercially, or what the right way to approach that conversation is. That's what I know."

This case suggests that the moderating role of prior knowledge extends beyond commercial domain expertise to encompass locally embedded, tacit forms of knowing that are particularly salient in non-metropolitan innovation contexts.

4.4 The Human-AI Boundary: Local Tacit Knowledge as the Irreducible Human Contribution

The fourth theme addresses not the mechanisms of AI augmentation but its limits. Across all eight cases — including those in which AI use was deepest and most effective — founders consistently identified a category of judgment that AI could not perform: the reading of local context, relational dynamics, and culturally specific logics that shape whether a commercially viable opportunity is also a practically accessible one in Yunnan's distinctive entrepreneurial environment.

This boundary was most vividly articulated in the contrast between Cases C and D. The intangible heritage founder (Case C), whose deep embeddedness in local community life was central to their success, reflected:

"AI told me the market existed. It couldn't tell me that the village elder I needed to speak to first would only take meetings after the harvest festival, or that the way I framed the proposal had to reflect the community's understanding of cultural stewardship, not commercial licensing. That's not in any dataset."

The hospitality tech founder (Case D), whose failure was in significant part a failure of local contextual understanding, drew an implicit contrast:

"I assumed Yunnan's guesthouse market would behave like the platforms I'd read about in Hangzhou or Chengdu. The data supported that assumption. The reality didn't."

The two low-AI-use success cases reinforce this finding from a different angle. Both founders in Cases E and F attributed a significant portion of their recognition success to local relational networks — the informal intelligence that flows through industry associations, supplier relationships, and long-standing personal ties. This form of market knowledge is not captured in the structured information environments that AI tools are designed to process. As the cross-border logistics founder (Case F) observed:

"The opportunity I found wasn't in any report. It came from a conversation at a trade dinner where someone mentioned, almost in passing, that a particular border crossing had just

changed its inspection protocols. That's how this business works."

Taken together, these accounts converge on a consistent characterization of the human-AI boundary in this context: AI tools are highly effective at processing structured, codifiable information at scale, but they are blind to the relational, cultural, and situationally embedded knowledge that determines whether a market opportunity is genuinely accessible to a particular founder in a particular place. In Yunnan's innovation ecosystem, where ethnic minority communities, non-standard regulatory implementation, and dense informal economic networks shape the opportunity landscape in ways that no training dataset fully captures, this boundary is not a marginal limitation but a constitutive feature of the entrepreneurial environment.

The four themes together describe a coherent cognitive picture. AI reduces the informational burden that crowds out deliberate judgment (Theme 1), and when engaged iteratively, enables a constructive rather than merely receptive mode of opportunity recognition (Theme 2). The quality of this engagement is moderated by the depth and character of founders' prior knowledge (Theme 3), and the entire process operates within a boundary defined by the irreducibly local, tacit knowledge that AI cannot encode (Theme 4). This picture provides the empirical foundation for the theoretical discussion that follows.

5. Discussion

The four themes reported in the preceding section collectively describe how AI tools enter, reshape, and are bounded by the cognitive process of entrepreneurial opportunity recognition. This section draws out the theoretical implications of those findings, considers their practical significance, and identifies the study's limitations alongside directions for future inquiry.

5.1 Theoretical Contributions

Extending cognitive entrepreneurship into the human-AI era

The foundational tradition of cognitive entrepreneurship — from Shane and Venkataraman's (2000) prior knowledge thesis through Baron's (2006) pattern recognition account and Grégoire et al.'s (2010) structural alignment model — was built on a premise that is now being tested in practice: the entrepreneur is the singular cognitive agent at work. The present findings challenge this premise empirically and invite a theoretical reformulation. In the cases examined here, opportunity recognition is not the product of an individual mind operating on an information environment; it is the product of a mind operating in conjunction with an AI system that absorbs, synthesizes, and generates portions of the cognitive work. Theme 1 establishes that AI reduces the extraneous cognitive load that previously consumed resources needed for genuine opportunity evaluation (Sweller, 1988; Arnold et al., 2023). Theme 2 demonstrates that the recognition process itself changes in character — from a moment of discovery or pattern recognition to an iterative, dialogic construction. These are not marginal modifications to existing models; they suggest that the cognitive architecture of opportunity recognition is fundamentally different when AI is present, and that frameworks developed to describe solo human cognition require extension rather than mere amendment.

