



From Entrepreneurial Intuition to Algorithmic Intelligence: A Conceptual Framework for AI-Driven Decision-Making and Startup Performance

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ABSTRACT

Artificial intelligence (AI) is transforming the way entrepreneurs make decisions by sifting through vast amounts of data, identifying patterns, predicting market trends, and proposing a range of potential scenarios for decision-making – all of which is particularly important when dealing with startups, which often find themselves facing uncertainty, limited resources, information gaps, and a pressing need for quick decision-making. Even as AI becomes ubiquitous, the theoretical knowledge on how AI uptake is associated with improved entrepreneurial decision making, and improved startup performance more broadly, is spread across several streams.

Nevertheless, the theoretical knowledge about how AI uptake relates to improved entrepreneurial decision making and, in turn, improved startup performance is still theoretically divided into several streams despite the diffusion of AI. This conceptual paper combines knowledge from entrepreneurship, information systems, strategic management and organizational decision-making research to create an integrative framework for understanding entrepreneurial decision making using artificial intelligence. The paper draws on the concepts of Technology–Organization–Environment (TOE) theory, Dynamic capabilities theory, Resource-based view of the firm, and Human–AI complementarity theory to conceptualize the organizational mechanism of AI-driven entrepreneurial decision-making capability (AI-EDMC) as how technological resources are transformed into entrepreneurial decisions and performance outcomes. It categorizes the factors related to the adoption of AI, the

AI-EDMC, the outcomes at the decision level, the outcomes at the startup level, the factors of the adoption barriers, and the boundary condition of human-AI complementarity and develops 14 theoretically grounded propositions linking these constructs. The main thesis is that sustainable advantage comes not from eliminating entrepreneurial intuition and relying on algorithms instead, but by combining algorithmic intelligence with entrepreneurial judgment. The framework proposes empirical tests to verify the findings and a research agenda for research on AI for entrepreneurialism, especially in resource-constrained and emerging startup ecosystems.

Keywords: artificial intelligence; entrepreneurial decision-making; startups; AI adoption; dynamic capabilities; human–AI complementarity; entrepreneurial intuition; competitive advantage.

1. INTRODUCTION

Entrepreneurial decision making plays a crucial role in the genesis, survival, development and evolution of entrepreneurial ventures. Entrepreneurs continuously make decisions regarding opportunity recognition, market entry, resource allocation, product development, acquiring customers, pricing, financing, recruitment, partnerships, innovation, and adapting their business model. However, entrepreneurs often make such decisions without a lot of historical data, routine, financial resources, or predictability in the market. It has therefore been traditionally connected with uncertainty, intuition, experience, heuristics, judgment, experimentation, and learning to make decisions.

This decision environment has been changing increasingly over the past few years as digital technologies have made an impact. With the advent of artificial intelligence (AI), machine learning, predictive analytics, natural language processing (NLP), recommendation systems, computer vision, and, more recently, generative AI, these information-processing capabilities have been greatly enhanced for entrepreneurs. Entrepreneurs can increasingly involve human judgment and algorithmically generated predictions,

simulations, classifications, recommendations and insights. It is well established that digital technologies have already started to influence the processes and nature of entrepreneurship uncertainty (Nambisan, 2017). AI accelerates this shift by bringing in its forms of computational intelligence that can directly engage in knowledge creation and decision support.

The cost of prediction is one of the key economic contributions of AI, which makes it particularly salient for entrepreneurship (Agrawal et al., 2018). For startups, better prediction can be used to make decisions regarding customer need, churn, cash flow, inventory management, product performance, competitive reactions, and investment risk. Additionally, generative AI can be used to interact with the AI using natural language, generate strategic options, compare various options, summarize complex information, simulate scenarios, conduct initial market research, and assist entrepreneurs with creative problem-solving, among many other potential uses, as summarized in a recent systematic review of the use of generative AI in entrepreneurial strategic decision-making (López-Solís et al., 2025).

But, the connection between AI and entrepreneurs' choices doesn't mean that AI is a purely technical replacement that will gradually supplant entrepreneurs. There are also other dimensions to entrepreneurial environments that go beyond computational complexity: ambiguity, novelty,

lack of information, social relationships, ethics, and truly unpredictable future states. There is still a role for human judgment, though. Human-AI symbiosis research suggests that while computational systems might excel at providing pattern recognition, which is vital for processing complex information, humans are crucial for intuition, contextual interpretation, ethical considerations and handling equivocality (Jarrahi, 2018). In the same way, the organization side of AI is a dynamic balance of replacing human tasks with automation and supporting human capabilities through augmentation (Raisch & Krakowski, 2021).

The tension is particularly acute in start-ups. Clusters of data, analytics teams, information systems and a good budget for digital transformation might be available in large organizations. Startups usually have the reverse issues: small data sets, poor capitalization, small size, dynamic business models, and high uncertainty and risk. At the same time, startups might have an agile organization, fewer legacy systems, cultures that are more open to experimentation, and quicker adoption of technology. Thus, it isn't enough that an AI is used in a startup; the ability of AI to be integrated into organizational capabilities and linked to entrepreneurial cognition and judgment constitute the entrepreneurial value of AI.

Recently, the relationship between entrepreneurship and artificial intelligence has received the attention of scholars, such as in the fields of opportunity recognition with AI, entrepreneurial learning with AI, generative AI and business model innovation, ecosystem dynamics with AI, and venture performance with AI. The most recent systematic review (Song & Sha, 2026) showing the fragmentation of the field identifies 7 dimensions of influence of AI on entrepreneurial decision-making (from opportunity assessment to entry and exit decisions) and does not provide an integrative causal explanation on how resources drawn from the field of AI are translated into entrepreneurial decision and performance outcomes. One of the key theoretical questions that has yet to be sufficiently addressed is how or why the adoption of AI translates to improved business decisions and startup performance.

