Review of Managerial Science
https://doi.org/10.1007/s11846-026-01008-x

ORIGINAL PAPER

Artificial intelligence and new venture creation: an entrepreneurial learning perspective

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Received: 24 May 2025 / Accepted: 18 January 2026

Abstract

The rapid advancements in AI have outpaced academic understanding of its effects on the new venture creation process. While the transformative potential of AI in learning processes in general is widely acknowledged, the mechanisms through which it impacts entrepreneurial learning remain largely underexplored. This study examines how AI influences entrepreneurial learning, focusing on a startup operating in the HR tech sector that extensively used AI during its early development phases. Our study contributes to our understanding of AI as an active entrepreneurial agent capable of both cognition and execution, while also offering a new theoretical framework for AI-enabled entrepreneurial learning.

Keywords Digital entrepreneurship · New venture creation · Artificial intelligence · Entrepreneurial learning · Entrepreneurship · Cognition

JEL M13; L26.

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Published online: 07 March 2026

1 Introduction

Over the past 15 years, both research and practice have increasingly recognized the transformative power of digital technologies in new venture creation (Kraus et al. 2019; Nambisan 2017; Uriarte et al. 2025; Yoo et al. 2010). Among these technologies, artificial intelligence (AI)[1] has more recently emerged as a primary enabler of entrepreneurial processes for several reasons (Davidsson and Sufyan 2023; von Briel et al. 2018). First, it impacts new venture processes, practices, and outcomes (Chalmers et al. 2021). Second, it improves the ability to identify promising entrepreneurial opportunities (Shepherd and Majchrzak 2022). Third, it enhances the reliability of the decision-making process (Chaudhary et al. 2025; Giuggioli and Pellegrini 2023), including strategic decision-making within entrepreneurial teams (Murtinu and De Massis 2025). Therefore, it contributes to making the entrepreneur "smart" (Obschonka and Audretsch 2020) and able to manage uncertain conditions more effectively (Shepherd and Majchrzak 2022).

Yet, the unprecedented speed of AI progress and its integration into entrepreneurial strategy practices, more broadly framed within the domain of digital entrepreneurship (Kraus et al. 2019; Nambisan 2017), have outpaced scholarly understanding of its effects and implications (Obschonka et al. 2024). This accelerating progress has sparked considerable scholarly attention, as reflected in recent calls for papers on the topic (Liguori et al. 2025; Obschonka et al. 2024).

Specifically, the increasing focus on the intersection of AI and entrepreneurship underscores the urgent need to deepen our understanding of how recent breakthroughs in AI are transforming entrepreneurial learning processes and their theoretical underpinnings (Chalmers et al. 2021; Murtinu and De Massis 2025; Obschonka and Audretsch 2020; Townsend and Hunt 2019). In particular, entrepreneurial learning refers to the process through which entrepreneurial agents acquire, refine, and apply knowledge, skills, and insights necessary to identify, create, and manage new ventures (Cope 2005; Politis 2005; Wang and Chugh 2014). As Minniti and Bygrave (2001, p. 7) aptly state, "entrepreneurship is a process of learning, and a theory of entrepreneurship requires a theory of learning." In a similar vein, the widely adopted lean startup methodology emphasizes that the primary task of an entrepreneur is to learn and generate knowledge through controlled experimentation (Blank and Eckhardt 2024; Cavallo et al. 2024; Miner et al. 2001). In addition, new ventures are temporary organizations that lack a proven business model, and no outcomes can be achieved without learning. In essence, new ventures serve as vehicles for learning.

Early empirical studies find evidence that AI holds unprecedented transformative potential in learning processes, particularly in how it impacts access, creation, and transformation of information into knowledge (Mollick and Mollick 2023). Scholars suggest that AI is more than just a support resource for new ventures due to its influence on strategic decision-making (Murtinu and De Massis 2025; Obschonka and Audretsch 2020), as well as on the "…myriad creative, cognitive and physi-

[1] AI is defined as "software and/or hardware that can learn to solve complex problems, make predictions, or undertake tasks that require human-like sensing (such as vision, speech, and touch), perception, cognition, planning, learning, communication, or physical action" (Murtinu and De Massis 2025; USPTO 2020).

cal processes enacted when launching a new venture" (Chalmers et al. 2021, p. 1029). Yet, we still possess limited understanding of how such influence unfolds and shapes entrepreneurial learning processes (see Chalmers et al. 2021; Obschonka and Audretsch 2020). Drawing on these observations, our study addresses the following overarching question: *What entrepreneurial learning mechanisms are enabled by human-AI interaction during the new venture development process?*

To address this research question and uncover the mechanisms of human-AI interaction through which new ventures are created, we employ a qualitative approach, which is a particularly suitable method to illuminate complex phenomena and open the 'black box' of the entrepreneurial learning process, a domain which has been found to be underdeveloped (Markowska and Wiklund 2020) and fragmented (Wang and Chugh 2014). Specifically, we investigate the entrepreneurial learning mechanisms enacted by a startup operating in the HR-tech industry that is developing a digital platform to support job seekers in drafting résumés, writing LinkedIn posts, and, more broadly, creating compelling personal storytelling based on their individual profiles.

