Perceived impact of AI on decision-making within the Food and Beverage industry

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Abstract

This research investigates how professionals in the Dutch food and beverage (F&B) industry perceive the impact of artificial intelligence (AI) on the speed and accuracy of strategic decision-making. Despite the growing adoption of AI, little research has explored its role in strategic contexts. Guided by Herbert Simon's theory of bounded rationality, this research examines how AI may enhance decision-making by mitigating human cognitive limitations. Using a qualitative research design, five semi-structured interviews were conducted with professionals in strategic roles, supported by secondary data analysis. The findings indicate that AI significantly accelerates data collection and insight generation, especially in the intelligence phase of decision-making. Participants also reported that AI improves decision accuracy by synthesizing large datasets and revealing patterns, while still requiring human oversight for context and judgment. While AI helps manage the inherent speed-accuracy trade-off (SAT), it does not fully resolve it. Overall, AI is perceived as a valuable support tool that enhances, but does not replace, human decision-making. This research contributes to both academic literature and managerial practice by clarifying AI's perceived strategic value and its limitations within a high-stakes, fast-moving industry.

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1. Introduction

1.1 Background and context

Businesses exist because of and are shaped by decisions that constitute and are constituted by their strategy (Mintzberg, 1972). Strategic decision-making is a dynamic process due to the complex environments in which organizations operate, and the impact decisions can have on stakeholders (Mintzberg, 1973). Traditional decision theory differentiates between decisions made under risk and those made under uncertainty (Goodwin & Wright, 2014). Risk-based decisions involve known outcomes and probabilities, decisions under uncertainty refers to making choices in situations where the outcome of an action is not certain (Trimmer et al., 2011). Strategic decisions fall under the latter category, influenced by various internal and external factors. Decisions in this category must therefore be taken in an adaptive mode to handle complexity.

Strategic decision-making in today's complex world is a dynamic process. To make qualitative decisions it is beneficial to include diverse perspectives, but consensus among the group is needed. Recognizing the need for different perspectives, most companies choose to leave strategic choices not to one single decision maker but to a team of decision makers, also called a decision-making unit. The decision-making unit needs enough knowledge about the subject before making a choice. To gain this knowledge, they conduct research on the topic and do analysis on the data found.

Herbert Simon (1979) rejected the idea of the "economic man" who has complete information and cognitive power to make the optimal decision every time (Sinebe, 2024; Campitelli & Gobet, 2010). Instead, he argued that people make decisions within the constraints of their cognitive abilities, the information available to them, and time constraints. These limitations make it impossible to fully consider and evaluate all possible alternatives and their consequences (Simon, 1979; Sinebe, 2024, Campitelli and Gobet, 2010; Schwarz et al., 2022).

It is suggested that this limited cognitive power of humans can be mitigated by incorporating artificial intelligence (AI) in the decision-making process. The application of AI and machine learning (ML), alongside data fusion, data visualization, and collaboration tools, aimed at enhancing and refining decision-making processes, is occasionally referred to as decision intelligence (DI) (Market Research Forecast, 2025). DI platforms offer users a comprehensive and accessible view of all the data within their organization, providing actionable insights that are challenging to obtain through manual analysis alone. DI enhances decision-making processes at strategic, operational, and tactical levels, boosting trust in AI tools that aid business automation and enable faster, more accurate decision-making.

According to Market Research Forecast (2025) the global market size of DI was valued at 14.66 billion USD in 2023 and is projected to reach 44.53 billion USD by 2032 which indicates that there is a trend in the adoption of AI and ML technologies. This trend is said to be caused by a growing demand for data-driven decision-making (Market Research Forecast, 2025). In their survey of 250 executives who are familiar with their companies' use of AI, Davenport and Ronanki (2018) find that threequarters of them believe that AI will substantially transform their companies by 2021.

One of the industries where AI is driving substantial change is the Food and Beverage (F&B) industry. This industry is evolving due to customers' increasing needs, the rising demand for automation, complexities in the supply chain, and the need for greater efficiency in decision-making (Mordor Intelligence, 2025).

Forecasts for AI's penetration into the F&B business suggest that this trend will continue in the coming years. The projected growth in the market for AI within the F&B industry is illustrated in Figure 1. The global market for AI in the F&B industry is projected to be worth 9.4 billion USD in 2024, 13.39 billion USD in 2025 and grow at a CAGR of 38.3% to reach 67.73 billion USD by 2030 (Mordor Intelligence, 2025; Technavio, 2025). The future of the F&B industry is uncertain, but one thing is clear: AI will play a crucial role in shaping its future.

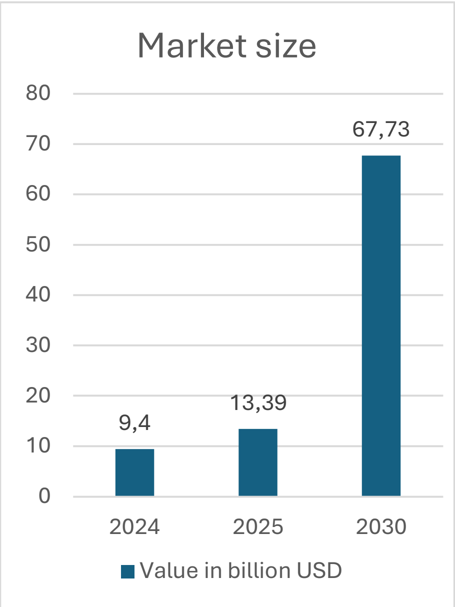

Figure 1: Market size of AI in the Food and Beverage industry.

Despite the rapid increase in AI applications and numerous claims about its substantial benefits and impact by developers and large corporates, there appears to be very limited academic research focusing on understanding the use and impact of the new generation of AI from a technology application perspective with rigorous investigation and theorization (Duan et al, 2019). Addressing this need for a more systematic understanding and theoretical grounding, Duan et al. (2019) propose that theorising the use of AI and impact on decision-making is necessary and that an integrated conceptual framework is needed to provide a systematic understanding of AI for decision making. This proposition highlights the need to develop a understanding of how AI is being used and how it affects decision-making processes. This research fulfils this need by focusing on a specific industry, The F&B industry, and examining AI's impact on strategic decision-making.

Furthermore, the role AI plays in decision-making is a subject of ongoing debate and is crucial to understanding its perceived impact. AI systems can serve multiple roles, from supporting human decision-makers to potentially replacing them (Jarrahi, 2018). While early AI systems showed effectiveness in replacement roles at operational and tactical levels, they had limitations at the strategic level. In contrast, AI systems in a support role were found to help users make better decisions across all three levels: strategic, tactical, and operational (Edwards et al, 2000). There is a significant discussion among practitioners and researchers suggesting that AI should primarily augment human judgment rather than automate tasks. This leads to the second relevant proposition by Duan et al. (2019), which states that AI plays multiple roles in decision making, but AI will be mostly accepted by human decision makers as a decision support/ augmentation tool rather than as the automation of decision making to replace them.

While this proposition predicts the acceptance of AI in a support/augmentation role, its application is highly relevant to understanding the perceived impact on accuracy and speed. The way F&B professionals perceive AI's influence on strategic decision-making accuracy and speed is likely intertwined with the role they believe AI plays or should play.

1.2 Research objectives and research question

This research aims to bridge the current gap in academic literature concerning the benefits and implications of AI in strategic decision-making processes, with a specific focus on the F&B industry. While AI’s application in operational and tactical domains has been extensively studied. However, its role in enhancing strategic decisions, particularly in terms of decision speed and accuracy, remains underexplored. The primary objective of this research is to investigate how professionals within the Dutch F&B industry perceive the impact of AI on the accuracy and speed of strategic decision-making. To achieve this objective, the research is guided by the following main research question:

How do food and beverage industry professionals perceive the impact of AI on the speed and accuracy of strategic decision-making?

In order to answer this question a multitude of sub-questions were formulated that allow for systematical exploration of the perceptions and experiences of industry professionals, thereby enabling an in-depth examination of AI's impact on strategic decision-making.

The first set of questions addresses the concept of decision speed, a vital element in maintaining competitiveness within rapidly evolving markets. Specifically, the questions “How do professionals describe AI’s role in accelerating data analysis for strategic decisions?” and “What are the perceptions of decision-makers regarding AI’s effect on the time taken to reach strategic decisions?” are designed to elucidate the ways in which AI may function as a catalyst for expediting the decision-making process. These inquiries are particularly relevant as they focus on the potential of AI to mitigate time-related constraints, facilitating swift responses in scenarios where timely action is imperative.

In addition, the research explores the notion of decision accuracy, wherein the questions “How do decision-makers perceive the influence of AI on the accuracy of their strategic decisions?,” “What are decision-makers’ experiences with AI in reducing errors during strategic decision-making?,” and “In what ways does AI assist decision-makers in identifying or choosing the most suitable strategic alternatives?” serve to investigate whether AI is perceived as a tool for enhancing accuracy in decision-making processes. These questions are essential as they delve into the core of strategic accuracy which is foundational to achieving long-term organizational success. By addressing AI’s potential to minimize human error and provide actionable insights, these questions aim to shed light on how AI contributes to more reliable and impactful strategic choices.