This conceptual paper is spurred by three emerging literature limitations. First, there is the assumption that the adoption and performance are synonymous, even as ownership or access to an AI application does not automatically create business value, there must be an intermediate capability in the organization to turn AI tools into effective decisions. Second, research on AI adoption tends to neglect the entrepreneurial mindset, resource constraints, organizational skills, and ecosystem factors. Third, research sometimes treats AI and human intuition as alternatives, but sometimes startup decision-making is best captured as a complementarity of the two.

Accordingly, this paper proposes the concept of AI driven entrepreneurial decision-making capability (AI-EDMC): the organizational capability of a Startup to systematically acquire, interpret, combine and apply AI generated information for entrepreneurial decision making with the integration of algorithmic outputs and human judgment, contextual knowledge and strategic goals. This is an important distinction between the use of AI and capability. Even if two start-ups are using the same AI technologies, they can still have very different outcomes due to differences in data quality, skills of employees, leadership, decision-making, absorptive capacity, governance and entrepreneurial judgment.

The paper addresses three research questions:

Artificial Intelligence is revolutionizing entrepreneurial decision making in the startup ecosystem. AI is reshaping entrepreneurial decision making in the Startup ecosystem.

RQ2: How do technological, organizational, entrepreneurial and environmental factors either support or hinder AI-based decision making in startups?

How can AI's contribution to entrepreneurial decision-making capacity affect a startup's performance and competitive edge?

The paper has three major contributions: First, it links the adoption of technology to entrepreneurial decision making by defining AI-EDMC as the process by which AI resources impact organizational outcomes. Second, it uses the TOE framework along with dynamic capabilities and reasoning based on resources to provide explanations to the antecedents and consequences of AI adoption. Third, it adds the human-AI

complementarity as a defining feature of the algorithmic intelligence–entrepreneurial judgment relationship. These contributions are summarized in 14 research propositions (Table 2) and an integrative conceptual figure (Figure 1), which are designed to inform further empirical research.

The rest of the paper discusses the conceptual underpinnings of AI-enabled entrepreneurship, provides the theoretical underpinnings for the proposed framework, explores antecedents and barriers to AI adoption, outlines the links between AI decision-making and start-up outcomes and outlines the conceptual framework and research propositions, and discusses the practical and theoretical implications for managers, policy makers, and future research.

2. Conceptual Review Approach

2.1 Review orientation

In this paper, a conceptual review approach was applied to integrate. The goal is not just to list the uses of AI for entrepreneurship, but to theoretically synthesize insights from a number of research fields and come up with an explanatory framework. An integrative approach is appropriate, as the use of AI in entrepreneurial decision-making is an intersection of entrepreneurship, information systems, organisational decision-making, innovation, strategic management and digital transformation.

A recent review shows that the industry of AI–entrepreneurship is expanding quickly, but there remains some conceptual disarray. Literature on entrepreneurial opportunity recognition, generative AI, automation, entrepreneurial learning, business-model innovation, intellectual capital, technology adoption, ecosystem interactions, and firm performance is diverse, laying the groundwork for the need to integrate these theories.

2.2 Literature identification

The review should be carried out systematically on Scopus and Web of Science Core Collection for a final reproducible version of this manuscript. The strings to search should include AI, machine learning, generative AI, algorithmic decision-making, entrepreneurship, entrepreneur, startup, new venture, decision-making, decision quality, firm performance and competitive advantage.

The main focus should be on peer-reviewed journal articles focusing on at least one of four analytical domains: (1) AI adoption and organizational readiness; (2) entrepreneurial or managerial decision-making; (3) AI-enabled organizational capabilities; and (4) performance, innovation, or competitive outcomes. Theoretical foundations are also built by including foundational literature on entrepreneurial cognition, digital entrepreneurship, dynamic capabilities, resource-based theory and technology adoption. To ensure that the identified gaps in the literature which are driving this framework – such as the lack of a link between the use of AI and decision-making capabilities, and the lack of clarity regarding the role of human–AI complementarity – remain relevant in the most recent literature, recent systematic reviews in the field of AI in Entrepreneurship (Ayinaddis, 2025) and Small-Business (López-Solís et al., 2025; Song & Sha, 2026) were consulted.

The synthesis is presented in a thematic way, not historical. The interpretative steps of studies are done according to the sequence that it is used to explain conditions of

startups before adoption of AI, use of AI to increase startup's decision-making capability, decision outcomes, and performance of startups.

This way, a set of theoretically testable propositions can be developed and the fact that evidence of the intersection of AI and entrepreneurship is heterogenous and constantly changing is acknowledged.

3. Theoretical Foundations

3.1 Entrepreneurial decision-making: intuition, uncertainty, and bounded rationality

Entrepreneurial decision-making: intuition and emotions. Business practice is always a situation of uncertainty. In reality, entrepreneurs do not have complete information about future demand for the products in their market, technology, competitor actions, financing conditions, and customers' reactions, and in that case, purely rational optimization is hard. This means that entrepreneurs have to use heuristics, intuition, prior experience, experimentation, networks and judgment. The effectuation perspective by Sarasvathy (2001) also shows that entrepreneurial action can occur in the absence of accurate forecasts of the future. Entrepreneurs should not try to predict the future perfectly, but rather take the resources at hand, try to restrict their losses, form relationships with others, look for contingencies to capitalize on, and try to shape the future. It creates an intriguing theoretical conflict within this one. It gives rise to a fascinating theoretical dichotomy in this view. AI augments predictive power, on the other. On the other side, the uncertainty of entrepreneurs can be translated into a quantifiable risk when the necessary data is relevant enough to be translated into meaningful patterns from which future outcomes can be estimated, but the truly unique can't be sufficiently represented by historical data. So algorithmic intelligence is not a substitute for entrepreneurial judgment; it is a new way of shaping the information world in which entrepreneurial judgment takes place. The central transition should not just be intuition to AI – it should be intuition-dominant decision-making to augmented entrepreneurial intelligence.

3.2 Technology–Organization–Environment framework

The Technology – Organization – Environment (TOE) framework is an appropriate context to discuss why

technological innovations are adopted by organizations.