This study makes two main contributions. First, we show how AI, through distinct entrepreneurial learning mechanisms, combines traditional execution support with cognitive capabilities. This builds upon existing research in digital entrepreneurship. Specifically, while previous studies have highlighted the role of digital technologies, including AI, in expanding the number of (human) entrepreneurial agents involved in the new venture creation process (Nambisan 2017), our research elevates AI to a new level, positioning it as an additional entrepreneurial agent capable of both cognition and the execution of complex tasks. Second, we provide a novel theoretical framework of AI-enabled entrepreneurial learning processes (Chalmers et al. 2021). Grounded in a detailed empirical examination, we show that entrepreneurial learning happens in a social context through a collective effort shaped by human-AI interaction.

The structure of this study is as follows. The next section offers a review of the literature on AI and entrepreneurial learning processes. Section 3 presents the research design and methods employed; Sect. 4 provides the findings. Finally, we discuss implications for theory and practice in Sect. 5 and conclude with the limitations and future research directions.

2 Theoretical background

2.1 Digital entrepreneurship: an evolving field

Digital entrepreneurship refers to the widespread integration of digital tools and systems within entrepreneurial activities, facilitating new modes of value creation and organizational transformation (Kraus et al. 2019; Nambisan 2017; Paul et al. 2023). This pervasive adoption has fundamentally reshaped the spatial and temporal dimensions traditionally associated with entrepreneurial activity, introducing greater flexibility and fluidity in how ventures are conceived, developed, and managed (Kraus et al. 2021, 2022; von Briel et al. 2018). Beyond altering when and where entrepreneur-

ial activities occur, digital technologies broaden access to entrepreneurial ecosystems by lowering geographical barriers and facilitating interaction with a more extensive and diverse network of stakeholders (Cosenz et al. 2024; Henfridsson and Bygstad 2013; Parker et al. 2017). At the same time, digital technologies reduce the dependence on conventional distribution channels and dissolve barriers between entrepreneurs and their target markets, thereby enabling more direct and scalable market access (Autio et al. 2018; Melović, Jocović, Dabić, Vulić, & Dudic, 2020). Moreover, the digitalization of products introduces modular architectures that decouple goods and services from fixed functionalities, enabling dynamic reconfiguration, experimentation, and innovation (Yoo et al. 2010). Yet, the extent to which digital tools enhance entrepreneurial activities remains contingent on entrepreneurs' digital skills and their ability to learn and adapt to the challenges posed by the unprecedented pace of AI-driven technological change (Bachmann et al. 2024; D'angelo et al. 2024; Davidsson and Honig 2003). To cope with such challenges, entrepreneurs can often count on entrepreneurial support organizations such as incubators or external advisors that facilitate venture development across multiple stages (Peretz-Andersson et al. 2024; Sansone et al. 2020).

2.2 Artificial intelligence and entrepreneurship

Among the broad spectrum of digital technologies enabling entrepreneurship, AI emerges as one of the most transformative and promising (Obschonka and Audretsch 2020; Shepherd and Majchrzak 2022). AI plays several roles within the digital entrepreneurial landscape, functioning as a digital artifact, a digital platform, or as an integral component of digital infrastructures, depending on its specific application and deployment context (Nambisan 2017). AI can enhance entrepreneurial processes across a variety of dimensions, from decision-making and opportunity recognition to product development and customer engagement (Chalmers et al. 2021).

AI is broadly defined as the capacity of machines and systems to perform tasks that traditionally require human intelligence, such as reasoning, learning, and decision-making (Agrawal et al. 2018; OECD 2019). AI relies on algorithms capable of identifying patterns within large datasets in order to generate predictions and inform actions (Haenlein and Kaplan 2019). As a general-purpose technology, AI exhibits a wide range of applications across various domains and industries (Kulkov 2021; Naeem et al. 2024; Secundo et al. 2024). Within organizational contexts, AI is gaining increasing relevance by enabling the automation of repetitive tasks traditionally performed by employees (Raisch and Krakowski 2021), as well as supporting more complex cognitive activities, particularly those involving the analysis of multiple variables for informed decision-making (Charlwood and Guenole 2022; Krogh 2018; Raisch and Krakowski 2021). Due to its capacity to process vast amounts of data with greater speed and accuracy than rationally bounded humans (Hallen and Pahnke 2016; Pollack et al. 2023), AI enhances the efficiency and effectiveness of decision-making processes (Dell'Acqua et al. 2025; Walters and Wilder 2023).

The advantages offered by AI are particularly important for entrepreneurs, who operate under conditions of uncertainty and are more exposed to the risk of erroneous or suboptimal decision-making (Giuggioli and Pellegrini 2023; Obschonka and

Audretsch 2020). AI enhances entrepreneurial cognition by augmenting the entrepreneur's capacity to identify and evaluate high-potential opportunities (Shepherd and Majchrzak 2022), while also improving entrepreneurs' ability to navigate and manage volatile or ambiguous environments with greater precision and confidence (Townsend et al. 2018, 2024).

AI is particularly valuable for entrepreneurs operating in highly innovative sectors (Brem et al. 2023), such as (among others) biotech (Garbuio and Lin 2019), nanomaterials (Lima et al. 2024), fintech (Ashta and Herrmann 2021), and human resource technology (HR tech) (Charlwood and Guenole 2022). In such contexts, AI supports the exploration of untapped market potentials and the identification of latent trends by leveraging large-scale, real-time data sources such as social media (Hollenbeck et al. 2019). It can assist entrepreneurs in shaping value propositions and defining viable business models through more informed and data-driven assessments (Davidsson and Sufyan 2023; Lehmann et al. 2025; Lupp 2023). AI can enhance the effectiveness of communication strategies, particularly in the context of fundraising, by optimizing textual content for clarity, persuasion, and impact (Short and Short 2023). Above all, AI represents a powerful ally of human learning processes.