Moreover, the research acknowledges the inherent speed-accuracy trade-off, a well-established tension that decision-makers often encounter in strategic contexts. The questions “How do decision-makers experience and describe the balance between speed and accuracy in strategic decisions?" and "How do decision-makers perceive AI's role in addressing the tension between decision speed and accuracy?" are pivotal as they explore whether AI technologies can strike an effective balance between these two often competing objectives. These queries are particularly significant as they enable a deeper understanding of how AI might mediate this trade-off, thereby potentially transforming the strategic decision-making paradigm.

The structured inclusion of these questions ensures that the investigation is both methodologically sound and theoretically informed. By centering the research around these well-defined and purposeful inquiries, the research facilitates a robust analysis while creating a clear pathway for reflecting on the findings in the results section. Furthermore, these questions are not only pertinent to the operational realities of the Dutch F&B industry but also contribute to a broader discourse on AI's transformative capabilities in strategic decision-making.

1.3 Theoretical and practical contribution

1.3.1 Theoretical contribution

This research extends on Herbert Simon's (1979) Decision Theory through the integration of AI as a cognitive and analytical support tool within the decision-making process. Simon's concept of bounded rationality emphasizes how human decision-makers are constrained by their cognitive and information processing capacities. Through this view, this research investigates how AI can be used as a tool to mitigate these constrains, possibly improving both the speed and accuracy of strategic decisions.

Additionally, this research adds to the limited amount of research regarding AI's impact on strategic decision-making within the F&B industry. Existing studies often focus on AI's applications in operational areas such as supply chain management and food safety.

1.3.2 Practical contribution

The results of this research provide industry professionals with practical advice on how AI can be effectively integrated into strategic decision-making processes to improve both speed and accuracy. By capturing the perceptions of professionals within the industry, the research identifies not only the potential benefits but also the perceived limitations and challenges of AI use in strategic contexts.

1.4 Scope

This research limits itself to the Food & Beverage industry in the Netherlands. The food and beverage (F&B) industry is defined as the industry involved in the processing, packaging, distribution, and sale of food and drink products, encompassing both manufacturers and service providers such as restaurants, caterers, and retail food suppliers.

Additionally, the research restrictions relate to the theoretical lenses of strategic decision-making, which refers to long-term, high-impact decisions that shape the direction, growth, and competitiveness of organizations. As such, the research specifically examines the experiences and perceptions of top and middle management professionals, including CEOs, operational directors, innovation managers, and strategy leads. These individuals are directly involved in shaping business strategies and are most likely to interact with or be affected by AI-driven decision-support tools.

The scope of primary data collection is limited to professionals currently working in the Dutch F&B industry. The research also includes a triangulation approach to ensuring validity, incorporating insights from AI experts, as well as analysis of relevant reports and articles.

This research does not aim to generalize findings across all industries or geographic regions. Instead, it seeks to provide a nuanced, contextual understanding of how AI is shaping strategic decision-making specifically within the Dutch F&B industry.

2. Theoretical background

This chapter outlines the theoretical foundations that guide the analysis of how AI influences strategic decision-making within the F&B industry in the Netherlands. It begins by exploring core theories of decision-making, with particular emphasis on Herbert Simon's concept of bounded rationality, which offers a realistic framework for understanding managerial choices under cognitive and informational constraints. Key constructs such as decision-making accuracy and speed are defined and discussed in relation to their strategic significance. The chapter also addresses the inherent speed-accuracy trade-off and evaluates the role of AI as a potential tool to navigate this tension. Finally, it provides an overview of AI's capabilities and its emerging relationship with strategic decision-making, laying the groundwork for the conceptual model used in this research. Together, these theoretical components establish a coherent framework for examining the interplay between human judgment, technological support, and strategic outcomes.

2.1 Decision-making

2.1.1 Definition of decision making

"Decision-making is the process whereby an individual, group or organization reaches conclusions about what future actions to pursue given a set of objectives and limits on available resources." (Schoemaker & Russo, 2013). Decision-making is typically defined as the process of selecting actions and allocating resources. From a strategic perspective decision-making focuses on long-term goals. It requires careful consideration of resources and potential uncertainties to secure the company's future (Kumar, 2024).

2.1.2 Herbert Simon's Decision Theory: Bounded rationality and satisficing.

Herbert Simon's work fundamentally shifted the understanding of how humans, particularly in organizational contexts, make decisions. He challenged the traditional economic view and proposed a more realistic model based on actual human capabilities and limitations (Simon, 1955, 1979; Sinebe, 2024). His theories provide a powerful foundation for analysing the dynamics of decision-making and evaluating the potential impact of tools like AI.

At the core of Simon's theory is the concept of bounded rationality (1955, 1979). This concept recognizes that human decision-makers operate within significant constraints:

- Limited Cognitive Capacities: Humans have limitations in memory, attention, and information processing speed.
- Limited Access to Information: Decision-makers rarely have complete or perfect information about the problem, alternatives, or future outcomes.
- Time Pressure: Decisions often need to be made quickly, limiting the time available for extensive information gathering and analysis.

These bounds make it impossible for humans to fully comprehend the complexity of many decision problems, especially high-stakes or strategic ones, or to evaluate all potential alternatives and their intricate consequences (Campitelli and Gobet, 2010). As a direct consequence of bounded rationality, Simon proposed that people do not strive to find the single optimal solution but instead aim for a "good enough" or "satisfactory" solution, a concept he termed satisficing (Simon, 1979; Phillips-Wren, 2013). Decision-makers search for alternatives and select the first one they find that meets their minimum criteria or "aspiration level". This aspiration level is not static; it can adjust based on changing experiences. In favourable environments when satisfactory solutions are easy to find, it tends to rise and fall in harsher environments (Simon, 1979). Satisficing is a practical and efficient strategy for humans operating under constraints. However, it can lead to sub-optimal outcomes compared to what might theoretically be achievable with complete information and unlimited processing power.

Simon described decision-making as a process involving distinct stages (1979):

- Intelligence Activity Stage: In this initial phase of the decision-making process, experts pinpoint the organization’s problems. Management will then seek solutions to address these issues effectively, aiming to create a conducive environment.
- Design Activity Stage: During this stage, multiple strategies are examined to resolve the identified problems. The primary focus is on analysing these strategies' strengths and weaknesses. Management evaluates the merits and demerits to determine the most suitable strategy for the problem at hand.
- Choice Activity Stage: The final stage delivers the decision output. Here, management selects the optimal strategy based on the comprehensive analysis from

the previous stage. This phase requires both qualitative and quantitative assessments of the strategies, along with creativity and sound judgment.

- Implementation Stage: This stage was later added to the model after a review by Herbert Simon. At this stage the chosen decision is put into action and the results are monitored, incorporating feedback loops. This stage is not included in this research because this research focuses on how the strategic decisions are made and not how they are implemented.

Each of these stages is influenced by the constraints of bounded rationality, potentially affecting the accuracy and speed of the decision process. Herbert Simon also suggests that the decision-making process is an iterative process because you always have to revise your earlier judgement. In Figure 2 the process as described by Herbert Simon is illustrated.

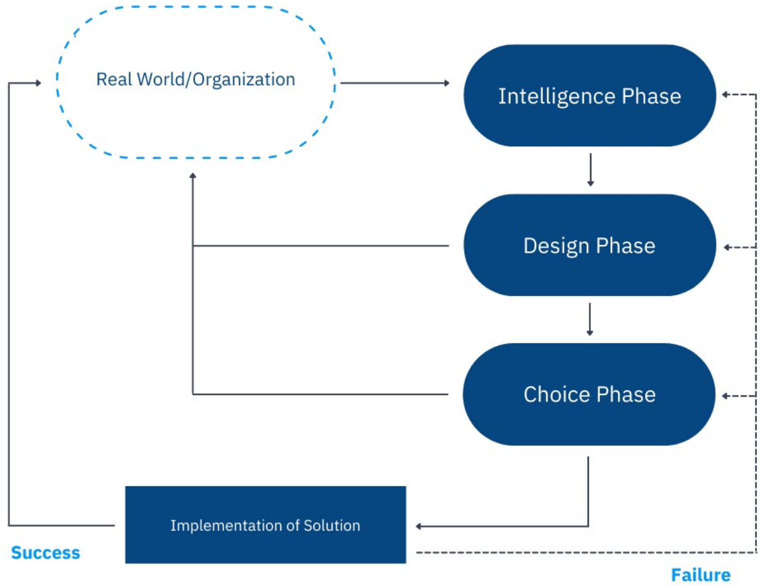

Figure 2 Decision-making process (Marković, 2025)

By applying Simon's theory of bounded rationality, I do not assess AI's impact against an unattainable standard of perfect rationality, but rather against the realistic constraints of human decision-making. This theoretical lens allows me to examine how AI can extend the boundaries of human rationality by enhancing the speed and accuracy of strategic decisions within real-world limitations. I also acknowledge the challenges inherent in this interaction, such as the quality and biases of the data that AI systems rely on, and the critical role of human trust and oversight. These factors align with Simon's view of decision-making as a dynamic process shaped by both cognitive limits and the tools available to the decision-maker.