According to the framework, technological factors, organizational factors and external environment influence the adoption process (Tornatzky & Fleischer, 1990). Technological context in startups includes digital infrastructure, data availability, data compatibility, perceived usefulness of the technology, accessibility to AI, system complexity, cybersecurity concerns, and integration needs. The organizational context includes leadership support, financial resources, technical skills, organizational culture, startup size, strategic orientation and readiness for change. Environmental context factors are competitive pressure, regulation, investor expectations, support in the ecosystem, external AI providers available, and government policy. The TOE framework is particularly relevant, given that it does not assume technological determinism—that is, that the mere availability of a technology is sufficient to drive its adoption—and that organizational resources and environmental conditions will influence the extent to which entrepreneurs find AI valuable, viable, acceptable, and suitable. However, TOE does not fully explain how adopted technologies become performance generating capabilities, which is why it is deemed a good explanation of adoption, but not of how technologies are adopted. It is also reflected in the existing literature on the adoption of AI in scale-ups and large enterprises: Recent bibliometric analysis of the literature on AI adoption in SMEs and large companies reveals that most empirical studies continue to focus on factors that influence adoption and explain how AI is diffused within the organization, while relatively little research examines the organizational capacities required for the technology to trigger decision or performance outcomes (Ayinaddis, 2025).

Therefore the present framework uses TOE in conjunction with the theory of dynamic capability.

3.3 Dynamic capabilities theory

Dynamic capabilities are the abilities of the firms to integrate, develop, and reconfigure internal and external capabilities in a context of uncertainty and change (Teece et al., 1997). Later elaborations typically identify three types of opportunities and threats: sensing, seizing, and structuring and resourcing. This attitude is similar to entrepreneurial AI. By constantly monitoring the behavior of customers, market trends, technological advancements, competition, and operational data, AI can reinforce the sensing. It can assist in the evaluation of opportunities, scenario analysis, resource allocation, and strategic selection, which can ultimately help to mitigate the risk of seizing. It can play a role in transformation by enabling experimentation, organizational learning, process redesign and business-model adaption. If this is the case, then AI itself is not a dynamic capability; it can be readily available in the market and can actually be competitive for a lot of organizations, but it's how they combine AI with the data, with the people, with the activities, with the learning processes, and with the strategic decision-making that makes it competitive for them. AI-EDMC is thusly conceived as a moving capacity of the organization, not just the possession of technology.

3.4 Resource-based view and AI resources

The resource based view (RBV) suggests that the performance gaps may result from the differences in the heterogeneous resources and capabilities that organizations possess and are valuable and hard to copy. The same approach needs to be used with AI: generic AI software is becoming readily available, and it is unlikely to provide a long-term basis for competitive advantage without being integrated into a larger system. Competitive advantage is more likely to be gained from the configuration of resources that includes AI technologies, proprietary or context-specific data, entrepreneurial knowledge, technical skills, organizational routines, customer relationships and decision capabilities. AI becomes strategically important when integrated into these complementary resources, which can be summarized as follows: AI technology + data + human expertise + entrepreneurial knowledge + organizational routines = AI-driven decision-making capability. This setup offers a theoretical insight into why AI can't necessarily guarantee superior performance by itself.

3.5 Human-AI complementarity

The third theoretical strand is human-AI complementarity. Jarrahi (2018) posits that AI and humans can bring complementary strengths to organizational decisions: Computational power, pattern recognition, consistency, and large-scale information processing power are all strengths of AI, while contextual understanding, intuition, social intelligence, ethical judgment, and the ability to deal with ambiguity are strengths of the human. Raisch and Krakowski (2021) make the same distinction between automation and augmentation, but highlight the concomitant nature of the two. The question is then, when applied to entrepreneurship, whether or not humans or algorithms should make decisions, and how decision authority and cognitive work are distributed between them. This paper suggests the complementary nature between humans and AI is a boundary condition of the effectiveness of entrepreneurial decision-making with AI. The most likely value that AI can bring is when the entrepreneur is able to critically make sense of what the AI has produced, integrate with their contextual understanding, and take ownership of strategic decisions that follow.

Table 1. Mapping of theoretical lenses to the proposed framework

Theoretical lens	Primary role in the framework	Key constructs contributed
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Technology–Organization–Environment framework (Tornatzky & Fleischer, 1990)	Explains why, and under what conditions, startups adopt AI	Technological, organizational, and environmental readiness (Layer 1 antecedents; P1–P6)
Dynamic capabilities theory (Teece et al., 1997)	Explains how adopted AI is converted into an organizational capability	Sensing, seizing, and transforming routines

Theoretical lens	Primary role in the framework	Key constructs contributed underlying AI-EDMC (Layer 3; P8)
Resource-based view	Explains when AI-EDMC yields sustainable advantage	Complementary resource configurations (data, expertise, routines) underlying competitive advantage (P12)
Human–AI complementarity (Jarrahi, 2018; Raisch & Krakowski, 2021)	Specifies the boundary conditions of AI-EDMC effectiveness	Critical human oversight versus algorithmic overreliance as moderators (P13, P14)
Effectuation and bounded rationality (Sarasvathy, 2001)	Explains why entrepreneurial judgment persists despite improved prediction	Limits of algorithmic prediction under genuine, non-probabilistic uncertainty (Section 3.1)

4. Artificial Intelligence in Entrepreneurial Decision-Making

4.1. Understanding the application of Artificial Intelligence in Entrepreneurial Decision-Making.

Someday I will integrate algorithmic intelligence into my business intuition. I will merge algorithmic intelligence into business intuition someday.

Traditional entrepreneurial decision making is greatly connected with intuition, experience, experimentation, and personal judgment. While these mechanisms are still useful, they are limited by human information processing capacity: entrepreneurs cannot process all of the thousands of interactions they have in the market, all of the signals from customers, signs from the financial market, the movements of competitors, and the technologies in the world.

