Using AI as a Disconfirmation Engine in Entrepreneurial Decision-Making: The A.D.A.P.T Framework

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Abstract
Entrepreneurial decision-making under genuine uncertainty remains a critical challenge, as neither artificial intelligence nor human judgment alone provides a sufficient response. This paper examines how their structured integration, within the context of Industry 5.0, can address this gap. While existing literature shows that AI excels in structured settings and that human-AI collaboration is effective, it fails to define how decision-making responsibilities should be distributed under highly unpredictable conditions and often treats human cognitive limitations in isolation. This study adopts a qualitative conceptual approach using secondary data from peer-reviewed articles, analysed through thematic synthesis. It proposes the A.D.A.P.T. (Adversarial Decision and Planning Technique) framework, which improves decision-making by using AI to disconfirm assumptions rather than validate them. The framework extends behavioural decision theory and effectuation theory, offering a practical tool for low-risk experimentation and positioning AI as a disconfirmation engine.

Keywords: Entrepreneurship, Decision-Making, Uncertainty, Artificial Intelligence (AI), Human Judgment, Human-AI Collaboration, Industry 5.0, Effectuation

1. Introduction

Entrepreneurial ventures often operate in uncertain environments. Volatile market conditions, limited resources and high level of uncertainty. Decision-making in the development process is difficult because the future is highly uncertain and historical data are unavailable. In such cases, entrepreneurs rely on different decision-making approaches. Two different methods that entrepreneurs employ in the process of developing new ventures are causation and effectuation (Chandler et al., 2011). Causation aligns with strategies that are planned (Ansoff, 1988; Brews and Hunt, 1999; Mintzberg, 1978, as cited in Chandler et al., 2011). Conversely, effectuation processes (Chandler et al., 2011) correspond to emergent strategies (Mintzberg, 1978, as cited in Chandler et al., 2011) or non-predictive strategies (Wiltbank et al., 2006).

Entrepreneurial decision-making highly depends on human judgment. However, recent technological advancements in the area of Artificial Intelligence have been changing the way organisations process data and make decisions. A large set of data can be analysed and processed, and quick decisions can be made with the help of AI, which could be difficult for human decision-makers to detect. The implementation of AI-enhanced decision-making is rapidly changing how contemporary organisations function, compete and expand (Raina et al., 2025).

Industry 5.0 is a recent concept that encapsulates this shift, characterised by a vision of technology in industry that emphasises human elements while addressing the needs of both workers and society, alongside the sustainable optimisation of energy usage, material processing and product lifecycle management (Barata & Kayser, 2022). By reintegrating human workers into production environments, the Fifth Industrial Revolution aims to combine human intellect and creativity with machinery to enhance process efficiency by merging workflows with intelligent systems (Nahavandi, 2019). While the focus of Industry 4.0 is on automation, Industry 5.0 emphasises collaboration between humans and autonomous machines (Nahavandi, 2019).

When multiple studies focus on improving the efficiency of AI in business organisations and decision-making under data-rich conditions where historical data on the relevant area is available, this research paper focuses on the integration of human intelligence and artificial intelligence in decision-making under scenarios of uncertainty. It explores how collaboration between humans and artificial intelligence can support such decisions. The discussion is framed within the context of Industry 5.0.

2. Research Objectives

1. To understand the role of artificial intelligence in the entrepreneurial decisions that are data-driven, such as forecasting, pattern recognition and optimisation of operations.
2. To understand the role of human judgment in entrepreneurial decisions under conditions of uncertainty, such as in cases of market innovation, product innovation, ethical decisions and negotiation with stakeholders.
3. To develop a conceptual understanding of the potential for collaboration between human intelligence and artificial intelligence in supporting entrepreneurial decisions in the context of Industry 5.0.

3. Literature review

3.1. Industry 5.0

Industry 5.0 has passed through three stages, starting with the focus on the "human aspect" of industrial progress, then moving to "technology impact on society/environment," and finally "smart cities" and "circular manufacturing," where there is a focus on reusing wastes (Barata & Kayser, 2022). "Human centricity, such as environmental sustainability, is prioritised over technological progress." (Barata & Kayser, 2022).