2.1.3 Decision-making accuracy

Accuracy is considered a key objective measure of performance in decision-making. Within decision science, *accuracy* in decision-making refers to the extent to which a chosen option reflects the best possible outcome based on available information. Researchers have defined decision-making accuracy in multiple ways, reflecting differences in discipline and purpose:

According to Russo and Schoemaker (1990), decision accuracy is “the extent to which a decision leads to the most favourable outcome given the information available at the time.” This approach evaluates decisions against an objectively “correct” or optimal outcome.

Hammond et al. (1987) argue that accuracy should also consider how the decision is made, not just the result. They focus on cognitive consistency, logical reasoning, and the use of valid heuristics or models.

In statistical decision theory, accuracy is often measured in terms of calibration, how closely probability judgments align with actual outcomes (Yates, 1990). A well-calibrated decision-maker accurately reflects uncertainty in their judgments.

In behavioural studies, researchers often refer to perceived accuracy, how accurate individuals believe their decisions to be, regardless of actual outcomes. This is closely tied to confidence and bias (Kahneman & Tversky, 1979).

In this research, decision-making accuracy is understood through a combined definition that integrates the outcome-focused perspective of Russo and Schoemaker (1990) with the cognitive and perceptual insights of Kahneman and Tversky (1979). This definition considers both the objective quality of a decision, how well it leads to a favourable outcome based on available information, and the subjective processes involved, including how decision-makers perceive risks, probabilities, and their own confidence. This dual perspective is especially relevant for my research, as it allows for a more nuanced analysis of how strategic decisions are made in practice. This combined definition aligns well with the research’s qualitative approach, offering a broader lens through which to interpret the complex, human-centred nature of strategic decision-making in a technologically evolving context.

2.1.4 Decision-making speed

Strategic decision speed refers to the pace at which organizations make crucial choices involving significant resource investment and impacting long-term profitability and growth (Baum and Wally, 2003). In today's rapidly changing business environment, reaching well-considered strategic decisions quickly has become increasingly important. Baum and Wally (2003) suggest that fast strategic decision-making is linked to better firm performance. In their 4-year study involving 318 CEO's they found that swift strategic decision-making predicts subsequent firm growth and profit in high velocity environments, like the F&B industry.

Despite becoming increasingly important, the speed of strategic decision-making lags in many organizations, and achieving strategic decisions rapidly remains a challenge. Traditional, deliberate rational decision-making can be slow. Causes of slow decision-making can include: a large distance between the decision and its execution, and static internal strategy processes ill-equipped for rapid external changes (Boom Management, 2022).

This is where AI comes in as a potential accelerator of strategic decision-making, particularly by addressing the limitations of traditional (human) processes.

2.1.5 Speed-accuracy trade-off

An important consideration when striving for faster and more accurate decision-making, both human and AI-driven, is the speed-accuracy trade-off (SAT). Standage et al. (2014) describe the SAT as a fundamental characteristic of decision-making: decisions are typically faster but less accurate when speed is favoured, and slower but more accurate when accuracy is prioritized. This has been observed across species, such as ant colonies that choose a new nest faster but less accurately in hazardous conditions (Franks et al., 2003). AI can potentially help manage and optimize this trade-off.

2.2 Artificial Intelligence

2.2.1 Definition of Artificial Intelligence

Artificial Intelligence (AI) fundamentally refers to systems and technologies designed to simulate or mimic aspects of human intelligence and cognitive functions (Stryker & Kavlakoglu, 2024). It is widely considered one of the most significant technological advancements of the current era. At its core, AI operates by using algorithms, which can range from simple rules to complex neural networks, to process and analyze data and information (Ter Maten, 2025; Intellias, 2025). A central and often dominant aspect of AI, particularly in its current applications, is ML. ML enables AI systems to learn from past experiences, such as data and outcomes, to continuously improve their performance, identify patterns, and develop predictive models without being explicitly programmed for every specific outcome (Intellias, 2025; Stone et al., 2020)

2.2.2 AI use and strategic decision making

The relationship between AI and strategic decision making is one that is not yet covered rigorously by current literature. Most literature focusses on the impact of AI in operational level and production management. Business literature identifies the following key characteristics and capabilities of AI systems that could help with decision-making:

- They can process and analyse vast amounts of data quickly and accurately. Advances in computing hardware and efficient algorithms have enabled AI to make near-instant decisions (Shrestha et al., 2019, Boom management, 2024)
- They excel at identifying complex patterns, trends, correlations, and anomalies within data that may be difficult for humans to detect (Duan et al., 2019; Jarrahi, 2018).
- It facilitates automation of repetitive and time-consuming tasks, freeing up human resources for more strategic work. AI streamlines process and optimizes workflows (Shukla et al., 2024).
- AI can provide insights and recommendations based on its data analysis, supporting more data-driven decision-making. DI, a specific application of AI, is designed to not only provide insights but also suggest actions (PMC, n.d.)

2.3 Conceptual model

The conceptual model, as shown in Figure 3, developed for this research is grounded in Herbert Simon's three-stage decision-making framework and aims to explore how AI improves strategic decision-making within the F&B industry. Central to this model are the interrelated concepts of decision accuracy, decision speed, and the speed-accuracy trade-off. Accuracy refers to the extent to which decisions lead to favourable outcomes based on available information, while speed reflects how quickly those decisions are made and implemented. The trade-off between these dimensions is a well-established dynamic in decision science, suggesting that gains in speed often come at the expense of accuracy, and vice versa. This research seeks to investigate whether and how AI can mitigate this trade-off by improving both speed and accuracy across the three decision stages identified by Simon. Specifically, the research explores how AI tools influence the identification of relevant problems and opportunities (intelligence), the generation and evaluation of alternative strategies (design), and the final selection of a course of action (choice). By examining these effects through qualitative insights from industry professionals, the model provides a structured lens to analyse AI's potential in improving speed and accuracy of strategic decision-making processes.

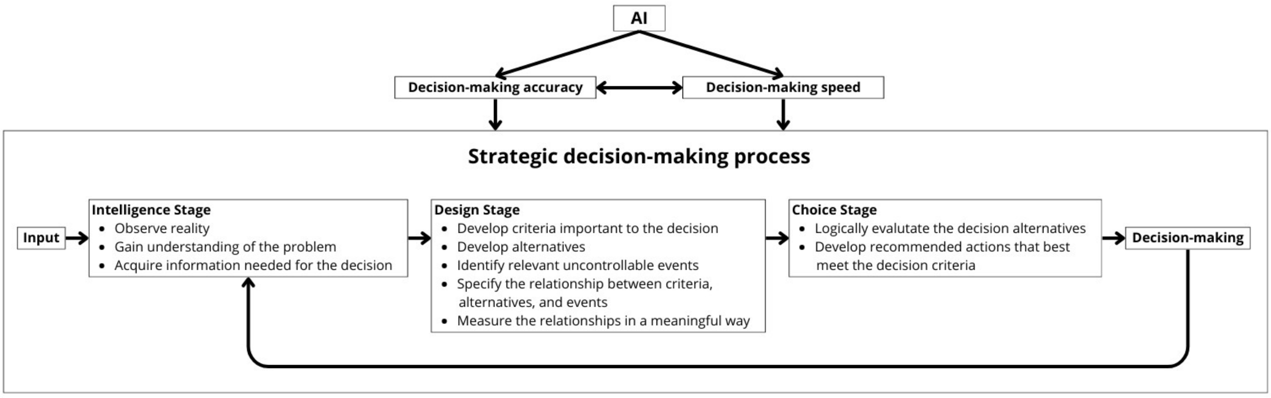

Figure 3: Conceptual model

3. Methodology

3.1 Research design and data collection techniques

In order to explore the perceptions and experiences of industry professionals, a qualitative research design was used. This aligns with the exploratory nature of the research and provides a thorough understanding of how AI influences strategic decision-making from the perspective of industry professionals. Data was collected through semi-structured interviews, which allowed for flexibility while guaranteeing that all constructs were covered. In order to support the findings from the interviews and provide extra context secondary data, including academic literature and white papers, were used. The data collection was guided by the research's central ideas: decision speed, decision accuracy, and the speed-accuracy trade-off, which are framed within Herbert Simon's decision-making model (intelligence, design, and choice stages).

3.2 Sampling

In order to find participants with relevant experience in strategic decision-making and with familiarity with the use of AI a purposive sampling strategy was used (Battaglia, M., 2008). In order to be considered to be part of the sample, the professional had to have at least 6 months of experience in the use of AI systems/tools in decision making, work within the F&B industry and be involved in part or all of a decision-making process.

Eventually, five professionals employed in the Dutch F&B industry made up the sample. Their job titles, which varied from Chief Operating Officer (COO) to Data Lead, guaranteed a blend of technical and executive perspectives. All of the participants were in a good position to consider the strategic implications of AI in their respective companies because they were all involved in the decision-making process.