AI extends this cognitive barrier. Machine-learning systems have the ability to find nonlinear patterns in large data sets; generative AI can summarize information, generate scenarios, organize unstructured data and enable conversational analysis. AI can then be a cognitive augmentation of the entrepreneur.

This is what these paper calls algorithmically augmented entrepreneurial intelligence: a decision configuration in which entrepreneurial cognition and computational analysis are combined to produce decisions.

4.2 Identifies and evaluates opportunities

Opportunity recognition is one of the most basic activities of entrepreneurship. Entrepreneurs look for shifts in customers' tastes, technologies, laws, population, and market organization that can generate new value streams.

Search behavior, customer reviews, social media interactions, industry reports, patent data, sales figures, and competitor activities can all be utilized to improve the opportunity sensing process using AI techniques. Recurring customer problems can be detected by NLP systems and demand can be predicted by predictive tools.

However, pattern recognition is not equal to opportunity creation. AI can help with opportunity recognition best when used alongside creativity and entrepreneurial imagination, as entrepreneurs can tap into opportunities for which there is no historical data.

4.3 Market and customer decisions

Marketing is one of the most readily available fields AI can be utilized by startups. By leveraging AI-powered customer analytics, businesses can enhance customer segmentation, personalization, churn prediction, forecasting demand, sentiment analysis, recommendations, and campaign optimization.

Another benefit of Generative AI is the ability to cut down on the expenses of creating and evaluating marketing content, customer interactions, product descriptions, and even different value propositions, which is especially critical for small startups without vast marketing departments.

AI-driven marketing decisions still rely on data quality and strategic positioning, though. While there may be numerous parameters to optimize in short-term engagements, they may not necessarily support long-term brand value and thus need human oversight to interpret what to optimize and why.

4.4 Financial decision-making

Financial distress is one of the biggest reasons for startup failures. The entrepreneur faces the challenge of determining the amount of investments to spend at a given time, when to hire additional workers, whether to invest in product development, pricing of products and when external funding is needed.

Financial analytics can also be enhanced by AI which can help with cash flow forecasting, scenario planning, fraud detection, credit assessment, cost prediction, pricing, and budgeting. Implementing predictive models can enable founders to assess various scenarios and identify potential financial issues early.

However, the choices made in finance involve strategic trade-offs which can't be boiled down to prediction. It may be a rational choice for the entrepreneur to accept short term losses in the interest of acquiring users, creating capabilities or entering a strategic market. AI should therefore be a guide to, not a decision maker for, financial strategy.

4.5 Operational and resource-allocation decisions

Startups suffer from a lack of resources. Employee deployment, inventory, supply chain, scheduling, procurement and production decisions have significant impact on survival.

AI can help by detecting inefficiency, predicting needs, optimizing schedules, eliminating repetitive work and aiding resource management, thereby allow small teams to accomplish activities that would have taken a substantially larger group to perform.

The strategic implication is great: AI could change the basic starting point required to build and grow a business — and this is something that should be explored more in entrepreneurship research.

4.6 Strategic decision-making

Examples of strategic decisions are going into a market, configuring the business model, forming partnerships, scaling, diversifying products and positioning the business against its competition. These decisions involve both ambiguity and uncertainty and quantitative information.

Generative AI opens up new opportunities for strategic analysis as a result of the ability to test assumptions, develop scenarios, challenge ideas, generate new strategies and have a conversation with a competitor analysis, among other things, as a tool for the business entrepreneur. It is in line with the main benefits of generative AI in entrepreneurial strategic decision-making, which are scenario generation, assumption-testing and information synthesis, and not providing a specific optimal answer (López-Solís et al., 2025).

Rather, the biggest payoff could be when AI presents the entrepreneur with an array of options they might not have thought to consider in the first place. AI can serve as an analytical companion, fostering reflection and alleviating limitations in information processing.

5. Antecedents of AI Adoption in Startups

5.1 Technological readiness

Technological Readiness is the readiness of digital infrastructure, digital systems, computational resources, technical architecture, etc. for the implementation of AI. Companies with established digital processes are more likely to successfully integrate AI than those with disjointed or manually driven processes.

P1: Technological readiness has a positive impact on the adoption of AI in entrepreneurial decision-making.

5.2 Data readiness

The quality and availability of data are crucial factors that influence the performance of AI systems. One common challenge startups often encounter is a data paradox: they might reap significant benefits from AI-driven analytics, but they may also lack the historical data sets that could be used to train or validate sophisticated AI models. Thus, data readiness should be considered separately from technological readiness.

P2: Data readiness has a positive correlation with AI adoption and with effective AI driven decision-making capability.

5.3 Organisational readiness and financial resources

The potential costs of implementing AI could include software, cloud infrastructure, integration, employee training, consultants, cybersecurity, and governance. In startups, opportunity costs are even more relevant, as time and money invested in AI are time and money not spent on other essential needs. Organizational readiness also entails leadership commitment, an experimentation culture, process maturity, and willingness to act on AI output by employees.

P3: Financial and human resources availability, and organizational readiness positively influence AI adoption in startups.

5.4 Entrepreneurial mindset

Young organizations may be especially susceptible to the influence of the entrepreneur's mindset, due to the disproportionate influence that the founder has on the technology investments within the company and on the organization's culture. An innovator or an entrepreneur who is more oriented towards innovation, learning, and experimentation is more likely to explore AI applications, accept uncertainty in the implementation process and facilitate employees' AI-related skill development.

P4: Innovation oriented entrepreneurial mindset has a positive impact on AI adoption and AI driven entrepreneurial decision-making capability.

5.5 Startup size and maturity

Established and larger startups might have more resources, larger data sets, dedicated staff, and established

decision-making procedures, which could support the adoption of AI. On the other hand, small businesses can be more flexible and not tied down by legacy systems. The size of startups should thus not be seen as merely a linear factor; its impact may vary with the specific and complex nature of the AI being used.

P5: Differences in resource availability, data accumulation, specialization, and organizational complexity are the indirect impact of startup size and maturity on AI adoption.