2.3 Artificial intelligence and entrepreneurial learning

Learning is a core cognitive function through which individuals acquire, adapt, and retain knowledge, skills, behaviors, or values via experience, instruction, or observation. It involves the encoding, storage, and retrieval of information and is central to human adaptability and development (Ardichvili et al. 2003; Cope 2005; Greeno et al. 1996; Tenenbaum et al. 2011). When AI operates in the role of a coach or mentor, providing continuous interaction, task support, and real-time feedback, it fosters a dynamic learning environment that facilitates cognitive development (Mollick and Mollick 2023; Zhou et al. 2024). In addition, when AI serves as a simulation environment based on the learner's choices, it creates a feedback loop that reinforces learning, reflection, and higher-order thinking (Mollick et al. 2024). This constant human-AI interaction stimulates thinking skills, such as the critical evaluation of AI-generated information, informed decision-making, and the generation of diverse and creative solutions (Kim et al. 2022; Walters and Wilder 2023).

In particular, human-AI interaction enhances two critical dimensions of the learning process (Mollick and Mollick 2022, 2024). The first is reflection, which is the capacity to navigate complex knowledge domains and extract relevant insights from past experiences to inform future decision-making (Seligman et al. 2013). The second is integration, which involves the synthesis and connection of ideas to construct consistent knowledge frameworks, essential for the development of new expertise (Caruana and McArthur 2019). This integrative learning is particularly enabled by the continuous, iterative question-and-answer dynamic that characterizes human–AI interaction (Wang et al. 2023).

Despite growing interest in the broad role of AI in learning, combined with the increasing significance of AI within the entrepreneurial landscape, its specific implications for entrepreneurial learning remain underexplored. This highlights the need for a comprehensive AI-driven entrepreneurial learning model that uncovers the

underlying mechanisms through which AI facilitates the acquisition, development, and transformation of entrepreneurial knowledge and capabilities.

3 Research design

Given the complexity and multifaceted nature of launching a new venture that draws on the latest AI advancements (Davidsson and Sufyan 2023), we selected a qualitative, longitudinal single-case study approach, allowing us not to be constrained by preliminary decisions regarding sources and types of data (Eisenhardt 1989; Yin 2009). The use of a single case study is particularly suitable for exploring new, emerging phenomena (Siggelkow 2007). Accordingly, we analyze an AI-enabled new venture creation process by focusing on human-AI interaction. From this perspective, we look at the evolution of entrepreneurial learning mechanisms throughout the development of a new venture.

Our empirical setting is the early development phases of a new venture, labeled in the paper as Alpha for confidentiality reasons, whose core value proposition is to empower job seekers to craft compelling personal stories and boost their visibility through a digital platform that creates content for social media, résumés, or motivational letters based on the user's personality. The business idea was born as a spin-off of another startup specialized in corporate storytelling consulting services. Since then, it has evolved into an independent initiative, developed as a standalone project with its own strategic vision and growth trajectory. At the time of the investigation, the new venture was led by two founders with a strong background in corporate storytelling and brand communication in general. The founders were supported by external advisors, engaged through traditional buyer–supplier contracts, without any equity involvement. The early phases of the new venture development were characterized by the extensive use of generative AI tools powered by large language models (LLMs). In these interactions, external consultants played an important role in helping founders cope with the rapid pace of AI progress, while the learning itself materialized within the new venture, our locus of investigation.

3.1 Data collection

Data collection was carried out over a period of approximately seven months, drawing on multiple sources, including interviews and archival records of both internal and external documents, as well as online video materials. The primary data collection phase spanned from October 2024 to January 2025, followed by additional data gathering in February 2025 to further refine the emerging findings. During this period, there was a significant surge in AI-based tools specifically designed to support all stages of entrepreneurial activity (Shay et al. 2025), such as Aipermind, Upmetrics, and StartUs Insights, to name a few. Leveraging diverse data sources enabled triangulation and contributed to the overall credibility and robustness of our results (Eisenhardt 1989; Siggelkow 2007; Yin 2009). A summary of all data sources is provided in Table 1.

Table 1 Data sources

Data type	Quantity	Data source
Semi-standardized interviews (face-to-face/video call)	16	8 Interviews with 2 founders (each interviewed 4 times)
		7 Interviews with 4 external advisors
Follow-up interviews (via call)	2	1 Founder
Internal documents	32 (pages)	Meeting minutes, notes, presentation decks, e-mails
External documents and sources	15 (pages)	News articles, industry reports
Video materials	3 (videos)	75 min publicly available video interviews

The core dataset comprised 16 interviews — six conducted face-to-face and ten via video call—with a total of six informants. Each of the two founders (Founder 1 and Founder 2), who served as our primary contact points, was interviewed four times. The remaining interviews were held with four external advisors (Consultant 1, Consultant 2, Consultant 3, and Consultant 4). All participants were directly involved in the new venture creation process. To assess the validity and practical relevance of our preliminary conceptual findings (Lincoln and Guba 1985), we conducted two follow-up telephone interviews.