Industry 5.0 will also employ advanced technologies like collaborative robots (cobots), Digital Twins, Fast 6G Internet and Blockchain to improve the health and supply chain industries, among others (Maddikunta et al., 2022). The overall objective of Industry 5.0 is to bring human creativity and intelligent machines together in a collaborative and efficient production process while addressing challenges like data security and employee training (Maddikunta et al., 2022). The concept will create new jobs while eliminating routine jobs to create a sustainable future (Nahavandi, 2019).

Despite its growing popularity, Industry 5.0 remains largely conceptual, with limited evidence on its implementation across industries. While Industry 5.0 emphasises human-machine collaboration, existing literature does not clearly explain how decision-making responsibilities are distributed between humans and AI under conditions of uncertainty.

3.2 Artificial Intelligence in Decision-making

The integration of Artificial Intelligence into organisations helps managers make decisions based on processed data. Researchers have clearly shown that AI surpasses human potential in terms of speed and accuracy in making decisions (Benhur-Aktürk, 2025; Zein, 2025; Raina et al., 2025; Nali, 2025). AI offers tremendous opportunities to companies to personalise consumer experience, save money and achieve rapid growth (Janardhanudu, 2025; Bhattacharjee, 2025). Expert systems and neural networks function as efficient consultants, which effectively eliminate human error and save valuable time (Bhattacharjee, 2025; Kurter, 2025; Raina et al., 2025).

As AI technology evolves, it often turns into a "black box" where the complexities of AI's decision-making process remain unknown (Nali, 2025; Raina et al., 2025). By greatly speeding up the decision-making process, AI minimises the chances of making wrong decisions, such as predicting machine failure before it leads to costly repairs (Zein, 2025; Raina et al., 2025).

However, there are significant limitations that have been identified by various researchers in the field, such as the fact that most people are against the use of AI due to various reasons, such as job loss and loss of power (Benhur-Aktürk, 2025; Janardhanudu, 2025; Raina et al., 2025).

The most significant challenges include the potential for hackers to steal sensitive information from companies, potential bias in algorithms (Bhattacharjee, 2025; Raina et al., 2025; Janardhanudu, 2025; Nali, 2025). The "black box" phenomenon may lead to laziness, where the manager is not interested in knowing the rationale of the decision and leaves it to the machines to take over the cognitive process (Nali, 2025; Bhattacharjee, 2025).

This emphasises that AI cannot fully replace human decision-making. Although AI excels in structured and data-driven settings, it may struggle in uncertain and complex situations. Current research suggests that combining AI with human judgment is necessary. This combination is particularly effective in unpredictable environments where neither human intuition nor AI alone is adequate, underscoring the significance of collaboration between humans and AI.

3.3 Human Decision-making

Human decision-making involves choosing the best option amid uncertainty, often using past trends in the absence of data. The literature on the effectiveness of decisions has shown that the effectiveness of the tools used for the decisions depends on the type of problem (Fedorova et al., 2021). For instance, the use of tools such as brainstorming is effective for idea generation, while other studies have shown that effective decisions are made by experienced managers compared to less experienced people (Fedorova et al., 2021). For effective decisions, it is important to understand the internal dynamics and the external environment (Fedorova et al., 2021).

The concept of satisficing also explains that people do not try for the best option but prefer the option that is above the minimum level acceptable to the person (Simon, 1955). This is also the concept of bounded rationality because people try to simplify the decisions they make (Simon, 1955). The decisions people make are not rational but behavioural; thus, the inclusion of psychology in the study of economics is more realistic (Simon, 1955; Smith, 2024).

However, existing decision-making theories tend to emphasise human limitations in isolation, without sufficiently taking into account the possibility of complementing human limitations through new technologies, such as AI, under conditions of uncertainty.