5.6 The environment and ecosystems are in good condition.

Entrepreneurial ventures exist in a context of investors, universities, incubators, accelerators, government, technology providers, customers, and competitors. The actors can help in the adoption of AI, providing finance, skills, infrastructure, knowledge, legitimacy, and experimentation opportunities. Competitive pressure can also drive adoption: When rivals leverage AI to offer more personalized services, reduce expenses or innovate faster, entrepreneurs may feel that not adopting AI is a strategic risk.

P6: Ecosystem support/competitive pressure positively affects AI adoption in startups.

6. Obstacles and dangers of AI-informed decision making.

6.1 Restrictions on cost and resources

While entry costs have decreased with cloud-based and generative AI, implementing AI can still be costly when it comes to sophistication. In addition to the cost of subscriptions or infrastructure, there are data preparation, integration, employee training, cybersecurity, monitoring and governance. When resources are scarce, startups may choose to use a set of disjointed tools, but without maturing the right complementary organizational capabilities to get value from the tools.

6.2 Gaps in skills and expertise

It takes more than just coding prowess to make AI work. Entrepreneurs must have enough AI literacy to know what AI can and cannot reliably achieve, to critically evaluate AI output, to ask the right questions, to spot mistakes and to know when they should turn to humans for help. Failure to have such ability can result in underutilisation or overconfidence.

6.3 Quality and availability of data

Bad data can lead to bad recommendations. The startup datasets might contain only a few data points, be skewed toward early adopters, be incomplete, or be volatile due to the changing nature of the startup's products and customer base. While algorithmic sophistication can't make up for unrepresentative input, entrepreneurs should regard data governance as a strategic rather than a purely technical activity.

6.4 Privacy, security and ethical issues.

AI systems can be used for commercially sensitive information, personal information, financial information, employee information, etc. The privacy, data protection, IP, cybersecurity, transparency, fairness and accountability are all factors that startups need to take into account. There can be repercussions from ethics violations other than the fines incurred; reputation loss is especially expensive for young companies looking for respect.

6.5 The bias and explainability of algorithms.

Algorithms can also reflect biases in training data or model design. These biases may impact on recruitment, pricing, customer targeting, credit assessment, or resource allocation. Evidence in the context of entrepreneurship is just starting to materialise: in a first look at AI bias from an entrepreneurial perspective, it was found that the lack of appropriate data-science expertise and internal audit capacity in smaller companies makes it particularly difficult for entrepreneurs to identify outputs that may be experiencing bias (Smacchia et al., 2025). Things get more complicated when entrepreneurs need to explain decisions to customers, employees, regulators, investors, or business partners, as some AI systems may be opaque.

6.6 Automation bias and overreliance

Another, less apparent danger is automation bias: relying on the recommendations of algorithms despite conflicting contextual data. While quantitative outputs can seem like objective facts, AI systems can make incorrect predictions or correlations and generate information that doesn't exist, or give recommendations based on assumptions that don't apply to a startup situation.

P7: Limited financial resources, skill gaps, data quality issues, privacy and ethical issues, and perceived risks of algorithms negatively affect AI adoption and utilization in startups.

7. AI-Driven Decision-Making Capability and Startup Performance

7.1 Adoption of AI vs AI capability

A key point that this paper makes is that "AI adoption is not the same as AI capability." One startup might use a few AI tools without altering the way strategic decisions are made, or another might have more complex AI apps and consistently feed the results into experiments, learning, forecasting, and allocating resources. AI-EDMC is, thus, the organizational capacity to render technological access into decision value.

P8: When complemented with complementary data, skills, organizational routines and managerial commitment, the adoption of AI positively impacts AI-driven entrepreneurial decision-making capability.

7.2 Speed and efficiency in decision making

Timing can be critical in the world of the entrepreneur. AI can speed up the retrieval of information, data

analysis, forecasting, reporting, and creation of decision alternatives. Although quick decisions can mean startups quickly act on feedback they receive and market opportunities that arise, speed doesn't necessarily equal quality.

7.3 Quality and correctness of decisions

AI has the potential to enhance the quality of decision making by analysing more data, uncovering patterns that humans might not notice and ensuring consistency. Decision quality is defined in this context as a multi-dimensional concept that includes the four dimensions of analytical accuracy, relevance, timeliness, and strategic alignment, plus adaptability.

P9: The entrepreneurial decision-making capability positively influences the decision quality, speed, analytical accuracy, and adaptability, with the support of AI.

7.4 Risk assessment and uncertainty management

The student will analyze the characteristics of risk and uncertainty in the context of project management.

AI could enhance the risk detection of operational, financial, market and customer risk. By using scenario analysis, entrepreneurs can examine potential scenarios before using precious resources. But under measurable risk, prediction should be more reliable than under radical uncertainty; AI must therefore decrease informational uncertainty without giving an illusion of it being absent, under entrepreneurial uncertainty.

7.5 Growth and profitability

Better decisions can impact performance in a number of ways. The benefits of better demand forecasts are that they can help minimize waste of resources; better customer targeting can lead to higher conversions; better pricing can help improve margins; early detection of finances can help save cash, and much improved opportunity evaluation can help guide resources to more promising endeavors.

Decision results therefore offer the link between AI capability and firm level performance.

P10: Decision quality mediates the positive relationship between AI-driven entrepreneurial decision-making capability and startup performance.

7.6 Innovation performance

By speeding up innovation processes, AI can facilitate idea generation, gain insights from customers, prototype, experiment, and recombine knowledge. Generative AI is especially relevant as it enables founders to experiment with other product ideas, business models, marketing approaches, and technical solutions.

But mass availability of such generative technologies can also result in imitation and homogenisation. The competitive advantage thus relies on the way in which the possibilities created by AI are brought together with special entrepreneurial knowledge.

7.7 Resilience and sustainability

Startup resilience is the ability to recover from disruption, adjust to change and remain operational when things go wrong. Environmental sensing and scenario analysis with AI could enable enterprises to spot threats sooner and shift resources more swiftly.