The interviews ranged from 36 to 96 min in duration, with an average length of 63 min, generating a total of 224 pages of transcripts. To ensure high data quality, interviews were recorded and transcribed within 24 h (Gibbert et al. 2008). We employed semi-structured interviews to capture the perspectives of individuals directly involved in the new venture creation process, allowing for both real-time insights and retrospective reflections. Participants from both organizations were invited to discuss and reflect on various aspects of the new venture creation process, including the underlying motivations, mechanisms emerging from human-AI interaction, and resulting outcomes. In accordance with our research question, the interviewees were asked to describe and reflect on the new venture creation process, with a particular focus on the learning mechanisms at the individual level that emerge from human-AI interaction during the early stages of ideation and validation. As a result, a first set of questions centered on the genesis of the business idea and the initial experimentation phase, with questions such as: "How did the idea for your venture emerge?"; "What role did AI tools or systems play in helping you generate or refine your idea?"; and "Can you describe specific moments when AI systems challenged or supported your thinking?" These questions were informed by the growing literature on AI-augmented entrepreneurship and early-stage learning, emphasizing the cognitive and interactive dimensions of idea development in complex, data-rich environments. A second set of questions addressed the process of validation—how initial ideas were tested, refined, or even abandoned based on feedback, data, or AI-enabled insights. This included questions like: "How did you validate the desirability or feasibility of your concept?"; "Did AI support you in running simulations, analyzing customer feedback, or iterating on your solution?"; and "How did human judgment and AI-driven suggestions interact in this phase?" These questions aimed to capture the hybrid learning mechanisms involved in moving from abstract ideation to concrete

opportunity recognition and refinement. Finally, the third set of questions focused on the interaction dynamics between AI systems and human actors within the venture team, exploring how these interactions shaped learning and decision-making. Based on existing work on socio-technical systems and human-AI collaboration, we asked: "How did you and your team engage with AI systems in practice?"; "Were there any tensions, complementarities, or unexpected outcomes from working with AI tools?"; and "How has your use of AI evolved over time as you learned more about its role in your venture?" These questions helped surface both reflective insights and real-time learning patterns.

As with the initial case, the interview protocol was revised iteratively after preliminary interviews and continuously adapted to avoid redundancy, allow space for more specific and emerging details, and capture unexpected findings related to the evolving human-AI collaboration. This ensured that the interviews remained responsive to new developments in the venture and that theoretical saturation could be reached with rich, nuanced data. To encourage candor among interviewees, the anonymity of the respondents and their organizations was agreed upon upfront (cf. Ozcan and Eisenhardt 2009).

To enhance the validity and reliability of our case study findings, we triangulated primary data with archival sources. These included internal documents—such as presentations, emails, reports, memos, and meeting minutes—as well as external materials like news articles and industry reports (see Table 1 for details).

3.2 Data analysis

Our data analysis followed well-established procedures in qualitative research, characterized by an iterative and systematic approach aimed at ensuring that emerging insights are both credible and firmly grounded in the empirical material (Corbin and Strauss 1990; Gioia et al. 2013; Maanen 1979). Data analysis and coding were independently conducted by two of the four authors using a predefined coding scheme to minimize bias and ensure the inclusion of distinct perspectives. The two authors (coders) subsequently compared their outputs and engaged in systematic discussions to resolve discrepancies until consensus was reached. This iterative procedure enhanced the rigor of the analysis by ensuring consistent and reliable application of the coding framework. Table 2 illustrates our data structure, outlining the progression from raw empirical material to first-order codes, and subsequently to second-order themes constructed through researcher-centric interpretations and theoretical engagement (Gioia et al. 2013; Maanen 1979). The analytical process began with the coding of both primary and secondary data using textual analysis facilitated by CAQDAS software (Sinkovics and Alfoldi 2012). We employed an open coding technique (Strauss & Corbin, 1990), allowing themes and concepts to emerge inductively from the data without being constrained by preconceived categories. This phase involved a detailed examination of all textual sources—interviews, observations, and documents—to identify recurring patterns, terms, and ideas expressed by the various actors involved in the new venture creation process. Conceptually similar text segments were then grouped and labeled with first-order codes that reflected either informants' exact

Table 2 Data structure

First-order concepts	Second-order theme	Aggregate dimension
Users do not challenge AI's output	Authority bias	Oracle Trap
AI's output is plausible		
AI's output is detailed and well-reasoned	Illusion of validity	
AI tends to agree with the user		
Discovering new use cases from unexpected behaviors	Structured workflow	Proving
Realigning product after discovering a different use case		
Adjusting for different user profiles	Grounding on scientific protocols	
Shifting from general advice to personalized stories		
Enriching the profiles with emotions and memories	Behavioral modelling	Conditional Interaction
Invalidating the basic assumptions		
Creating human alike synthetic users	Customer interview simulation	
Adjusting core narrative to emphasize what users found most appealing		
Incorporate AI with scientific frameworks	Scientific interview protocol	Inquiring
Testing the interaction with corporate and professionals		
Users have natural tendency to reinforce their expectation	External interviewer	
Interview skewed confirmation bias		
Making sense of each output	Interpreting information	Information Overload
Connecting the prompt and the responses		
Select the relevant information	Cognition burden	
Massive amount of data to be processed		
From the applications to knowledge	Systematizing output	Reversing
Sensing contrasting output		
Forming well-reasoned judgments	Critical reflection on output	
Explore the 'why' and 'how'		

words (in vivo codes) or, when necessary, descriptive researcher-generated terms (Strauss & Corbin, 1990).