The most productive direction for that extension, this study suggests, is to treat opportunity recognition as a distributed cognitive process in which human and AI make qualitatively different contributions. The human entrepreneur supplies goal direction, domain-based evaluation criteria, contextual judgment, and the tacit local knowledge that shapes which opportunities are practically accessible — the distinctly human capabilities that Shepherd and Majchrzak (2022) identify as irreducible even as AI augments other aspects of entrepreneurial activity. The AI system supplies information processing at scale, scenario generation, and the synthesis of codifiable market signals. Neither contribution is sufficient alone — Cases E and F demonstrate that prior knowledge without AI can produce successful recognition, but at high efficiency cost; Case D demonstrates that AI without critical human engagement produces recognition that is superficially confident but cognitively ungrounded. The most robust outcomes, seen in Cases A, B, and C, arise from genuine complementarity between the two — consistent with Hemmer et al.'s (2023) finding that human-AI complementarity, when realized, produces outcomes that neither agent achieves independently.

Specifying the cognitive load mechanism

Cognitive load theory (Sweller, 1988) has been applied to entrepreneurial decision-making primarily at the level of general proposition — information overload degrades decision quality — without specifying the mechanisms through which this dynamic plays out or the conditions under which it might be interrupted. The present findings offer that specification. Theme 1 identifies AI-assisted information management as a mechanism for reducing extraneous load in a way that is qualitatively different from prior knowledge-based filtering: rather than requiring years of accumulated experience, it is potentially available to any founder who engages AI tools with sufficient intentionality. The scale and velocity of market information that founders now face — conditions that Arnold et al. (2023) document as substantially amplified by the digital information environment — make this AI-mediated load reduction particularly consequential.

Theme 3, however, introduces a critical qualification: the effectiveness of AI as a load-reduction mechanism is itself moderated by prior knowledge, because the quality of AI engagement — and therefore the quality of the load reduction — depends on the founder's capacity to ask productive questions and critically evaluate the answers. This creates what might be called a recursive dependency: AI is most effective at reducing cognitive load precisely for those founders who need it least, because they have the domain knowledge to use it well. This dynamic stands in partial tension with Brynjolfsson et al.'s (2023) finding that generative AI disproportionately benefits less experienced workers in structured task environments, and highlights the importance of task ambiguity and contextual complexity as boundary conditions for that finding. Opportunity recognition in early-stage ventures is neither structured nor narrowly defined; it is precisely the kind of open-ended, high-uncertainty task where domain knowledge remains the primary determinant of AI engagement quality.

Theorizing the human-AI boundary in non-metropolitan contexts

Jarrahi's (2018) complementarity framework proposes that AI handles analytical complexity while humans handle uncertainty and equivocality — a division of cognitive labor that the present findings broadly support but significantly enrich. Theme 4 identifies a specific form of human contribution that the existing literature has not adequately theorized: locally embedded tacit knowledge. In Yunnan's innovation ecosystem, the opportunity landscape is shaped by ethnic community dynamics, cross-border trade relationships with Southeast Asian markets, non-standard regulatory implementation, and informal economic networks that are not captured in any training dataset. This means that the human-AI boundary is not only a matter of uncertainty versus complexity, as Jarrahi's framework suggests, but also a matter of local versus codifiable knowledge — a distinction with particular salience in non-metropolitan and institutionally informal contexts.

Entrepreneurs whose prior knowledge is constituted by deep embeddedness in local community and relational networks — Case C is the clearest exemplar — can engage AI effectively for what it does well while preserving independent judgment for what it cannot. This finding extends Giuggioli and Pellegrini's (2023) systematic review, which identifies opportunity recognition as a domain where AI's enablement potential is high but empirically underexamined. The present study provides precisely the naturalistic, process-level evidence that review calls for, and does so in a setting — regional China — that is rarely the locus of foundational theorizing in entrepreneurial cognition research. The Yunnan context makes visible a form of tacit knowledge that remains invisible in studies conducted closer to the centers of codified information production.