P11: AI as entrepreneurial decision-making capacity is positively associated with the adaptability of startups, their innovation capability, and organizational resilience.

7.8 Competitive advantage

With many AI tools available, AI adoption is not likely to create a sustainable competitive advantage. The true power of AI lies in its integration with unique combinations of data, human skills, company learning, customer knowledge, and entrepreneurial decision-making.

P12: The entrepreneurial decision-making capability, based on AI, has a positive effect on the competitive advantage of the entrepreneur, especially if integrated with complementary firm-specific resources and capabilities.

8. The Missing Link: Human-AI Complementarity

Entrepreneurial intuition is contrasted with algorithmic intelligence, but the framework proposed in this paper cannot be considered as an either-or choice.

Entrepreneurial intuition involves tacit knowledge that is gained through experience, social interaction, pattern recognition and context. Algorithmic intelligence is powerful because it's based on the scale of computation, consistency, pattern recognition, and speedy processing of structured and unstructured information. Their strengths are complementary, as well as their weaknesses: human judgment can be affected by cognitive bias, fatigue, selective attention, and limitations in processing capacity, whereas AI can be affected by poor data, model bias, contextual blindness, hallucination, opacity, and inability to assume moral responsibility.

The interesting combination from a theoretical point of view is thus human intuition, contextual knowledge and ethical judgment, plus AI prediction, pattern recognition, information processing and scenario generation – a combination this paper calls augmented entrepreneurial intelligence.

Complementarity between humans and AI will likely play a crucial role in strategic, as opposed to routine, decision-making. Novel, ambiguous, ethically sensitive and irreversible decisions may necessitate higher

levels of human involvement, while, for routine, data-rich, repeatable decisions, greater automation may be permitted.

P13: Human–AI complementarity positively moderates the relationship between AI-driven entrepreneurial decision-making capability and decision quality, where entrepreneurial judgment and algorithmic outputs are effectively integrated to enhance the relationship.

A related implication is about the overreliance:

P14: When facing high environmental uncertainty and high data scarcity, excessive algorithmic dependence negatively moderates the relationship between AI-driven decision-making capability and decision quality.

These propositions transcend technological determinism and focus on the ongoing role of entrepreneurs.

9. The following is a proposed Integrative Conceptual Framework.

The conceptual framework presented in this paper consists of five layers which are interconnected and summarised in figure 1.

Layer 1 — Antecedents. The technological context consists of technological readiness, technological infrastructure, accessibility of AI, system compatibility and data readiness. Organizational/entrepreneurial context involves entrepreneurial mindset, entrepreneurial leadership support, financing, AI expertise, organizational readiness, startup size and startup maturity. The environmental context includes competitive pressure, government support, investor expectations, startup-ecosystem support, availability of technology partners, and the regulatory environment. These jointly define the intensity of the adoption of AI (P1–P6).

Layer 2 — AI adoption. Adoption of AI does not mean binary choice of adopting or not adopting, but rather the extent, adoption level and strategic integration of AI technologies into start-up activities.

Layer 3: AI-informed entrepreneurial decision-making capability (AI-EDMC). AI is adopted and AI-EDMC (P8) is generated with complementary resources. This is ability to include AI assisted opportunity sensing, predictive analysis, synthesizing information, scenario generation, decision support, organizational learning, AI-assisted resource allocation, and to combine algorithmic information with entrepreneurial intuition.

Layer 4 — Decision-level outcomes. AI-EDMC impacts the quality of decisions, their speed, accuracy in analysis, adaptability, consistency, risk assessment, and effectiveness of learning (P9, P10).

Layer 5 — Startup-level outcomes. Better decision results in turn impact on revenue growth, profitability, innovation performance, resource efficiency, resilience, scalability, sustainability and competitive advantage (P11, P12).

As shown in Figure 1, AI adoption is shaped by antecedents which, together with complementary resources, leads to AI-EDMC, which in turn improves decision-level outcomes leading to startup-level performance outcomes. This pathway is surrounded by two sets of boundary conditions. First, the obstacles to adoption – cost, technical expertise, data limitations, cybersecurity, privacy, ethical concerns, explainability, and algorithmic bias – can be a limiting factor in adoption and effective capability formation (P7). Second, how much AI-EDMC is transformed into better decisions depends on human-AI complementarity (P13, P14).