These first-order concepts captured a wide range of aspects, including specific actions, decision-making rationales, and perceived needs associated with the emergence of a viable value proposition and business model. The coding process was inherently iterative and collaborative: all authors engaged in regular discussions to reconcile interpretive differences, refine categories, and deepen the analytical understanding of the venture development dynamics and the enabling mechanisms that surfaced. Through this rigorous process, we identified 24 distinct first-order concepts. The reliability of the narratives was further enhanced through verification with the organizations involved. Subsequently, we aggregated the first-order concepts into

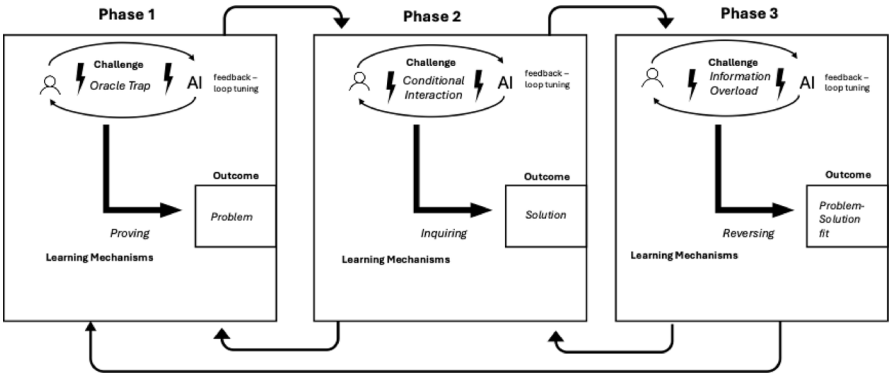

Fig. 1 Process model of AI - entrepreneur interaction learning

second-order themes by identifying conceptual linkages and engaging in dialogue with relevant theoretical frameworks. This stage involved multiple rounds of discussion among the researchers until consensus was achieved. To minimize interpretive bias and further strengthen the credibility of our analysis, these emerging themes were also validated by key informants. Ultimately, 12 s-order themes were distilled from the data. In the final step, these second-order themes were grouped into six aggregate dimensions that encapsulate the entrepreneurial learning challenges and learning mechanisms fostered by human-AI interaction. This data structure—built through successive layers of abstraction and theoretical integration—formed the foundation for identifying the emergent theory, defined as "a statement of concepts and their interrelationships that shows how and why a phenomenon occurs" (Corley and Gioia 2011, p. 12). It is important to note that while Table 2 presents the foundational structure for our grounded theory model, it does not aim to capture the dynamic interplay among second-order themes. Rather, it serves as a conceptual scaffold for the theorization developed in the findings section, where the relationships and mechanisms are further elaborated (see Fig. 1). In doing so, we align with Gioia et al.'s (2013, p. 21) call to move beyond methodological rigor toward theoretically informed engagement with the data.

4 Findings

The findings reveal that the human-AI interaction shapes new venture development through a dynamic process of addressing emerging challenges via distinct learning mechanisms. In analyzing the early development of the new venture, we gained insights into how human-AI interaction evolves through these mechanisms—insights that ultimately influence the broader dynamics of entrepreneurial learning. Figure 1 illustrates the three mechanisms. These are: *proving* – i.e., entrepreneurs critically test, validate, and refine AI-generated suggestions, thereby overcoming the oracle trap and supporting robust opportunity exploration; *inquiring* – i.e., entrepreneurs generate structured, objective interactions with AI—such as through synthetic customers and interviewers—to explore ideas and gather knowledge, overcoming the biasing effects

of their own pre-existing assumptions and mental models; and *reversing* – i.e., entrepreneurs abstract general concepts and insights from specific AI-generated outputs, consolidating knowledge across contexts to manage information overload and inform scalable solutions. Hereafter, we discuss further details about the development of the new venture and the key learning mechanisms involved.

4.1 Phase 1

In the initial development phase of Alpha, which emerged as a spin-off from its parent company, the founders leveraged AI to explore and brainstorm potential new applications of their existing core knowledge and expertise, namely corporate storytelling consulting services. Their interactions with AI focused primarily on identifying new applications of corporate storytelling that aligned with real customer challenges and on uncovering untapped problems faced by potential clients. During this stage, the interactions with AI were frequent and primarily exploratory in nature. Feedback from each interaction allowed the entrepreneurs to refine their input prompts, creating a form of *feedback-loop tuning*. For example, when the AI's output was too vague or overly technical, they responded by clarifying or adjusting their subsequent prompts to achieve more precise results. The main challenge encountered in this initial phase was what is commonly refer to as the *"oracle trap*", defined as the tendency of entrepreneurs to uncritically trust AI's responses, misled by the perception of the system as an "oracle" endowed with absolute knowledge. Similar to the way entrepreneurs may overestimate human mentors, the oracle trap stems from blind trust in algorithmic outputs, leading users to believe that AI systems are inherently more objective and accurate than humans. Generative AI tools, by producing fluent, confident, and well-structured answers, create a strong impression of authority, which can lead users to place excessive and uncritical trust in them. Taking from the very words of Founder 1, *"I was very impressed by the quality of output produced*, *in some cases it was difficult to question such accurate responses."* Furthermore, AI fosters an illusion of validity through responses that are typically long, detailed, coherent, grammatically correct, and seemingly well-reasoned. As a result, users may conflate verbosity with truthfulness, accepting outputs without adequate scrutiny.

Consultant 1, who actively supported the entrepreneurs in this phase, said in this regard that *"Language models… carry with them an almost unlimited experience…*, *in fact*, *the generalist ones are by definition unlimited. That's what they brought to the project. They are also very diligent and not lazy at all*, *and so they produce and elaborate on any prompt with readiness*, *with a high expenditure of tokens*, *of words*, *which makes the result seem valid*, *because we are used to thinking that if we can argue with many words*, *then we are being competent" (Consultant 1)*.