5.2 Practical Implications

For entrepreneurs, the most direct implication concerns the mode rather than the volume of AI engagement. Case D's failure was not caused by too little AI use but by a fundamentally passive mode of engagement — treating AI as an oracle rather than an interlocutor. The iterative, critical engagement seen in Cases A, B, and C — characterized by deliberate prompt refinement, scenario testing, and willingness to challenge AI outputs — is both a learnable skill and a consequential one. Founders operating in information-dense environments should invest not just in access to AI tools but in developing the prompt literacy and critical evaluation practices that determine whether those tools reduce cognitive load or simply replace one form of information overload with another (Arnold et al., 2023).

For incubator managers, and specifically for the K-Stack Yunnan Branch, the findings suggest two priorities. First, AI literacy training should be designed around the quality of human-AI engagement rather than tool familiarity alone. The founders who used AI most effectively were not those with the most technical sophistication but those with the clearest conceptual frameworks for interrogating AI outputs — a capacity that is more pedagogically tractable than domain expertise. This finding is consistent with Fossen et al.'s (2024) observation that AI's entrepreneurial value is mediated by how entrepreneurs engage with it, not simply by whether they have access to it. Second, the findings highlight the irreplaceable value of local network embeddedness as a complement to AI-based market analysis. Mentorship programs and peer learning structures that help founders build relational and contextual knowledge that AI cannot supply are not peripheral to an AI-enabled incubator's mission; they are structurally central to it.

For policymakers supporting innovation in non-metropolitan regions, the study points to a risk that warrants attention: the potential for AI tools to systematically underweight local contextual knowledge in favor of nationally or internationally aggregated market data. Founders who rely heavily on AI-generated market intelligence without correcting for local specificity — as in Case D — may make investment decisions that are well-supported by codifiable data but poorly calibrated to the actual opportunity environment in which they operate. This concern echoes Fossen et al.'s (2024) caution that AI's capacity to reduce uncertainty through prediction may be unevenly beneficial across entrepreneurial contexts. Policies supporting AI adoption in regional ecosystems should be accompanied by investments in local knowledge infrastructure — community networks, cross-sector advisory relationships, and regional market intelligence platforms — that give entrepreneurs the contextual grounding needed to use AI tools critically rather than credulously.

5.3 Limitations and Future Research

The study's contributions must be read in light of three limitations. First, the single-site design, while conferring depth of contextual knowledge, limits the transferability of the findings. The Yunnan Branch context — non-metropolitan, culturally heterogeneous, cross-border oriented — is theoretically productive but distinctive. Whether the same mechanisms operate in Chinese coastal science parks, in Southeast Asian incubators, or in Western innovation ecosystems remains an open question. Cross-site replication with deliberate variation in regional context would be a valuable next step for both theoretical refinement and boundary condition identification.

Second, the cross-sectional interview design captures founders' retrospective accounts of their opportunity recognition processes but cannot trace the cognitive dynamics of those processes as they unfold. Retrospective accounts are subject to reconstruction bias: founders may narrate their AI engagement more coherently and purposively than it actually was at the time. Longitudinal designs, experience-sampling methods, or protocol-based studies in which founders are observed using AI tools on live tasks — along the lines of Grégoire et al.'s (2010) think-aloud approach — would provide a more granular and less reconstruction-dependent account of the mechanisms identified here.

Third, the first author's insider position, while enabling privileged access, introduces the possibility of social desirability effects in interview responses and interpretive bias in data analysis. The mitigation strategies described in the methodology section — reflexivity journaling, dual coding, member checking — reduce but cannot eliminate these risks, and readers should weigh the findings accordingly.

Future research might pursue three directions. Comparative studies across regional innovation contexts would test whether the salience of locally embedded tacit knowledge as a moderator is distinctive to non-metropolitan settings, or characterizes AI-augmented opportunity recognition more broadly. Longitudinal designs tracking the same founders across multiple recognition episodes would examine whether AI engagement quality evolves with experience and whether the cognitive anchoring risk identified in Theme 3 persists or attenuates as founders develop greater AI literacy. Finally, mixed-methods studies combining the cognitive depth of qualitative inquiry with the statistical reach of survey or experimental designs could test whether the mechanisms proposed here — particularly the moderating role of prior knowledge (Shane, 2000; Baron, 2006) on AI engagement quality — hold across more diverse founder populations and at larger analytical scale.