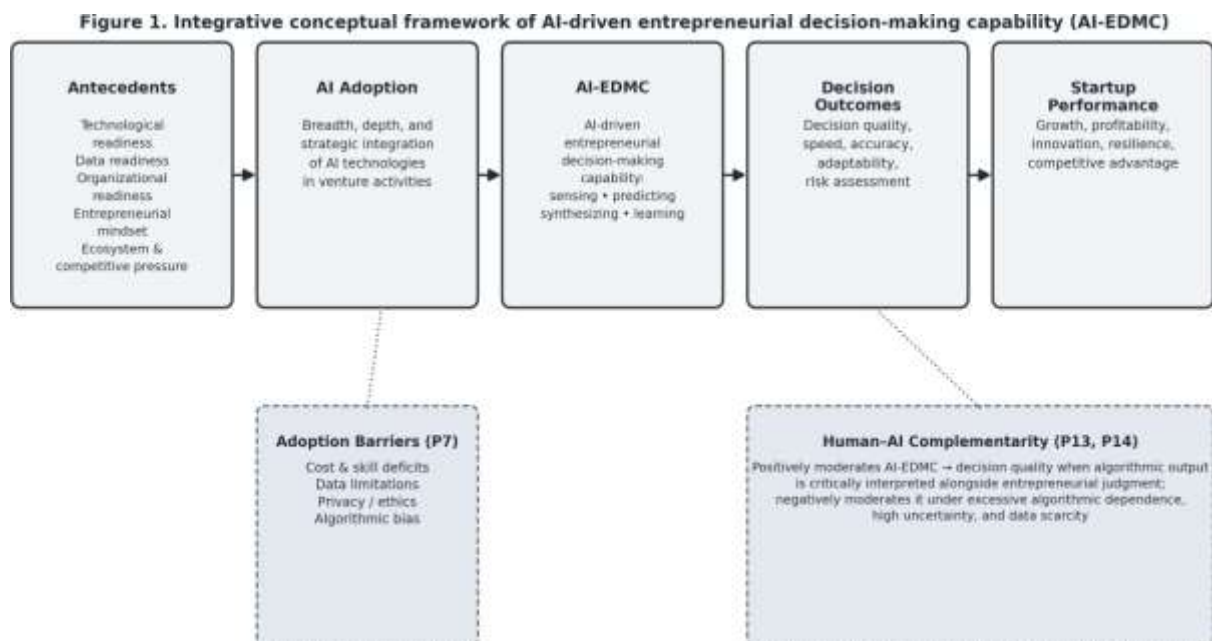


Figure 1. Integrative conceptual framework of AI-driven entrepreneurial decision-making capability (AI-EDMC)

Table 2. consolidates the fourteen propositions advanced in this paper together with their primary theoretical anchors.

Table 2. Summary of research propositions

#	Proposition	Primary theoretical anchor
P1	Technological readiness is positively associated with the adoption of AI for entrepreneurial decision-making.	TOE (technological context)
P2	Data readiness is positively associated with AI adoption and with effective AI-driven decision-making capability.	TOE (technological context); RBV
P3	Organizational readiness and the availability of financial and human resources positively influence AI adoption in startups.	TOE (organizational context)
P4	An innovation-oriented entrepreneurial mindset positively influences AI adoption and AI-EDMC development.	Entrepreneurial cognition; TOE
P5	Startup size and maturity influence AI adoption indirectly, through resource availability, data accumulation, specialization, and organizational complexity.	TOE (organizational context)
P6	Ecosystem support and competitive pressure positively influence AI adoption in startups.	TOE (environmental context)
P7	Financial constraints, skill deficits, inadequate data, privacy and ethical concerns, and perceived algorithmic risk negatively influence effective AI adoption and utilization.	TOE; human–AI complementarity
P8	AI adoption positively contributes to AI-EDMC when supported by complementary data, skills, organizational routines, and managerial commitment.	Dynamic capabilities; RBV
P9	AI-EDMC positively influences decision quality, speed, analytical accuracy, and adaptability.	Dynamic capabilities
P10	Decision quality mediates the positive relationship between AI-EDMC and startup performance.	Dynamic capabilities; RBV
P11	AI-EDMC positively influences startup adaptability, innovation capability, and organizational resilience.	Dynamic capabilities
P12	AI-EDMC positively influences competitive advantage, particularly when embedded in complementary firm-specific resources and capabilities.	Resource-based view
P13	Human–AI complementarity positively moderates the AI-EDMC–decision quality relationship, strengthening it when algorithmic outputs are combined with entrepreneurial judgment.	Human–AI complementarity (Jarrahi, 2018)
P14	Excessive algorithmic dependence negatively moderates the AI-EDMC–decision quality relationship under high environmental uncertainty and data scarcity.	Human–AI complementarity; automation–augmentation paradox (Raisch & Krakowski, 2021)

This framework differs from simple AI–performance models because it does not assume that adoption directly causes startup success. Instead, it proposes a multi-stage value-creation process in which technology must first become an organizational decision capability.

10. Discussion

The framework presented in this paper provides a new understanding of the connection between entrepreneurship and AI. The main issue is not that of the replacement of entrepreneurial intuition by AI, but rather that entrepreneurial decision-making is being reconfigured by the combination of human and algorithmic intelligence.

This distinction is significant because entrepreneurial decision making is very different than a lot of routine organizational activities. Entrepreneurs face new opportunities, incomplete markets, shifting customer preferences, resource scarcity TOE and dynamic capabilities provides a more comprehensive sequence from antecedents to capability formation and outcomes.

Thirdly, it resonates with dynamic capabilities theory by considering AI-EDMC as a sensing, seizing, and transformation mechanism; AI enhances sensing by processing information, seizing by evaluating and allocating resources, and transformation by learning and adapting.

Fourth, it adds to resource-based reasoning by specifying the complementarity of the generic AI technologies to be sustainable strategic resources themselves, but only when combined with firm-specific resources.

Finally, the framework supports human-AI research by making complementarity a boundary condition as opposed to a secondary implementation concern. The performance of entrepreneurs is not only based on the sophistication of AI but also on the architecture of interaction between algorithmic and human intelligence.

11. Managerial Implications

There are a number of implications for entrepreneurs and startup managers on the framework.

Firstly, founders must think beyond the digital subscription as a measure of AI adoption. So the question isn't "what AI tools do we have?" it's "what decisions are better because of them? Before making a huge investment in AI, startups should find high-value decision domains, where they can see the impact and benefits of the AI's output, such as customer segmentation, demand forecasting, financial planning, opportunity screening, and operational optimization.

Second, founders need to invest on data readiness. Even advanced AI models are unable to provide consistent insight when internal information is disjointed, imprecise, unavailable, or difficult to manage.

Thirdly, AI literacy needs to become an entrepreneurial skill, in and of itself. Don't need to be machine-learning engineers but need to know enough to evaluate what comes out, know when there are limitations, know about uncertainty, be wary of problems with sensitive information, and know when to call in specialist help.

Fourthly, human-oversight mechanisms should be put in place for decisions with strategic consequences. The aim should not be total trust in algorithms, nor a knee-jerk response to AI suggestions, but rather conscious decision-making processes where computational evidence and domain expertise are blended.

Last but not least, startups should measure the success of investing in AI according to the actual results it enables, not the novelty of their presence in the company's processes — increased speed of making decisions, customer acquisition, cost efficiency, forecasting or innovation.

12. Policy and Startup-Ecosystem Implications

The framework is especially relevant to emerging start-up ecosystems where high quality data and technical expertise, finance and infrastructure may be a significant challenge for firms.