3.4 Entrepreneurship and Effectuation

The literature on Effectuation presents a fundamental shift from traditional predictive models of entrepreneurship to more flexible and adaptive approaches (Wiltbank et al., 2006; Perry et al., 2012). While conventional models based on causation suggest that entrepreneurs start with a specific goal and select the best means to achieve it, these models often fall short in dynamic and uncertain environments where future conditions cannot be reliably anticipated (Chandler et al., 2011; Fisher, 2012; Sarasvathy,

2008).
Research indicates that expert entrepreneurs, particularly in uncertain market scenarios, heavily rely on effectual principles by collaborating with stakeholders to co-create new markets instead of solely forecasting demand (Read et al., 2009; Sarasvathy, 2008; Wiltbank et al., 2006). While traditional managers often rely on market research and predictive planning, expert entrepreneurs prioritise flexibility, strategic partnerships and iterative learning (Read et al., 2009).
Key principles underpinning effectuation include the use of available means, a focus on affordable loss, leveraging contingencies, building partnerships and exercising control over future outcomes (Sarasvathy, 2008). Together, these principles suggest that entrepreneurship is less about forecasting and more about a learnable process driven by action, experimentation and collaboration (Chandler et al., 2011; Fisher, 2012). Although recent studies have introduced validated survey instruments to assess entrepreneurial behaviour, there is still a need for further research employing larger sample sizes and more rigorous quantitative methodologies (Chandler et al., 2011; Fisher, 2012; Perry et al., 2012). Additionally, integrating effectuation with established theoretical frameworks is crucial for a deeper understanding of its role in entrepreneurial decision-making (Perry et al., 2012).

3.5 Human & AI Collaboration

The outlook on the future of work is shifting toward viewing it as a partnership between humans and machines, rather than as technology replacing human labour (Dellermann et al., 2019). The process of human–AI collaboration can be categorised into three phases (Hao et al., 2023). In the pre-decision phase, humans set ethical standards and outline the limits of AI usage (Hao et al., 2023). In the decision-making phase, AI executes data-heavy tasks while humans supervise its operations and step in as needed (Hao et al., 2023). In the post-decision phase, humans assess AI results to verify fairness, accuracy and alignment with the organisation's objectives (Hao et al., 2023).
The literature also introduces the idea of "Hybrid Intelligence," which merges the advantages of both humans and machines (Dellermann et al., 2019). Humans bring creativity, empathy and intuitive judgment, while AI contributes speed, large-scale data analysis and pattern recognition (Dellermann et al., 2019).
Building trust is essential for fostering productive human–AI collaboration (Dellermann et al., 2019; Wen et al., 2025). While AI facilitates faster data processing and information gathering, the final decisions should remain with humans, as AI lacks the capacity to understand ethics and the complexities of human emotions (Hao et al., 2023; Trunk et al., 2020). Therefore, it is essential to invest heavily in training employees to collaborate with AI systems safely and effectively (Trunk et al., 2020).
Despite its benefits, AI possesses intrinsic limitations (Hao et al., 2023; Trunk et al., 2020). It lacks human traits such as empathy, creativity and the ability to interpret emotional and contextual signals (Trunk et al., 2020; Dellermann et al., 2019). To achieve effective collaboration, managers must foster AI literacy and establish robust ethical guidelines (Trunk et al., 2020). However, if AI is seen as having too much autonomy or a sense of "free will," it may provoke fear and identity concerns among users, thus diminishing trust and undermining collaboration (Wen et al., 2025).
Thus, the literature highlights the effectiveness of human-AI collaboration in decision-making by leveraging the strengths of both humans and AI. However, it lacks insights into its application in highly uncertain situations, especially regarding the balance of responsibilities when outcomes are unpredictable or information is incomplete. This study aims to address this gap in the context of Industry 5.0.

4. Research Methodology

This conceptual and qualitative study utilises secondary data from 24 peer-reviewed articles, focusing on Industry 5.0, AI's impact on decision-making, entrepreneurship and human-AI collaboration. It examines the evolving integration of humans and AI, highlighting that there is no clear framework for decision-making roles yet. The study assesses the pros and cons of AI and human decision-making in various contexts and proposes a conceptual framework for decision-making responsibilities. It addresses challenges related to uncertainty and explores AI's role as a data engine alongside human judgment. Emphasising the importance of both human and machine intelligence, the research highlights effective managerial decision-making in organisations facing the complexities of Industry 5.0.

5. Discussion

5.1 Decision-making Under Uncertainty

Uncertainty stems not from a lack of data but from unreliable information, unpredictable outcomes and dynamic environments (Zein, 2025). This is particularly relevant in “Knightian Uncertainty” where past patterns or probabilities are absent, complicating decision-making (Wiltbank et al., 2006). Entrepreneurship often encounters these scenarios, especially in early development stages, where incomplete information hampers effective business planning (Wiltbank et al., 2006; Read et al., 2009; Sarasvathy, 2008).