Although this research is based on a limited number of interviews (n = 5), this sample size is justified within the context of qualitative research, which prioritizes depth of insight over generalizability. The participants were purposively selected for their expertise and strategic roles within the F&B industry, ensuring that each interview provided rich, detailed, and contextually relevant data. Additionally, the research focused on a specific and highly targeted group, top and middle managers with direct experience in strategic decision-making and exposure to AI tools, which naturally limits the pool of suitable respondents.

3.3 Measurement instruments

A semi-structured interview guide which can be found in Appendix 1 was created in accordance with the theoretical framework and research objectives served as the main tool for gathering data. The three core concepts of this research, decision speed, decision accuracy, speed-accuracy trade-off, were accompanied by open questions about AI limitations and the specific context of the participant. The purpose of the questions was to investigate participants' perspectives, experiences, and understandings of AI's impact on strategic decision-making. During the interviews, follow-up questions were employed to collect more detailed information and clarify answers.

3.4. Empirical research

The interviews were conducted over a two-week period and lasted between 30 to 85 minutes. The interviews were conducted in Dutch or Englisch depending on the preference of the participant and were audio and video recorded with consent. The interviews were automatically transcribed by Microsoft Teams during the interviews and were later checked for faults and inconsistencies. The analysis of the interviews followed the six stages of thematic analysis process introduced by Braun and Clarke's (2006). The coding process was guided by the research’s conceptual model and involved both deductive and inductive approaches, this resulted in the codebook found in Appendix 2. Codes were organized into themes corresponding to the core concepts of the research, decision speed, decision accuracy, and the speed-accuracy trade-off.

3.5 Secondary research

To strengthen the validity of the findings and reduce potential bias from single-source data, a triangulation approach was employed. In addition to the primary data collected through semi-structured interviews, secondary sources were analyzed to contextualize and corroborate the findings. The keywords used in the search of this data included: AI, DI, decision-making, decision-making accuracy, decision-making speed, speed-accuracy trade-off. Eventually this led to a review of white papers from consultancy firms

(Boom Management, Intellias, LexisNexis and PmC) and academic journal articles on decision making and AI in decision-making, a full list of all the secondary data can be found in Appendix 3. The sources were selected by their relevance to the constructs of this research, their recency, and their authority in the field. This triangulation enabled a more nuanced interpretation n of the interview data and contributed to the robustness of the conclusions.

3.6 Quality of research

Several steps were taken to guarantee the research's credibility. Triangulation, which combined primary and secondary data sources, increased credibility. In order to address transferability, thorough explanations of the participant roles and research background were given. Clear documentation of the research process, including the interview guide, coding scheme, and analytical stages, was maintained to enhance reliability. Last but not least, interpretations were grounded in the data and backed up by direct quotes and, when appropriate, outside sources to establish confirmability.

3.7 Research Ethics

Ethical considerations were taken into account for the thesis research to safeguard participants' rights and well-being. Informed Consent: Participants were able to give consent for in interviews to be transcribed and recorded or not. Data Anonymity: Data was anonymized to protect participant identities and statements about their companies' names were anonymized so that it would not be possible to trace it back. Compliance: The research adheres to GDPR and university ethical guidelines for data handling and participant rights.

4. Results

This chapter presents the results of the research but before the results are presented it is important to know how the interviews were analysed. The analysis followed Braun and Clarke's (2006) six-phase thematic analysis framework. The initial coding was done with a deductively derived codebook informed by the research's conceptual model. This codebook was later adapted with inductive codes emerging from the interview data itself because the initial deductive codes did not fully cover the participants findings. Before coding the interview, transcripts were first reviewed for familiarization, followed by the coding according to the process described above. These codes were then reviewed, refined, and clustered into overarching themes aligned with the three core constructs of this research. Additionally, attention was paid to how each theme reflected different stages of Herbert Simon's decision-making theory. This structured approach allowed for a coherent and theory-driven interpretation of the data, while still leaving room for insights from participants' unique experiences. The findings are further substantiated through secondary data analysis, including academic literature and white papers. The themes are discussed in the following paragraphs, each linked back to the corresponding sub-research questions mentioned in paragraph 1.2.

4.1 Decision-Making Speed

AI's role in accelerating data analysis

This section examines how professionals in the F&B industry describe the ways in which AI supports and speeds up the analysis of data used for strategic decision-making by answering the sub-question 'How do professionals describe AI's role in accelerating data analysis for strategic decisions?'. The focus is on understanding how AI tools contribute to faster insight generation and reduce the time spent on manual or repetitive analytical tasks.

Across interviews, participants emphasized that AI drastically reduces the time required to process large volumes of information. Participant 4 noted:

> "We try to keep track of everything happening, and we do that using extensive dashboards. They are not easy to read. AI is very good at that."
>
> *(Participant 4, personal communication, 28-05-2025)*

This underscores a common view that AI excels at processing complex or large datasets (Intellias,2024, Csaszar et al. 2024), making it easier and quicker for decision-makers to spot trends, assess changes, and prepare strategic options. Several participants highlighted the value of AI in transforming unstructured data into actionable insights. For example, Participant 5 (personal communication, 22-05-2025) described using AI to analyse scientific literature and stakeholder interviews more efficiently. This points to AI's role not just in data processing but also in generating insights, giving managers a faster and clearer picture of relevant information.

AI is also viewed as effective in automating repetitive research tasks (Shukla et al., 2024), such as literature scanning, trend monitoring, and scenario modelling. Participant 1 explained their use of AI as a search tool:

> *"The way that I use AI is by asking questions, searching for specific things, and making sure that I get fast results and valid results."*
> *(Participant 1, personal communication, 30-05-2025)*

Such tasks, previously time-consuming and manual, are now executed in a fraction of the time, enabling decision-makers to reach the design stage much sooner. The benefits of AI in this context were repeatedly associated with the intelligence phase of Simon's model, where data is collected, problems are defined, and environmental scanning takes place. Participant 3 made this link explicit:

> "In the data gathering, like the intelligence phase, AI is used to provide insights from the market… that's where it's really making an impact."
> *(Participant 3, personal communication, 21-05-2025)*

Other participants echoed this, confirming that AI's strength lies in preparing and framing the problem, the critical groundwork upon which strategy is built.

AI systems, particularly those built on DI platforms, are recognized for their ability to aggregate, structure, and analyse massive datasets in real-time, enabling organizations to react faster to emerging trends. LexisNexis (2025b) specifically highlights using Generative AI for powerful summaries and extracting data points from long documents to get insights faster and accelerate data-intensive business research. It's also worth noting that participants highlighted efficiency, not automation of decisions, as the primary benefit.

While AI provides faster insights, it does not yet replace human evaluation or judgment. As Participant 4 clarified:

> *"We haven't yet set things up so AI can make the decision — it stops at delivering the insights. Then we use those to make the human decision."*
> *(Participant 4, personal communication, 28-05-2025)*

This delineation between insight generation and decision execution suggests that the real value of AI's lies in enabling faster and more informed decision preparation, rather than in full process automation.

In summary, decision-makers perceive AI as a critical enabler of speed in strategic decision-making by accelerating data analysis, simplifying insight generation, and automating repetitive tasks. It plays a dominant role in the intelligence phase of the decision process, where it supports data gathering, analysis, and insight generation. This allows businesses to prepare, explore, and respond with significantly greater agility. While the ultimate decision remains in human hands, AI enables for the decision to happen sooner, and with more confidence, than traditional processes typically allow.

AI and strategic decision-making speed

This section provides an answer to the sub-research question 'What are the perceptions of decision-makers regarding AI's effect on the time taken to reach strategic decisions?'. Here, the research explores whether and how professionals perceive AI as influencing the overall time it takes to make strategic decisions.

A recurring theme in the interviews is that AI's impact on speed is most visible in the intelligence and design stages of decision-making. Participant 2 (personal communication, 26-05-2025) noted that AI allows them to react more quickly to data and insight needs, because the data is made available with the click of a finger. This observation aligns with a broader sentiment among participants that AI empowers business to act faster, not only by delivering information more quickly but also by structuring it in a way that facilitates faster understanding and decision-making as mentioned by participant 3.

“Speed-wise, it’s much more helpful... I think it’s enabled me to respond better to different market changes or trends.”
(Participant 3, personal communication, 21-05-2025)

Several participants mentioned the time savings achieved through the automation of information processing. Some quotes mentioning time savings:

“Sometimes you go to 5% of the original time needed to do something. That’s nice.”
(Participant 4, personal communication, 28-05-2025)

“It really depends on how you use it and so on, but I would say. Yeah, maybe I would say even 50% of the time.”
(Participant 1, personal communication, 30-05-2025)

However, the interviews also surfaced an important caveat: AI's speed advantage has limits when it comes to the choice stage of Simon’s decision-making model. Participant 1 remarked:

“In that stage (choice), there is a little bit of limitation. That’s where human touch is needed to actually make the decision.”
(Participant 1, personal communication, 30-05-2025)

This suggests that while AI can prepare and inform, the final synthesis and organizational consensus-building remains a slower, human processes. Some decisions involve multiple stakeholders, political considerations, or long approval cycles, factors AI cannot influence. Participant 2 reinforced this by distinguishing between increased speed in data access and unchanged speed in decision execution:

“AI speeds things up, yes, especially in the intelligence phase. But decision-making as a process still takes time.”
(Participant 2, personal communication, 26-05-2025)

In summary, decision-makers perceive AI as having positive and accelerating effect on the time required to reach strategic decisions. Particularly by reducing the time required to gather, process, and interpret information. However, this perception is nuanced: while AI significantly reduces the time spent on data-related tasks, participants emphasized that final strategic decisions still depend on human interpretation, coordination, and approval, which can limit the extent of overall time saved.