Thus, public policy should go beyond abstractly encouraging the adoption of AI. Potential, effective interventions in the ecosystem include accessible and affordable computational infrastructure, founder AI-literacy programs, technical training, shared innovation facilities, regulatory guidance, AI support, and access to financing for digital-capability building.

Incubators and accelerators can play an intermediation role between technological possibility and entrepreneurial application. Instead of providing general AI workshops, they can help ventures discover use cases for AI that apply to their specific decisions, determine data readiness, and evaluate risks and return on AI investment.

These implications are especially relevant for entrepreneurial ecosystems in the region, including Kerala, India, where we have a rapidly expanding technology and start-up scene and a large pool of small, resource-restricted businesses. Future empirical studies would be interesting to explore if ecosystem support is a moderator between organizational readiness and AI adoption or if there is a lowering of gap in capabilities between small and larger startups.

13. Future Research Agenda

The framework will guide the way for future research in a number of ways.

First, the AI-EDMC construct should be validated by empirical studies. A recent systematic review of AI in entrepreneurial and small-business decision-making (Ayinaddis, 2025; López-Solís et al., 2025; Song & Sha, 2026) offers a good starting point for the development of candidate indicators for the scale.

Second, mediation should be studied as such in the future. However, decision quality, organizational learning, innovation capability or AI-EDMC itself should be analyzed as mediators between the relationship between AI adoption and start-up performance (P8, P10).

Thirdly, it is essential that the complementarity of human-AI be explored. The decision quality of entrepreneur-only, AI-only, and human-AI decision configurations can be compared in experimental studies to identify which configuration yields the best decision quality at various levels of uncertainty (P13, P14).

Fourth, the possible dark side of algorithmic entrepreneurship, including the algorithmic bias, deskilling, entrepreneurial idea homogeneity, privacy issues, algorithmic discrimination, algorithmic hallucination, IP issues, and reliance on external AI platforms, deserves considerable research.

Fifth, differences in life cycles of start-ups should be studied. AI can be used in various ways across opportunity discovery, venture creation, early commercialization, scaling, and maturity; generative AI might

find its primary use in ideation and market exploration for early-stage ventures, while predictive analytics and operational optimization may be more relevant for scaling ventures.

Sixthly, research into context is required. While many management theories on AI are developed in technologically rich environments and mature organizations, emerging economies provide valuable settings with different forms of resource scarcity, institutional context, digital infrastructure and informal knowledge, in which entrepreneurs operate. Future comparative studies could explore the effect of institutional support, digital infrastructure, entrepreneurial culture, and technical talent availability on AI adoption among startups in different regions of India, while empirical studies focusing on IT startups in Kerala could further operationalize the constructs of this study, including the measures of technological readiness, entrepreneurial mindset, organizational readiness, perceived barriers to AI adoption, AI adoption intensity, AI-EDMC, decision quality, innovation, growth, profitability, sustainability, and competitive advantage, and use structural equation modelling to test the mediation and moderation effects proposed in this study.

Lastly, research in the longitudinal direction is required. Both cross-sectional and survey studies can find relationships between AI adoption and performance, but they can't tell if AI improves performance or if successful startups have more resources to adopt AI. Longitudinal designs might follow the evolution of capability over time and determine if the advantages of AI continue to grow as organizations become more data-rich, experienced, and have complementary capabilities.

14. Limitations

There are some drawbacks to this conceptual paper. Firstly, it is a theoretical integration and not empirical validation; the proposed propositions, therefore, will need to be tested in the future through quantitative and qualitative testing.

Secondly, AI is changing so fast. The capabilities, costs, accessibility, regulatory conditions, and user practices may evolve more rapidly than typical academic publication cycles, and conceptualizations of AI adoption should be mindful of technological progress.

Third, the framework incorporates several theories. While this offers breadth of explanatory power, future research could focus on the need for all of the components across organizational and institutional settings.

Fourth, the framework focuses mainly on the outcomes at startup stage; more work is needed on the individual level factors of founders, team level factors, investor influences and ecosystem level implications.

Lastly, the impact of AI can vary dramatically across businesses, sectors, stages, and countries, and for various decisions. These should be tested explicitly, not assumed to be universal, contextual conditions.

15. Conclusion

Entrepreneurship is witnessing a transformation of its informational and cognitive bases with the help of artificial intelligence. Artificial Intelligence (AI) is now emerging as a powerful tool that startups can leverage to uncover opportunities, comprehend customer needs, anticipate demand, allocate resources, assess risks, plan strategies, and fuel innovation. However, access to technology does not necessarily translate into better decision making or better performance.

This paper has presented an integrative framework (shown in Figure 1 and Table 2) that describes the influence of technological, organizational, entrepreneurial and environmental conditions on the adoption of AI and how adoption can be translated into AI-based entrepreneurial decision-making capability. This capability enhances decision quality, decision speed, analytic accuracy, adaptability, and risk assessment which, in turn, lead to growth, profitability, innovation, resilience, and competitive advantage, as the framework suggests.

The core theoretical thesis is that the future of entrepreneurial decision-making cannot be thought of as a mere substitute of human intuition with algorithms. Where conditions are new, uncertain, socially complex and real, entrepreneurial intuition is still valuable, but where algorithmic intelligence can provide computation scale, analytical consistency, prediction and information-processing, entrepreneurial intuition is required. The most effective set-up is one of complementarity, an evolution towards the augmentation of entrepreneurial intelligence, with AI complementing data, organisation learning, entrepreneurial judgment and responsible governance.

From an academic point of view, the framework offers propositions which can be empirically examined within different industries, venture stages and institutional settings. It underscores the need for data preparation, competencies, processes, and essential human oversight in the AI investment process, especially for entrepreneurs. It shows policy makers and entrepreneurial ecosystems the importance of facilitating capabilities as opposed to just facilitating technology uptake. Since AI is becoming increasingly available, the competitive advantage of startups may thus not rely on the availability of artificial intelligence, but on how well they are able to integrate artificial intelligence with entrepreneurial intelligence.

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