While Artificial Intelligence (AI) is powerful, it struggles without high-quality, structured data, as it relies heavily on it (Benhur Aktürk, 2025; Bhattacharjee, 2025; Dellermann et al., 2019; Hao et al., 2023). AI also faces challenges in qualitative assessments involving human instincts, such as market volatility or cultural shifts and can provide misguided advice if data is biased (Benhur Aktürk, 2025). Its “Black Box” nature lacks transparency in decision-making logic (Nali, 2025).

Conversely, human decision makers, while relying on intuition and past experiences, often face their own limitations. They struggle to process complex information effectively (Hao et al., 2023; Simon, 1955) and can be influenced by cognitive biases like the framing and anchoring effects (Hao et al., 2023; Smith, 2024).

5.2 Data Dominant Decision-making

AI performs the best in data-rich situations. For AI to perform at its best in the decision-making process, it has to satisfy three specific conditions, which are the availability of historical data, recognisable patterns and probable outcomes (Dellermann et al., 2019; Hao et al., 2023). When these conditions are present, AI acts as an incomparable scientific tool.

AI demonstrates superior performance across data analysis, pattern recognition, forecasting and operational optimisation tasks that require processing large volumes of structured information at speed and scale (Nali, 2025; Janardhanudu, 2025; Hao et al., 2023; Bhattacharjee, 2025; Raina et al., 2025).

AI reduces the mental load and complexity in interpretation. Due to “Bounded rationality”, human decision makers would not be able to analyse data sets in large volumes and identify subtle correlation patterns and constantly optimise mathematical models without workload (Dellermann et al., 2019). AI handles computational work effortlessly, eliminating human error (Hao et al., 2023; Kurter, 2025).

However, these strengths work perfectly when the data is reliable, the environment is stable and the required variables are known. If an AI system is fed incomplete, biased or unreliable data, the decisions generated will be incorrect and may misguide the organisation. AI is powerful in structured decision-making, but may break down in an unpredictable environment.

5.3 Uncertainty Dominant Decisions

When the level of uncertainty increases, the existing data loses its value and judgment becomes more important. In certain circumstances, human decisions tend to dominate. It is highly required when a new market is to be created, when an innovative or novel product is to be launched, when ethical choices are to be made, considering social and cultural conflicts and building alliances, including managing human emotions, shifting power dynamics and managing trust (Read et al., 2009; Wiltbank et al., 2006; (Hao et al., 2023; Zein, 2025; Wen et al., 2025; Trunk et al., 2020).

Human intelligence dominates during uncertainties, mainly because of their approach towards the respective problem. Humans have the ability to gain a deeper understanding of the scenario, handle immediate surprises and ethical reasoning (Nali, 2025; Dellermann et al., 2019). AI cannot interpret extreme uncertainty nor can it comprehend human factors that cannot be quantified (Hao et al., 2023; Trunk et al., 2020).

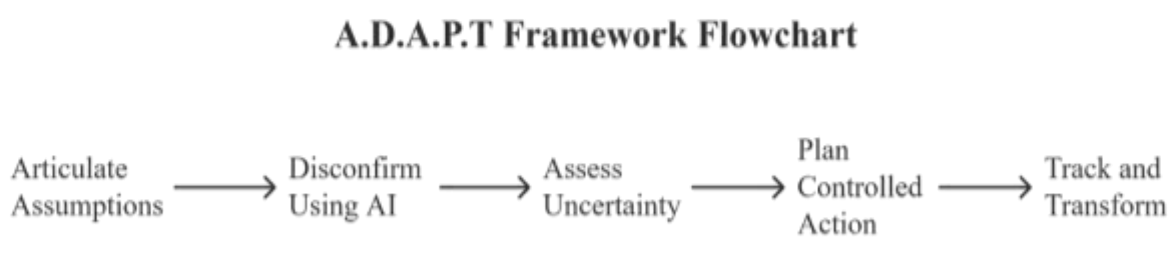
In this kind of situation, the concept of effectuation comes into play. Human experts use the available resources, create new markets instead of anticipating demand, assure commitment to their shareholders and adapt quickly to the dynamic environment (Sarasvathy, 2008; Fisher, 2012; Read et al., 2009; Chandler et al., 2011).