4.2 Decision making accuracy

AI’s contribution to decision accuracy

This section addresses how professionals view AI’s role in improving the accuracy of their strategic choices by answering the research’s sub-question ‘How do decision-makers perceive the influence of AI on the accuracy of their strategic decisions?’. It looks at whether AI helps decision-makers base decisions on more complete, objective, data-driven insights, and whether it improves the quality of outcomes compared to traditional decision-making approaches.

Across interviews, participants consistently acknowledged AI’s strength in data aggregation, pattern recognition, and historical analysis. For example, one participant explained how AI tools help uncover long-term market trends:

> *“AI gives you the opportunity to analyse how the market has changed in the last 30 years… and do cross selection, cross reference of all this data where there could be opportunities in the future”*
> *(Participant 1, personal communication, 30-05-2025)*

This illustrates how AI contributes to deeper, more data-rich analysis than what might be possible through human effort alone, thereby increasing the accuracy and comprehensiveness of strategic inputs. This capability allows managers to make data-driven decisions more efficiently and accurately than relying solely on intuition or limited analysis (Ter Maten, 2025) and overcome their cognitive limitations. Other participants echoed this view, citing AI's ability to produce a complete and objective picture of available data. Participant 5 described using ChatGPT to synthesize a broad range of sources into a concise summary:

> *“Then I see much faster… the general conclusion across all the data. And that is less coloured by the seven interviews I’ve done.”*
> *(Participant 5, personal communication, 22-05-2025)*

This use of AI not only supports a more objective interpretation but also contributes to more confident and evidence-based decision-making.

Nevertheless, many participants emphasized that while AI helps increase the accuracy of inputs, the final judgment still relies on human interpretation and contextualization. One participant noted:

“AI is not a self-thinking mechanism… you still have to create something from the output that you believe in and that the data supports”
(Participant 2, personal communication, 26-05-2025)

This sentiment highlights a recurring theme: AI can suggest or support, but cannot replace the creative, intuitive, and value-driven aspects of strategic decision-making. AI is seen more as an assistant than a decision-maker (Duan et al.,2019; Jarrahi, 2018). Another key point raised in several interviews is the idea that AI’s contribution to accuracy is conditional, not only on the quality of its data and algorithms but also on the user’s ability to interpret and apply its outputs effectively.

In summary, decision-makers perceive AI as a powerful tool for improving the accuracy of strategic decisions, particularly in the intelligence stage and the design stage. It enables more accurate decision making through generating a more complete and data-rich picture of the situation. However, they also recognize that accuracy does not come automatically with AI; it depends on human oversight, contextual judgment, and proper integration into decision-making processes.

AI reducing strategic decision errors

‘What are decision-makers’ experiences with AI in reducing errors during strategic decision-making?’ is the sub-question that will be answered in this section. It considers how AI systems support consistency, uncover hidden insights, and help minimize bias, while also acknowledging potential new types of error introduced by AI.

A consistent theme across the interviews is that AI contributes to error reduction by improving consistency, enabling comprehensive data coverage, and revealing non-obvious insights. One participant highlighted this benefit when describing how AI-assisted summarization of multiple interviews led to a more complete and less biased interpretation of the data:

“I think you’re less biased in your decision-making… because you’re seeing a complete picture of all the data, and you’re less likely to miss things.”
(Participant 5, personal communication, 22-05-2025)

This kind of support is particularly useful in complex strategic decisions where cognitive overload or fatigue might lead to overlooked details or premature conclusions. In the article of Intellias (2024) it is also mentioned that AI easily processes and analyses vast amounts of both organized and unstructured data and can identify complex patterns and correlations that humans might overlook.

Ter Maten (2024) and Stone et al. (2020) also suggest that AI has the potential to limit human biases (like confirmation bias or anchoring bias) by making decisions based on facts and data. By automating tasks and operating with consistent accuracy, AI minimizes errors caused by human factors such as fatigue, oversight, or subjective biases (Intellias, 2024; Shukla et al., 2024). AI systems are generally not influenced by emotion or cognitive bias, and they can flag outliers or contradictions that humans might overlook under pressure.

Nonetheless, interviewees also acknowledged that AI does not eliminate all types of error, and in fact, can introduce new errors if misused. Participants repeatedly stressed the need for double-checking AI outputs, particularly when outputs are vague, overly generic, or lack contextual nuance. Indicating the issue of trust. Participant 5 discussed the need to develop internal trust in AI systems before relying on them fully:

“We’ve seen examples where it just wasn’t correct… and if you rely too much on that, you could make completely wrong decisions.”
(Participant 5, personal communication, 22-05-2025)

This echoes a core concern in the literature: AI may deliver high-speed outputs, but if human users cannot or do not verify the quality of those outputs, the illusion of accuracy can create new risks, particularly in high-stakes strategic decisions (Fok & Weld, 2024). Humans may find it difficult to discern correct from incorrect AI recommendations, and over- or under-reliance can be detrimental to the final decision accuracy (Schoeffer et al., 2023). Likewise, participant 4 remarked that contextual misalignment can lead to significant misunderstandings:

“If you don’t provide the right context, AI is capable of approaching everything incorrectly.”
(Participant 4, personal communication, 28-05-2025)

This closely correlates with the user's skill in using AI and the prompt quality. Participant 5 (personal communication, 22-05-2025) explicitly connected the effectiveness of AI output to the level of user input. Hallucination, AI generating plausible but incorrect information, is also an issue that saw repeated mentions in the interviews. Such experiences highlight the risk of over-trusting AI and the need to build user awareness and skills for validating outputs.

In the context of AI-assisted decision-making, where a human makes the final call, Rastogi et al. (2022) highlight that human cognitive biases like anchoring bias can still distort judgment and lead to distorted and inaccurate decisions, even when presented with AI predictions. The AI's recommendation can act as an anchor, and decision-makers may adjust away from it insufficiently, especially under cognitive load or time pressure.

The concept of "appropriate reliance" is therefore key (Fok & Weld, 2024). AI is most effective when humans maintain a balance: trusting AI when its outputs are sound but overriding them when they are clearly flawed. Achieving this balance requires not only explainable AI systems but also organizational training and decision-making frameworks that encourage critical evaluation.

In summary, the interview data indicates that professionals in the Dutch F&B industry experience AI as a valuable support tool for reducing strategic decision-making errors, especially in data-heavy scenarios. Its strengths lie in uncovering patterns, improving consistency, and reducing human bias. However, AI is not seen as foolproof. Participants frequently pointed to both AI's ability to correct for human shortcomings and the risks of generating misleading or incomplete outputs if not properly managed. Suggesting that effective error mitigation depends on human expertise, high-quality data, skilled prompting, and a careful balance of trust and skepticism. This reinforces the notion that AI enhances, but does not replace, the judgment of experienced professionals in strategic contexts.

AI's support in identifying strategic alternatives

This section addresses how professionals view AI's role in improving the accuracy of their strategic choices by answering this research's sub-question 'In what ways does AI assist decision-makers in identifying or choosing the most suitable strategic alternatives?'. It considers AI's role in broadening the range of options considered and providing input that may guide or challenge human intuition in strategic decision-making.

A keyway AI supports this process is through its capacity to analyse large volumes of structured and unstructured data to uncover patterns, trends, and non-obvious correlations (Intellias, 2024). One participant shared an illustrative example where AI uncovered a surprising link between vegan consumers and pet ownership:

> *"We discovered that people who eat vegan have a disproportionately high chance of also being cat owners… That insight led us to consider a partnership between a vegan brand and a cat food brand"*
> *(Participant 4, personal communication, 28-05-2025)*

This example highlights how AI can reveal novel insights that would not have emerged through traditional, linear data analysis, and can help companies identify unconventional strategic directions.

Several interviewees noted that AI-generated insights serve as a starting point for deeper exploration. For example, Participant 3 (personal communication, 21-05-2025) described how ChatGPT offers a variety of "different angles and perspectives" that they might not have initially considered, effectively broadening the decision frame:

> *"Sometimes I don't think about some other angles… and then ChatGPT is able to provide them. That helps me a lot."*
> *(Participant 3, personal communication, 21-05-2025)*

Another participant explained how AI contributes to the design stage by accelerating the comparison of alternatives through dashboards and data visualizations:

> "We use dashboards to simplify massive datasets. Then we let AI analyse them to uncover other insights or relationships that aren't obvious… that leads us to better strategic options faster"
> *(Participant 4, personal communication, 28-05-2025)*

This reflects AI's role as an enhancer of analytical efficiency, allowing organizations to evaluate more options in less time, increasing both thoroughness and speed.