To address this authority bias, the entrepreneurs – supported by the consultants – critically evaluated AI-generated outputs by examining them in depth, requesting supporting sources, simulating alternative scenarios, and comparing the results against structured theoretical frameworks grounded in scientific, literature-based practices. Through structured feedback-loop interactions, the entrepreneurs engaged in a learning process centered on *proving* AI-generated suggestions rather than accepting them as authoritative. As Consultant 4 highlights: *"Obviously*, *it's not a real person*, *so*

everything needs to be taken with a grain of salt and evaluated carefully. However, for that particular phase, they are extremely useful — this way you can immediately get a concise first feedback on your idea, your product, or your service, which you can then iterate on, resubmit to it, and keep refining further" (Consultant 4).

This is further confirmed by Consultant 2, who highlights the importance of interacting with AI through simulations and adhering to specific, scientific frameworks: *"The way to overcome this is by using simulation tools that are still based on artificial intelligence, but in a more immediate way, through simulation processes, context-specific ontologies, and specific methodologies" (Consultant 2).*

The entrepreneurs treated AI outputs as provisional hypotheses to be critically examined using supporting evidence. This process counteracted the oracle trap by preventing uncritical reliance on AI's confident responses and fostering reflective judgment, iterative refinement, and grounded sensemaking during early opportunity exploration.

What entrepreneurs learned from proving was then used to identify a problem they found compelling and meaningful to address. Their exchange with AI revealed a gap in the market for a ready-to-use solution to support storytelling and personal branding. The problem that was at the core of Alpha's business idea was that mid-career job seekers often struggle to communicate their unique professional narratives through clear, persuasive stories that capture employers' attention. This communication gap reduces their visibility and limits their chances of securing interviews. Interviews with job seekers and early exploratory research confirmed that crafting personalized, effective self-presentations is a common and significant challenge. Defining this problem was the main outcome of Phase 1 and also served as input of Phase 2.

4.2 Phase 2

In this second phase, the founders used a specific AI tool to explore potential solutions to the problem faced by mid-career job seekers, as identified in Phase 1. Specifically, the proposed solution is an AI-based platform designed to generate textual content that enhances individual storytelling based on résumés and past LinkedIn posts. The AI tool was employed to simulate interviews with fictional customers modeled with diverse demographic, social, and behavioral characteristics. This process helped gather preliminary feedback on the offering and further refine the solution. The phase remains exploratory, as the entrepreneurs experimented with the AI to model various configurations of value propositions, customer segments, and technical features.

As Founder 1 states: *"We realized that we needed to benefit from that framework also for a more comprehensive business use, more internal and connected to what we do as consultants. This is because some of the elaborations that the product can generate could also benefit the consultative use of storytelling that we apply more broadly in companies" (Founder 1).*

In this second phase, the main challenge underlying the human-AI interaction concerned *conditional interaction*, a situation in which the dialogue is shaped by the entrepreneurs' pre-existing mental models, assumptions, and personal beliefs regarding the new applications. Such cognitive frames can lead to less effective interactions by unconsciously leading the conversation toward a desired outcome. In these cases,

the AI's responses may inadvertently reinforce the entrepreneurs' initial hypotheses, thereby introducing bias and confirming their expectations. Taken from Founder 1's very words: *"during the process, I saw the risk to reinforce or orient my interaction with AI towards my pre-existing beliefs, which are not very easy to spot though".*

This is also stated by Consultant 4: *"The entrepreneur within the company had introduced biases in his dialogue with the AI generated customers, and it was difficult to carry out this activity properly without anyone from outside – not impossible of course but more difficult" (Consultant 4).*

Similarly, as Founder 1 states: *"We realized that we needed to benefit from that framework also for a more comprehensive business use, more internal and connected to what we do as consultants. This is because some of the elaborations that the product can generate could also benefit the consultative use of storytelling that we apply more broadly in companies" (Founder 1).*

To overcome this challenge, the entrepreneurs generated not only synthetic customers but also a synthetic interviewer, an external agent modeled on scientific protocols for conducting interviews. These synthetic interviewers objectively conduct neutral interviews by applying structured protocols and standardized workflows. Through this systematic questioning aimed at understanding markets, customers, and technologies, the entrepreneurs acquired new knowledge through *inquiring*.

In fact, Founder 2 states: "*We assigned a task to an interlocutor — that is, an interviewing agent — to extract and conduct an interview with the synthetic user, putting into play the best practices of problem-validation interviews, solution-validation interviews, and competitor-comparison interviews. In short, there is evidence in the literature, of course, on how questions should and should not be asked, what should be asked, and how the conversation should be organized" (Founder 2).*

Similarly, Founder 2 also notes: *"We realized that, in fact, the work the platform does for a job seeker can also be applied in the more complex context of the brand and corporate world, with other stakeholders and so on. Can it really do that? We are currently completing the evaluation to understand the extent to which it can actually do it, and where it cannot" (Founder 2).*

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As in Phase 1, the outcome of each interaction served to refine subsequent prompts through a generative *feedback loop tuning* process, which continued until the entrepreneurs reached the desired outcome. The knowledge developed through this iterative inquiry enabled them to identify a potential solution that effectively addressed the problem defined in Phase 1. The outcome of Phase 2 served as the input for Phase 3, during which the entrepreneurs would interact with the AI to work toward achieving product–market fit.