6. Conclusion

This study set out to examine two questions: how entrepreneurs use AI tools in the process of identifying and evaluating business opportunities, and through what cognitive mechanisms AI engagement shapes the quality and character of that recognition process. The findings, drawn from a qualitative multiple case study of eight early-stage ventures at the Tsinghua University Science Park Yunnan Branch, offer clear answers to both. In response to RQ1, entrepreneurs use AI tools not as passive information repositories but as active cognitive partners — most productively when engagement is iterative, goal-directed, and critically interrogative rather than single-shot and receptive. In response to RQ2, the primary cognitive mechanism is the reduction of extraneous cognitive load: by absorbing the information-intensive work of market scanning and competitive mapping, AI frees working memory for the higher-order, schema-building judgment that genuine opportunity evaluation requires. This mechanism, however, operates conditionally — its effectiveness is moderated by founders' prior domain knowledge, which determines the quality of human-AI engagement, and it reaches a boundary at the edge of locally embedded tacit knowledge that AI tools cannot encode.

These findings advance the field in three ways. First, they extend the cognitive entrepreneurship tradition into the human-AI era by demonstrating that opportunity recognition is no longer accurately described as a solo cognitive act: it is increasingly a distributed process in which human judgment and AI capability make qualitatively distinct and complementary contributions. The foundational frameworks of Shane and Venkataraman (2000), Baron (2006), and Grégoire et al. (2010) remain theoretically generative, but they require extension to account for an entrepreneurial cognition that is now routinely augmented by machine intelligence. Second, the findings specify a cognitive load mechanism that prior theory had identified at the level of proposition but not yet traced at the level of process: AI-assisted information management reduces extraneous load in ways that are distinct from, and partially substitutable for, the load-reducing function of domain expertise — but with the critical caveat that this substitution is most effective for founders already equipped with the prior knowledge to use AI critically. Third, by grounding the analysis in Yunnan's non-metropolitan innovation ecosystem, the study theorizes a form of human contribution — locally embedded tacit knowledge — that the existing human-AI collaboration literature, developed largely in large organizational settings in primary urban economies, has not adequately captured. The human-AI boundary is not only a matter of uncertainty versus complexity; it is also a matter of what is locally knowable versus what is globally codifiable.

For practitioners, the study's most immediate message is that the value of AI in opportunity recognition lies not in the tools themselves but in the mode of engagement they enable. Founders who used AI iteratively and critically — treating it as a sparring partner rather than an authority — consistently achieved richer, more contextually grounded opportunity assessments than those who relied on AI outputs without interrogation. Incubator managers and entrepreneurship educators can act on this finding directly: AI literacy programs designed around prompt quality, critical evaluation, and the productive combination of AI-generated intelligence with local relational knowledge will yield more durable capability development than training focused on tool access alone. For policymakers seeking to extend the benefits of AI-enabled entrepreneurship to regional innovation ecosystems, the study highlights both the opportunity and the risk: AI can meaningfully reduce the information disadvantage that non-metropolitan founders have historically faced, but only if the local knowledge infrastructure — community networks, advisory relationships, regional market intelligence — is strong enough to ground AI-generated insights in the realities of the local opportunity landscape.

The relationship between artificial intelligence and entrepreneurial cognition is still in its early stages, both as a phenomenon in practice and as an object of scholarly inquiry. The present study offers one empirically grounded account of what that relationship looks like in a specific and theoretically productive context — but the broader landscape of questions it opens is considerably larger than the answers it provides. How AI engagement quality evolves as founders gain experience, whether the cognitive risks of anchoring and dependency attenuate with AI literacy, and how the mechanisms identified here travel across cultural and institutional contexts are questions that deserve sustained empirical attention. What the present findings establish with reasonable confidence is this: AI does not replace entrepreneurial cognition — it restructures it. Understanding how, and for whom, and under what conditions that restructuring is beneficial is among the most consequential research questions the field of entrepreneurship now faces.

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