Still, the decision-makers unanimously stressed that AI does not make strategic decisions, but humans do. Participant 2 explicitly stated:

"Human decision-making remains dominant. AI is used to support where you want to go."
(Participant 2, personal communication, 26-05-2025)

This reinforces the view that AI serves as an extension of analytical capability, not a replacement for judgment. DI can provide practical, concrete recommendations based on data analysis and predictions (LexisNexis, 2025a; Ai4work, 2024). Ter Maten (2024) and Proces Bouwers (2025) emphasizes AI's capacity to reduce cognitive load. By automating data processing and presenting complex information clearly AI can reduce the cognitive load on decision-makers, freeing them to focus on higher-value strategic tasks and making choices.

However, both participants and literature caution that AI suggestions are only as good as the data quality and relevance of the training models. If the data is outdated or not reflective of the industry context, recommendations may be misleading or irrelevant. Therefore, critical evaluation and contextualization remain essential.

In summary, participants revealed that AI plays a supportive role in during the intelligence and design stages by assisting decision-makers in identifying and evaluating strategic alternatives. However, its effectiveness relies heavily on human interpretation, contextual knowledge, and a strong understanding of organizational goals. AI's current role is not to choose but to equip decision-makers with the best possible foundation for making informed, strategic choices.

4.3 Speed-Accuracy Trade-Off (SAT)

Experiences with the speed-accuracy trade-off

This section answers the sub-question 'How do decision-makers experience and describe the balance between speed and accuracy in strategic decisions?' and sheds a light on whether they perceive the SAT.

Across all interviews, it became evident that this balance is highly context-dependent, shaped by the type of decision, the data available, and the role of human judgment. Participant 2 clearly articulated the traditional view of the trade-off:

"That's just how it is: when someone works quickly, you may overlook certain things in terms of accuracy, and the other way around."
(Participant 2, personal communication, 26-05-2025)

In fast-changing markets like the F&B industry, decision-makers often face pressure to act quickly, but with limited feedback and high stakes, the cost of inaccuracy is also considerable. Duan et al. (2019) and Gigerenzer and Gaissmaier (2011) highlight that in such conditions, organizations must balance the need for quick responses with the risk of making ill-informed choices.

Interestingly, one participant indicated that through implementing AI, especially in structured systems, it enables both speed and accuracy:

> *"Wherever AI is embedded in systems, the possibility for both speed and accuracy improves, because it's focused on a well-defined task."*
> *(Participant 4, personal communication, 28-05-2025)*

This response reflects a growing optimism in managerial thinking: that digital augmentation can break through traditional constraints, allowing organizations to make better decisions faster (Shukla et al., 2024).

In summary, decision-makers revealed diverse and nuanced experiences with the SAT in strategic decision-making. While some participants perceive a natural tension, where increasing speed may compromise accuracy, others believe that with proper tools and processes, it is possible to improve both simultaneously.

AI's role in managing the speed-accuracy trade-off

This section explores whether professionals believe AI helps manage the SAT by answering the sub-question 'How do decision-makers perceive AI's role in addressing the tension between decision speed and accuracy?'. It investigates whether AI is seen as a tool that can improve both dimensions simultaneously, and under what conditions this is most likely to occur.

A recurring insight from the interviews is that AI improves both the quality and speed of decision-relevant inputs, helping reduce the perceived need to choose between speed and accuracy. Participant 4 said:

> *"AI doesn't have to reduce accuracy just because it's fast. In fact, it's fast because it's good."*
> *(Participant 4, personal communication, 28-05-2025)*

This perspective reflects a growing belief that AI can shift the decision-making paradigm, allowing decision-makers to act quickly without sacrificing the thoroughness traditionally associated with accuracy (Daniel et al., 2025). Another participant echoed this optimism, viewing AI as a means to improve strategic response time while maintaining high-quality analysis:

"Yeah, for sure. 100%. That's why it's here. For sure."
(Participant 1, personal communication, 30-05-2025)

This strong affirmation suggests that some decision-makers see AI as purpose-built to resolve the SAT, especially in time-sensitive environments.

Participant 4 (personal communication, 28-05-2025) implies that AI's ability to balance speed and accuracy depends on task structure and clarity. When used in a well-scoped analytical context, such as data aggregation or trend detection, AI can produce fast, accurate, and reliable outputs that inform high-quality decisions. However, other participants were more cautious. Participant 2 emphasized that AI may improve speed but not necessarily accuracy, depending on how it is used and what kind of data is involved:

"I can't say that AI improves both speed and accuracy… there's not necessarily a correlation."
(Participant 2, personal communication, 26-05-2025)

One way AI addresses the SAT is by reducing cognitive load. When AI handles initial data analysis and filters relevant insights, human decision-makers are freed to focus on higher-level evaluation. This not only speeds up the process but can also improve accuracy by ensuring humans are working with clearer, more comprehensive information. Participant 5 described this dynamic as follows:

"It helps me see the big picture faster and more completely… so I'm less likely to miss something or make a biased decision."
(Participant 5, personal communication, 22-05-2025)

Here, AI's value lies in enhancing the conditions under which decisions are made, thus enabling better outcomes in less time.

One participant highlighted the importance of context and the human element in balancing speed and accuracy:

"AI is fast, but the actual decision-making… that still needs human touch. You need that balance between automated insights and human

judgment"

(Participant 1, personal communication, 30-05-2025)

This observation aligns with the concept of bounded rationality, introduced by Herbert Simon (1979), which recognizes that decision-makers operate with limited time, information, and cognitive resources. AI, in this framework, is seen as a tool to extend the boundaries of human capability, navigating the SAT but not eliminating it altogether.

In summary, decision-makers generally perceive AI as a valuable tool for mitigating, though not fully resolving, the SAT in strategic decision-making. Particularly by accelerating data processing and enhancing the clarity of decision inputs. While AI does not eliminate the need for judgment or reduce all uncertainty, it shifts the boundary conditions under which decisions are made, offering the potential for both faster and better-informed choices. Realizing this potential, however, depends on the quality of the tools, the data, and the skill with which AI is integrated into the strategic decision-making process.

5. Conclusion

The research question, "How do food and beverage industry professionals perceive the impact of AI on the speed and accuracy of strategic decision-making?" has been explored through various sub-questions.

Professionals in the F&B industry see AI as a critical enabler of speed in strategic decision-making. AI accelerates data analysis, simplifies insight generation, and automates repetitive tasks, allowing businesses to respond with greater agility. AI empowers decisions to happen sooner and with more confidence.

In terms of accuracy, decision-makers perceive AI as a powerful tool for improving the accuracy of strategic decisions by generating a more complete and data-rich picture of the situation. AI is also experienced as a valuable support tool for reducing errors during strategic decision-making, especially in data-heavy scenarios. Its strengths lie in uncovering patterns, improving consistency, and reducing human bias.

Finally, decision-makers recognize the SAT in strategic decisions, which are complex and high-stakes. AI is perceived as a key asset in managing this trade-off by accelerating data processing and enhancing the clarity of decision inputs. While AI does not eliminate the need for judgment or reduce all uncertainty, it offers the potential for both faster and better-informed choices.

Despite the significant advantages AI offers, its full potential is realized only when combined with human expertise, judgment, and contextual understanding. The ultimate decision remains in human hands, and the actual speed of making a strategic decision depends on human-led processes such as evaluation, discussion, and approval. Accuracy also depends on human oversight, contextual judgment, and proper integration into decision-making processes. Effective error mitigation relies on human expertise, high-quality data, skilled prompting, and a careful balance of trust and skepticism. The effectiveness of AI in identifying and choosing suitable strategic alternatives also relies heavily on human interpretation, contextual knowledge, and a strong understanding of organizational goals.

To conclude, AI is seen as a transformative tool that improves the speed and accuracy of strategic decision-making in the F&B industry. However, its full potential is realized only when combined with human expertise, judgment, and contextual understanding.

6. Discussion

6.1 Theoretical implications

Herbert Simon's theory of bounded rationality provides a foundational framework for understanding decision-making under real-world constraints such as limited time, information, and cognitive capacity (1979). His three-stage model, intelligence, design, and choice, offers a structured lens through which to interpret how decision-makers in this research perceive and use AI in strategic contexts.

The findings of this research suggest that AI plays a significant role in expanding the boundaries of rationality within each of Simon's decision stages. During the intelligence stage, where problems are identified and relevant information is gathered, participants consistently described AI as enhancing their ability to process and synthesize vast volumes of data. Tools like ChatGPT and advanced dashboards were perceived as accelerating and deepening this stage, allowing managers to identify market trends and opportunities more quickly and accurately than through manual methods. This aligns closely with Simon's concept of bounded rationality, as AI acts as a cognitive extension, reducing information overload and improving the clarity of the decision environment.

In the design stage, where alternatives are developed and evaluated, AI was seen to stimulate strategic creativity by uncovering novel correlations and presenting decision-makers with options they might not have otherwise considered. Participants shared examples of AI-generated insights that inspired cross-sector partnerships or highlighted unexpected consumer behaviours. Here, AI serves not only as an analytical tool but also as a facilitator of idea generation, contributing to a richer and more diverse strategic design process.