4.3 Phase 3

In the third phase, the founders' primary goal was to position the solution developed in Phase 2 for potential scaling to the main target market. This marked the point where 'things got serious', and the founders of Alpha began exploring with AI how to transform their entrepreneurial idea into a viable new venture. Their interactions with AI focused on analyzing competitors, conducting benchmarking analyses to compare their solution with existing offerings, identifying strengths and weaknesses, and assessing the overall feasibility of the proposed solution. The main challenge in this phase was managing *information overload*, understood as the massive volume of information generated by AI that must ultimately be processed by humans. This obstacle arises from the entrepreneur's limited cognitive capacity as individuals and the difficulty of processing large volumes of information. The resulting cognitive load constrained their ability to effectively iterate and adapt the original idea.

This is highlighted by the Consultant 1, who states that: *"Market validation and estimation essentially involve mapping competitors, looking at the degree of overlap, or whether there's what's known as a blue ocean rather than a red one, meaning a real market opportunity. But even here, mapping competitors in the pre-AI era is very different from doing it in AI era, because with AI we can process many more variables that define the competitive landscape" (Consultant 1).*

In this third phase, entrepreneurs systematize the outputs generated from Phase 2 in order to generate knowledge that can be applied across contexts. To process such massive cognitive burden, they must generalize broader concepts from specific interactions. We refer to this learning mechanism as *reversing*, involves interpreting results, identifying conceptual connections, and, more broadly, abstracting knowledge from concrete cases. In other words, reverse learning inverts the traditional approach in which general theoretical concepts are applied to practice. Instead, when the entrepreneur interacts with the AI, general concepts emerge from practice (or applications) and can then be transferred to other contexts.

In fact, Founder 2 states: *"These are all… briefing elements that I carry with me from the first two phases, and that's where the AI can give me much support and has definitely helped and continues to help me… we used AI both to simulate technical aspects of the platform and to model user audience responses. Specifically, we worked with synthetic audiences that were carefully designed and segmented. This led to further insights that helped refine not only the user experience and functionality of the platform, but also key business aspects and the way we communicate the value proposition" (Founder 2).*

Founder 1 also states: *"Basically, when we discovered that there were prompts that actually helped us both in terms of efficiency and effectiveness, we created a playbook that we then updated over time. This playbook contained those prompts and was gradually expanded and refined, serving as a resource for the entire organization" (Founder 1).*

Founder 1 further explains: "*… the speed at which AI gave me answers, evaluates hypotheses, and provides insights is much faster, even compared to what I can do myself, despite all my experience and the deep awareness I have of the project. So, it gives me very quick responses, and I then overlay my own reasoning and expert*

judgment, *drawing from my experience. From there*, *I refine the initial hypothesis and continue fine-tuning it by adjusting and reworking it through additional prompts" (Founder 1).*

As in Phases 1 and 2, the human-AI interaction in this stage was recursive, with prompts continuously refined based on the AI's responses. This process created a feedback-loop tuning that concluded once the entrepreneurs achieved a satisfactory output – based on entrepreneurs' judgment. The insights gained through this iterative approach enabled them to consolidate product–market fit and articulate a scalable solution. If the outcome of this third phase proved unsatisfactory, or if the competitive analysis fails to reveal a meaningful market gap for the proposed solution, the entrepreneurs could return to Phase 1 to identify and define an alternative problem to address. This flexibility was made possible by the dynamic nature of the interaction with AI, which allows entrepreneurs to smoothly revisit earlier phases in response to unsatisfactory or negative results.

5 Discussion

We began by noting that although researchers have recognized AI's influence on strategic decision-making (Obschonka and Audretsch 2020), there is little understanding of how such influence unfolds and shapes entrepreneurial learning in early new venture creation. Through an in-depth investigation of a new venture operating in the HR-tech sector, we developed a conceptual model that explains how entrepreneurial learning mechanisms resulting from human-AI interaction characterize the early phases of new venture development. Our findings show how AI is becoming a true additional agent of the entrepreneurial process, beyond efficiently supporting the execution of narrow tasks, as it can alter entrepreneurs' cognition and trigger learning through *proving*, *inquiring* and *reversing*. These mechanisms can lead to a change in the speed and scale of early experimentation phases in digital entrepreneurship.

5.1 Theoretical implications

Our findings on the influence of AI on entrepreneurial learning in early new venture creation have several implications for scholarly research. First, we showed how human-AI interaction during early experimentation phases can alter entrepreneurs' cognition and trigger entrepreneurial learning. This extends prior research on digital entrepreneurship, which has well explained how digital technologies have made the entrepreneurial process more collective, making it possible to have more agents involved in the entrepreneurial process (Autio et al. 2018; Nambisan 2017; von Briel et al. 2018). Our study extends this stream of research by showing how AI's influence goes beyond being a mere support tool in the entrepreneurial process to enhance collaboration among multiple individuals. *AI shifts from being an enabler to become an entrepreneurial agent with valuable data*, *cognitive*, *and analytical capabilities.* Therefore, an implication arising from our research is the need to broaden the perspective of entrepreneurial agents in digital entrepreneurship. Rather than considering AI only as an enabler in digital entrepreneurship (cf. von Briel et al. 2018), we

propose that AI, together with entrepreneurs, can address a range of core problems from new venture creation. Regarding the new venture creation process, there is a need to rethink how to leverage AI to encompass not only the execution of narrow tasks originating from recent pre-AI progress but also the long-term benefits associated with learning through shared cognition and action between humans and AI. While the focus on improving the entrepreneurial process in new venture organizations has been more closely linked to actions, our study illustrates that this may also play a role in active learning and cognition.