However, it is important to recognise that humans are naturally flawed. Human cognitive capacity is limited compared to artificial intelligence. Humans tend to be more biased and inconsistent. The human brain tends to move in shortcuts and choose to stop at "good enough" option, rather than the best, fearing failure.

5.4 A.D.A.P. T Framework (Adversarial Decision and Planning Technique)

To overcome the disadvantages of the existing techniques, the A.D.A.P.T framework introduces an architecture for decision-making, where AI is used not just as an aid but as a tool for the disconfirmation of entrepreneurial decisions.

Fig 1.1 Detailed Explanation of Each Stage



1. **Articulate Assumptions:** This phase involves articulating the assumptions made in the decision. Entrepreneurship decisions are made based on various implicit assumptions regarding market demand, customer behaviour, pricing and competition. If these assumptions are not articulated, it will lead to incorrect decision-making. This phase begins with articulating the decision problem, the assumptions made in the decision and the expected outcomes. Human intelligence frames the decision situation and identifies the basic assumptions, while artificial intelligence enhances the set of assumptions and identifies the hidden assumptions.

2. **Disconfirm Using AI:** This phase is the major innovation in the framework, where artificial intelligence is used for disconfirming the assumptions instead of confirming them. This phase involves identifying contradictory evidence and analysing the weaknesses in the decision logic through historical data analysis, relevant case studies and the identification of negative patterns. Artificial intelligence performs extensive analysis to identify patterns of failure, which serve as evidence against the initial assumptions. Human intelligence analyses the information obtained from artificial intelligence to identify the relevant information and eliminate irrelevant information from influencing the decision-making process. This phase ends with the development of a Disconfirmation Assessment, which shows the extent to which the initial assumptions have been challenged.
3. **Assess Uncertainty:** The next step is to assess the different types of uncertainty. Uncertainty can be broadly classified into three types: known risk, ambiguity and cognitive error. While artificial intelligence can assist in the assessment of uncertainty in the form of probabilities, human intelligence is required to accurately classify the type of uncertainty. The classification is an important factor in the next steps of the process.
4. **Plan Controlled Action:** The next step is to select the strategic action in response to the type of uncertainty. The strategic action is such that it is not risky or requires significant investments. The strategic actions can be in the form of testing, adapting or aborting the idea. While artificial intelligence can assist in the process of testing the idea, adapting the idea or aborting the idea in the form of experiments or estimation of the outcome or the risk involved in the idea, human intelligence can assist in the finalisation of the idea. The result is the development of the decision strategy.
5. **Track and Transform:** The last stage focuses on monitoring the outcomes and developing continuous learning. Decision-making improves through continuous tracking and feedback mechanisms, including the use of performance metrics and comparing actual outcomes against expectations. Artificial intelligence helps in tracking the data in real time, while human intelligence helps in interpreting the results for strategic changes. This leads to changing assumptions and improving the decision-making process for continuous learning.

   The A.D.A.P.T framework offers a structured and dynamic approach for entrepreneurial decision-making in situations involving uncertainty. It improves decision quality, reduces cognitive biases and facilitates adaptive learning by incorporating human intelligence with AI-based disconfirmation. It is a significant contribution to the field of entrepreneurship and strategic decision-making due to its simplicity, theoretical basis and practical application.

6. Implications

6.1 Theoretical Implications

The A.D.A.P.T framework makes a contribution to existing literature by altering the position of artificial intelligence in decision-making processes.

Firstly, A.D.A.P.T changes the position of artificial intelligence in decision-making processes from an assistive role to an adversarial role. The majority of existing literature focuses on artificial intelligence for prediction and optimisation. A.D.A.P.T. introduces artificial intelligence in terms of disconfirmation. This creates a new path of inquiry in terms of artificial intelligence and human collaboration.

Secondly, A.D.A.P.T extends behavioural decision theory, particularly in terms of confirmation bias as presented by Daniel Kahneman. Existing literature identifies confirmation bias; however, A.D.A.P.T creates a mechanism to reduce confirmation bias, thereby applying theory to practice.

Thirdly, A.D.A.P.T extends bounded rationality theory as presented by Herbert Simon by using artificial intelligence to enhance cognitive processes. This demonstrates how artificial intelligence can be used to overcome cognitive limitations in an uncertain world.