However, it is in the choice stage that the limitations of AI were most apparent. While AI was credited with improving readiness to decide, by streamlining inputs and highlighting strategic options, participants unanimously emphasized the enduring role of human judgment in making final decisions. This underscores Simon's view that decisions are never purely rational but shaped by context, values, and experience. In practice, AI did not replace decision-making, but rather supported it, extending rationality without eliminating the need for human oversight.

The findings further reinforce Simon's assertion that tools and context shape decision-making behaviour. AI is not a neutral enhancer but interacts dynamically with user skills, organizational culture, and trust. For instance, some participants noted that poor prompting or misunderstanding AI outputs could lead to misleading conclusions. This reflects Simon's view that tools must be appropriately integrated and interpreted within a broader organizational and cognitive framework.

In sum, this research supports and extends Simon's theory by showing that AI helps mitigate the constraints of bounded rationality in complex strategic environments. By improving the speed and quality of data analysis (intelligence stage), broadening the scope of feasible alternatives (design stage), and increasing decision readiness (choice stage), AI improves decision-making without replacing the need for human judgment. These findings suggest that AI functions most effectively not as a substitute for human reasoning, but as a complementary resource that amplifies bounded rationality in practice.

6.2 Practical and managerial implications

The practical implications of AI in strategic decision making within the F&B industry are profound. Managers can leverage AI to significantly improve the speed of their decision-making processes. By utilizing AI to accelerate data analysis, simplify insight generation, and automate repetitive tasks, businesses can respond to market changes and opportunities with greater speed. This means that managers should invest in AI tools that streamline data processing and integrate these tools into their decision-making workflows to ensure timely and confident decisions.

AI also plays a crucial role in improving the accuracy of strategic decisions. By providing a more complete, objective, and data-rich picture of the situation, AI helps decision-makers uncover patterns, improve consistency, and reduce human bias. Managers should focus on implementing AI systems that improve the reliability of their decisions and reduce the likelihood of errors. This involves selecting high-quality AI tools, ensuring access to accurate and comprehensive data, and training staff to effectively use these tools.

The inherent tension between speed and accuracy in strategic decisions can be managed more effectively with AI. Managers should recognize AI as a key asset in accelerating data processing and enhancing the clarity of decision inputs. However, it is crucial to balance the need for speed with the need for accuracy. While AI can provide faster and better-informed choices, managers must still exercise judgment and consider the broader context of their decisions. Investing in AI tools that offer both speed and accuracy, and integrating them thoughtfully into the decision-making process will help managers navigate this trade-off.

Despite the advantages of AI, its full potential is realized only when combined with human expertise, judgment, and contextual understanding. Managers should ensure that AI tools are used to support, rather than replace, human decision-making. This involves maintaining human oversight, contextual judgment, and proper integration of AI into decision-making processes. Managers should also focus on training their teams to work effectively with AI, fostering a culture of collaboration between human and machine intelligence.

6.3 Limitations

6.3.1 Methodology limitations

While this research offers valuable insights into how AI is perceived to influence strategic decision-making within the Dutch F&B industry, several limitations must be acknowledged.

The most significant limitation concerns the sample size. A total of five semi-structured interviews were conducted, which, while sufficient for in-depth qualitative analysis, limits the breadth and generalizability of the findings. The small sample size was not due to a lack of effort in recruitment, but rather reflects the challenges associated with accessing qualified professionals within a highly specific target group.

Recruitment efforts were extensive and included outreach via LinkedIn and email to a large number of relevant professionals in the industry. However, the overall response rate was extremely low, approximately 10%. Among those who initially responded, around 50% did not reply to follow-up messages, and an additional 25% declined participation, either due to time constraints or because their organizations had not yet integrated AI into strategic processes, making them ineligible for the research.

These limitations highlight the difficulties of accessing top and middle management professionals within a specific industry segment, especially on a niche and emerging topic such as AI in strategic decision-making.

6.3.2 Limitations of the Researcher

Another limitation concerns the execution and quality of the interviews. As a relatively inexperienced interviewer, there were instances where participants misunderstood the question or where the questions were not asked clearly or precisely. In some cases, this led to answers that did not fully address the intended research questions. Although efforts were made to steer the conversation where necessary, this was not always possible in real-time, and valuable opportunities for clarification or follow-up were missed. As a result, not all data collected was equally usable or relevant, which may have limited the depth and consistency of the analysis across all sub-questions.

Furthermore, the interviews were conducted in either Dutch or English, depending on participant preference. While this flexibility supported participant comfort and engagement, it introduced an additional limitation related to translation accuracy. The Dutch-language interviews required translation into English for analysis and presentation, particularly for the inclusion of direct quotes. Although these translations were performed with the utmost care and attention to detail, there remains a possibility of loss in context, nuance, or tone. Subtle meanings may have been altered unintentionally, potentially affecting the interpretation of some responses.

Together, these limitations suggest that while the research's findings offer useful insights into the perceptions of AI in strategic decision-making, they should be interpreted with caution, especially when considering their generalizability. Future research could benefit from a larger and more diverse sample, more structured interview protocols, and the support of bilingual transcription or professional translation services to minimize interpretation bias.

6.4 Further research

Building on the findings and limitations of this research, several recommendations can be made for future research exploring the role of AI in strategic decision-making within the F&B industry and beyond.

6.4.1. Expand Sample Size and Diversity

Future research should aim to include a larger and more diverse sample of participants. While this research provided valuable insights from five professionals, a broader range of perspectives would improve the generalizability of findings.

6.4.2. Explore Longitudinal Studies

Given that AI adoption is evolving rapidly, future studies could benefit from a longitudinal design, tracking how perceptions and applications of AI change over time within organizations. With longitudinal research the effect of AI on the speed and accuracy could also be more easily measured by taking multiple measure points throughout the research. Additionally, comparative research between industries or countries could uncover industry-specific patterns, adoption barriers, and cultural influences on AI-driven decision-making.

6.4.3. Improve Interview Design and Facilitation

Subsequent studies should consider using a refined interview guide, possibly developed through pilot testing or expert feedback, to reduce ambiguity and ensure alignment with research objectives. In addition, involving multiple interviewers or external moderators with experience in qualitative methods could help mitigate interviewer bias and improve the depth and accuracy of participant responses.

6.4.4. Address Translation and Language Challenges

As language and translation posed potential limitations in this research, future research involving multilingual participants should consider professional translation and transcription services to preserve the nuance and accuracy of interview data. Alternatively, conducting interviews in a single language with participants fluent in that language could reduce the risk of interpretive loss.

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Appendices

Appendix 1: Interview Guide

Understanding the Context

1. Can you describe your current role and how it relates to strategic decision-making within your organization?

2. What kinds of strategic decisions are most critical in your part of the F&B industry?

AI Usage in Strategy

3. How is AI currently being used in your strategic decision-making processes?

4. What types of AI tools or systems do you commonly rely on (e.g., predictive analytics, machine learning models, AI-driven dashboards)?

5. Who in the organization typically interacts with AI tools, and what level of training or expertise is required?

Perceived Impact on Speed

6. How has AI affected the time it takes you to gather and analyze data for strategic decisions?

7. Can you recall a time when AI enabled you to make a decision significantly faster than traditional methods would have allowed? What was the impact of that speed?

8. Which parts of the decision-making process have become noticeably quicker due to AI integration (Intelligence stage, desgin stage, choice stage)?

9. Has AI enabled you to respond to market changes (e.g., consumer trends, supply chain issues) faster than before?

10. Has AI improved real-time or near-real-time decision-making in your operations? Could you provide an example?

11. How does the speed of AI-powered decisions compare to decisions made manually or by traditional data systems?

Perceived Impact on Accuracy

12. How has AI contributed to improving the precision of your forecasts or projections?

13. In what ways has AI helped reduce errors or misjudgments in strategic decisions?

14. Have you experienced situations where AI provided insights that led to more accurate decision outcomes than human judgment alone?

15. Can you share a time when AI helped avoid a poor strategic decision due to its accuracy or predictive capabilities?

16. Are there particular types of data (e.g., sales data, customer feedback, market trends) where AI enhances accuracy more effectively?

17. How do you validate the accuracy of AI-generated insights before making a decision?

18. Have there been instances where AI's recommendations were inaccurate? How did you detect and respond to that?

Speed-accuracy trade-off

19. Do you find there's a trade-off between speed and accuracy when using AI in strategic decision-making? Why or why not?