Second, we contribute to the entrepreneurial learning literature by showing how entrepreneurial learning unfolds during new venture creation. Specifically, we revealed how human-AI interaction operates as the foundation for three entrepreneurial learning mechanisms: (i) *proving*, ii) *inquiring*; iii) *reversing* (as defined in Sect. 4). These practices then lead to changes in the firm's stock of knowledge, which is expanded and leveraged for future experimentation aimed at rapid growth and scaling. More importantly, cognition in entrepreneurial learning has predominantly been viewed as the antecedent to entrepreneurial action (Anderson et al. 2015; Cavallo and Burgers 2025). Our study suggests that human-AI interaction makes the boundaries and sequence between cognition and action much more blurred in entrepreneurial learning mechanisms, where both components are inherently present in the new venture creation process. Cognition arises not only from the entrepreneurs' mental models but also from their interactions with AI. Experimenting with digital twins of customers is an action that is constantly driven by cognition. This also adds to the long-standing debate on whether lean startup being more an action-based learning approach or a more theory-based approach (Adner and Levinthal 2024; Ehrig and Schmidt 2022; Leatherbee and Katila 2020; Zellweger and Zenger 2023). In line with Blank and Eckhardt (2024), we argue that there cannot be any rapid experimenting without cognition (or theory) driving it in the entrepreneurial process. Recent advances in AI only make this more evident through the entrepreneurial learning mechanisms that we shed light on.

Third, although much of the entrepreneurial learning literature focuses on "who the entrepreneur is" – linking their 'total stock' of experiences at a given point of time to variations in new venture performance (e.g. Sapienza and Grimm 1997; Bailey 1986), entrepreneurship can be also be learned through a process (e.g. Gartner 1988; Politis 2005; Cope 2005). For example, scholars analyze failure as a relevant type of experience that could enable or hinder entrepreneurial learning in new ventures (e.g. Cope 2011; Ucbasaran et al. 2013; Mueller and Shepherd 2016; Amankwah-Amoah et al. 2022). We extend Markowska and Wiklund (2020)'s work on the actual social and collective process of entrepreneurial learning, as our study specifically points to entrepreneurial learning stemming from human-AI 'social' interactions, with neither failure nor success yet determined.

Finally, our study also contributes to the growing interest in the HR-tech sector, which has in recent years seen a transition from being a relatively slow innovation domain to increasingly evolving at fast-pace (Harney and Collings 2021). Having one job for an entire lifetime is no longer the norm. Rather, workers will need to seek jobs multiple times in their lives and upskill their competencies along the way. Our

findings resonate with the changing role of job seeking companies with AI offering the opportunity to support their main value proposition.

5.2 Managerial implications

Our study can help entrepreneurs conceive of and make use of AI in the new venture creation process as an active and supportive agent. First, entrepreneurs seeking to fully leverage recent advances in AI should actively engage with AI not only to execute actions, but also to reason through them and even assess them within simulated digital environments. This can be achieved by developing and interacting with digital twins (or replicas) of the market, enabling a far more cost- and time-efficient market validation phase. This represents a highly relevant addition to the entrepreneurial process brought about by the rapid progress of AI. For a long time, research has focused on the relevance of product digital twins; however, enabling entrepreneurs to interact with a *market twin* can significantly accelerate business validation and scaling. Second, entrepreneurs should consider cognition and action concurrently as part of the same human-AI interaction process that will lead to learning outcomes, which will expand the action space and the stock of knowledge for future experimentation needed for scaling the new venture. Third, incubators, venture capitalists, and other organizations supporting entrepreneurship processes should encourage entrepreneurs to engage with AI, potentially helping them to extend and keep their AI competences up to date to better shape the new venture creation process. This is particularly important because many tech entrepreneurs may be highly specialized in narrow technical areas, yet lack knowledge of the entrepreneurial process and the ability to integrate the benefits that the most recent advances in AI can provide.

5.3 Limitations and future research

First, our study was limited by our focus on a single new venture, which hinders the generalizability of our findings and implications. Yet, given the very early stage of research on entrepreneurial learning stemming from human-AI interaction, we deem that a single case offers the opportunity to get a more in-depth understanding and to unpack processes and mechanisms. Future studies may expand the scope of this research by, for example, comparing multiple new ventures from different sectors or at different development stages, which could yield important insights into the boundary conditions of when and how AI supports entrepreneurial learning.

Second, our study refers to the early stage of the new venture creation process, and thus it does not yet contemplate either success or failure. It was not within the scope of this investigation to identify successful or unsuccessful strategies to leverage AI. Rather, we wanted to shed light on how entrepreneurs are embedding the most recent advances in AI and which entrepreneurial learning mechanisms this enables. Future research will probably account for both successful and failed cases, which can further the debate. For example, researchers may investigate which types of learning mechanisms, and which type of AI tools/practice are most effective in enhancing the scaling of new ventures.

Third, while our findings align with prior studies showing that cognition and action are both part of early experimentation (Blank and Eckhardt 2024), we challenge the dominant view that sees them as distinct. In the entrepreneurial learning mechanisms illustrated in our framework, we argue that cognition and action are both present and increasingly difficult to separate, as AI blurs the boundaries between them. What our study does not address is how AI should be oriented to make the most out of such overlapping cognition and action, which constitute key components of entrepreneurial learning mechanisms in new venture creation.

Funding Open access funding provided by Consiglio Nazionale Delle Ricerche (CNR) within the CRUI-CARE Agreement.

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