Finally, A.D.A.P.T extends effectuation theory as presented by Saras Sarasvathy by formalising experimentation in a structured decision architecture, rather than an informal approach to entrepreneurship.

6.2 Practical Implications

1. **For Entrepreneurs:** The A.D.A.P.T framework serves as a practical decision-making tool for entrepreneurs operating under uncertainty. It enables them to clearly articulate their assumptions before taking action, thereby reducing the risks associated with flawed strategic decisions. By using AI to disconfirm assumptions rather than validate ideas, entrepreneurs can identify potential pitfalls early in the decision-making process. Additionally, the framework supports lean experimentation, allowing entrepreneurs to test ideas with minimal financial exposure. Its iterative nature further helps entrepreneurs continuously refine their strategies, enhancing adaptability in dynamic business environments.
2. **For Organisations**: For organisations, the A.D.A.P.T framework enhances the quality of strategic decision-making by introducing a structured process of critical evaluation. It encourages organisations to move beyond consensus driven approaches and adopt a culture of constructive challenge. The framework also improves decision transparency, as assumptions, risks and outcomes are systematically documented, enabling organisations to assess decision effectiveness. Furthermore, the integration of AI into the process helps achieve a balance between data-driven insights and human judgment, resulting in more robust and informed decisions.
3. **For Industry 5.0:** The A.D.A.P.T framework aligns closely with the principles of Industry 5.0, which emphasises human-centric, resilient and sustainable systems. Unlike Industry 4.0, which focuses on automation and efficiency, Industry 5.0 highlights human–AI collaboration. In this context, the framework promotes human–AI synergy, where AI acts as a disconfirmation tool while human creativity and judgment remain central. It also supports the development of resilient and adaptive systems through continuous tracking and transformation, enabling organisations to respond effectively to uncertainty. Finally, the framework encourages responsible and transparent use of AI by emphasising critical evaluation over blind reliance, which is essential for building trust and ensuring ethical implementation.

7. Limitations of the study

A few drawbacks of A.D.A.P.T need to be highlighted. First, the approach is purely theoretical, meaning it does not have any empirical validation. Therefore, it cannot be generalised. Second, the successful implementation of A.D.A.P.T depends on the accuracy of information being entered into an AI program. The erroneous data will make A.D.A.P.T fail. Third, even though A.D.A.P.T tries to overcome cognitive bias through its framework, it is possible that some bias will persist since human beings interpret information entered into the program. However, it must also be understood that A.D.A.P.T provides a robust foundation for enhancing decision-making capabilities in uncertain situations

8. Conclusion

Entrepreneurial decision-making under uncertainty is complex as the environment is novel and unpredicttable, historical data is absent and outcomes cannot be forecasted (Read et al., 2009; Chandler et al., 2011; Fisher, 2012). In such vague situations, neither Artificial Intelligence that heavily relies on historical data and recognisable patterns nor human intelligence that has constraints of bounded rationality and cognitive bias is sufficient to obtain optimal solutions (Raina et al., 2025; Dellermann et al., 2019).

The review of existing literature established that Artificial intelligence provides extraordinary abilities in analysing large data, automating everyday activities and generating predictive perception with accuracy and speed (Hao et al., 2023). However, human decision makers have maintained crucial positions throughout the AI lifecycle, especially in responsibilities that require contextual understanding, careful decision-making or ethical reasoning (Hao et al., 2023). The theory of effectuation explains how entrepreneurs navigate these uncertainties by optimum utilisation of available resources, working within their loss appetite and negotiating with their stakeholders and building confidence rather than following the predictive strategy (Chandler et al., 2011; Fisher, 2012).

Based on these insights, the study introduces the A.D.A.P.T framework, allocating decision-making authority between human decision makers and AI algorithms. This approach can be used in the current scenario supporting Industry 5.0 as it involves synergising human and artificial intelligence, rather than treating them as alternatives. It highlights how decision authority should shift based on context, thereby offering a more precise and actionable approach to managing uncertainty in entrepreneurial settings. Ultimately, the effectiveness of entrepreneurial decision-making will depend not on choosing between humans and AI, but on designing systems where each is used at the right time and in the right way.

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