20. In your experience, does AI allow you to maintain or even increase accuracy while speeding up decisions? How?

21. Are there any strategic scenarios where AI improves both speed and accuracy simultaneously? Could you describe one?

22. How confident are you in the outputs of your AI systems, especially under time-sensitive decisions?

Challenges and Limitations

23. Have there been situations where AI has not improved, or even hindered, the decision-making process?

24. What are some of the limitations or challenges you've faced when integrating AI into strategic workflows?

Comparative Insights

25. How did your strategic decision-making process look before AI was introduced? What were the key differences?

26. If AI were removed from your processes today, what would be the immediate effects?

Appendix 2: Code book

Theme	Code	Description	Examples
Role Context	Strategic Role	Participant's role in the organization and their involvement in strategic decision-making.	"Part of executive board, so I am directly involved" "Providing insight"
	Strategic Decisions	Types of strategic decisions seen as most important in their specific industry context.	"Of what is commercially the best approach whenever you want to, let's say bring a new client", "OGSMs", "What is the most important customer problem to solve."
AI usage in strategic DM	Current AI Integration	How AI is currently applied in strategic workflows.	"You use AI to basically provide you with data", "whenever we need some like, inspiration", "actually take the biggest insights from that and summarize it"
	AI Tools Used	Specific AI systems or platforms mentioned.	"I will use either ChatGPT or Gemini", "Own version of ChatGPT"
	User Interaction with AI	Who uses AI tools and what level of expertise is required.	"We do have access to some of those kinds of prompt engineering courses.",
Perceived impact on Speed	Faster Data Gathering/Analysis	AI's effect on data collection and processing time.	"Maybe it saves you I would say one to two hours if you use it correctly", "It gives insight faster", "Yes a lott"

Perceived impact on Speed	Accelerated Decision-making	AI's role in enabling faster decisions.	"100%" "I think speed wise, I think it's much helpful."
	Stage-specific Speed Impact	Which phase of decision-making was sped up.	"I would say for us now the first one." "Yes that's still really where it has the most impact"
	Real-Time Responsiveness	AI's contribution to timely reactions to market dynamics.	"Yes, I think so, yeah" "If you have that kind of thing mapped out very quickly, then you can respond to that, quickly"
Perceived impact on Accuracy	Improved alignment with goals	AI's ability to help decisions align more closely with predefined strategic objectives or KPIs.	"I would say like 70 to 80% is accurate." "Most of the time it's not really relevant to the business context, although that I provided you know like this is the context you know."
	Prevention of Strategic Errors	Describes how AI helps reduce or prevent human mistakes, flawed reasoning, or poor strategic decisions. This includes both error detection and the avoidance of suboptimal or harmful outcomes.	"Because. I believe in the human error. I believe in, I believe in the human error and I believe that AI has the intelligence to really identify where something is off." "So I think mainly you are more complete in your analysis and that can improve accuracy yes"
	AI Enhancing Human decision making	Refers to situations where AI supports or improves human strategic decision-making by offering	"That's generally better than humans can deliver now"

Perceived impact on Accuracy		insights, identifying patterns, or generating alternatives that complement human reasoning.	"So at the end I think you can, you know, improve up to certain level. But I think in the end at work, yeah, human will have to do it especially"
	AI Inaccuracy Cases	Times when AI made wrong predictions/suggestions and user responses.	"I had. I had times that I had recommendations that I knew that they are off." "Yeah look yeah easy, look there too is if you give the context, not proper context to it, then it's able to completely get everything wrong."
	High-Value Data Sources	Types of data where AI contributes most to accuracy.	"I would say market trends." "It's much better able to look at a lot of numbers and say, this is going on, so that's very valuable to us from."
	Accuracy Validation	If and how users assess or confirm AI outputs before acting.	"Yeah. And and like you, you have to really double check" "Yes, yes yes yes, and so we did. Well, we also did it manually, just to check how accurate it is. But we do see good results now if you enter the data in the right way with the right format, you know. And then yeah, then you can also lean

Perceived impact on Accuracy			on it a little bit more if you know it's working well”
	Trust in AI	The degree to which decision-makers feel confident in, rely on, or defer to AI systems when making strategic decisions.	“So yes, it is a, There is a, There is a foundation, but not yet a flawless foundation, so to speak. Wouldn't dare give it up yet.” “Yes look in itself, I would almost say somewhere between 9 and 10, but that's provided you own yes, your own skill.”
Speed-Accuracy Trade-Off	Trade-Off Perception	Whether users perceive a compromise between speed and accuracy.	“I cannot say if there is a correlation between speed and accuracy.”, “Yeah, I think it’s half and half”
	AI Balancing Speed & Accuracy	Perception that AI maintains or enhances both dimensions.	“AI does not need, accuracy does not need to go down because of AI, because it is so good, so fast.”
	Optimises trade-off	Situations where both speed and accuracy improved due to AI.	“I think there the possibility of speed and accuracy both benefit very much”, “Yes yes exactly yes so it doesn't have to be a trade-off actually”
Challenges and limitations	AI pain points	This may include usability issues, integration challenges, lack of transparency, or poor contextual fit.	“It is not a self-thinking mechanism.” “Yes, exactly, the, there's a lot of difference in how you do the, well, in that way the

Challenges and limitations			prompting. If you also, with what you get out because if you do that well poorly, you get nothing out of it”
	Data limitations	Problems or limitations with data feeding the AI	“You need to feed it, feed it, feed it, feed it so it can have all the data to work in the future.” “AI is as good as the data behind it, right.”

Appendix 3: Secondary data list

Type of source	Authors	Study details
White paper	Ai4work	This article explains how artificial intelligence supports organizations in making faster and more well-informed decisions.
White paper	Boom management	This article addresses the paradox many organizations face: the world is changing rapidly, yet decision-making remains sluggish. While many businesses adopt agile methods and self-steering teams, real decisiveness is often lacking due to outdated decision structures.
Academic journal article	Csaszar, F. A., Ketkar, H., & Kim, H.	This study looks at how artificial intelligence might change the way entrepreneurs and investors make big strategic decisions. It shows that AI tools, especially large language models, can produce and assess strategies just as well as people involved in startups and investing.
Academic journal article	Daniel, J., James, C., & Yusuff, M.	This paper digs into the tricky balance between speed and accuracy in AI-driven data analysis, how AI models juggle processing results quickly without losing reliability.
Academic journal article	Duan, Y., Edwards, J.S., & Dwivedi, Y.K.	The paper discusses the importance of understanding the challenges and opportunities of Artificial Intelligence (AI) for decision making and proposes 12 research propositions to guide future research in this area, focusing on theoretical development, technology-human interaction, and AI implementation.

Academic journal article	Fok, R., & Weld, D. S	This paper digs into why AI explanations often don’t help humans make better decisions when working with AI advice. It argues that explanations only really work if they let people verify whether the AI's prediction is correct.
Academic journal article	Gigerenzer, G., & Gaissmaier, W	The research suggests that heuristics, which are simple decision-making strategies, can sometimes outperform more complex methods in terms of both accuracy and effort.
White paper	Intellias	Here, the transformative impact of AI on decision-making is explored. From basic automation to advanced algorithms, AI enables faster pattern recognition and predictive insights without the need for time-consuming manual analysis.
Academic journal article	Jarrahi, M.H.	The article discusses the growing integration of AI in organizational decision-making and addresses concerns about AI replacing humans. Instead, it argues for a complementary relationship between humans and AI, where each leverages their unique strengths.
White paper	LexisNexis a	LexisNexis introduces the concept of "Decision Intelligence," which combines AI and data analysis with human context and business goals. The article outlines a step-by-step approach: define clear objectives, ensure data quality, implement proper governance, and start on a small scale. This creates a decision-making process where technology and people work together to make smarter and faster choices.
White paper	LexisNexis b	This article presents LexisNexis’ own AI platform: Nexis+ AI. The platform helps professionals quickly find and analyse information, complete with source citations and context. It streamlines research workflows and improves decision quality. The focus is on reliability, transparency, and ease of use, especially for business and legal applications.

White paper	Proces Bouwers	The website explains how artificial intelligence (AI) can be used to make business processes more efficient, reliable and smart
Academic journal article	Rastogi, C., Zhang, Y., Wei, D., Varshney, K. R., Dhurandhar, A., & Tomsett, R.	This work aims to bridge the gap between artificial intelligence and human decision-makers in AI-assisted decision-making by accounting for cognitive biases, specifically anchoring bias, and providing a general framework to understand the interplay between cognitive biases and human-AI accuracy.
Academic journal article	Schoeffer, J., Jakubik, J., Voessing, M., Kuehl, N., & Satzger, G.	The article discusses the interdependence between human reliance behaviour and decision-making accuracy in AI-assisted decision-making. It proposes a framework to analyse this relationship and make it more tangible through visualization.
Academic journal article	Shukla, M., Dubey, S., & Mishra, S. (2024).	This research investigates the impact of Artificial Intelligence (AI) on the efficiency and accuracy of managerial decision-making.
Academic journal article	Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J., & Machtynger, L.	The report discusses the importance of scaling Artificial Intelligence (AI) across organizations to achieve growth objectives.
White paper	Ter Maten, J.	This article discusses the strategic value of AI in modern organizations. AI can make more accurate predictions about things like customer behaviour, leading to better-informed decisions and reduced risks.

White paper	Van Slijpe, F.	This article illustrates how generative AI is being applied within financial departments to enhance decision-making. By integrating technologies such as natural language processing and large language models into financial planning and reporting tools, professionals can analyse data more quickly and efficiently.