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**A Contingent Approach to the Use of Artificial Intelligence in  
Business Decision Making**

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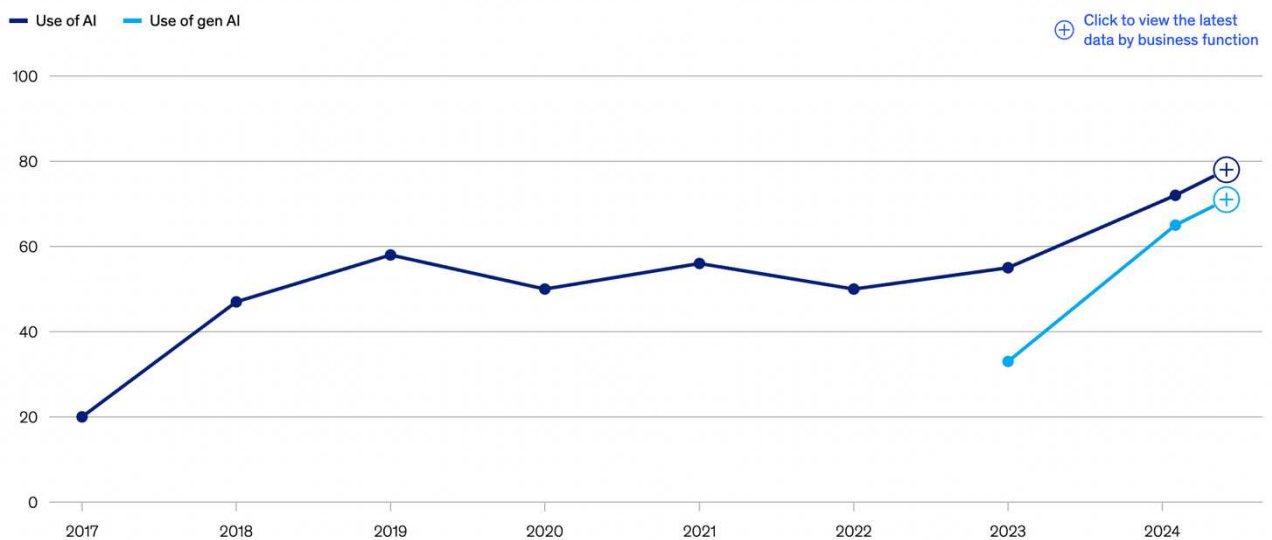
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# EXECUTIVE SUMMARY

The use of Artificial Intelligence (AI) in business decision-making processes is becoming increasingly important, especially in a context marked by growing complexity, uncertainty, and competitive pressure. According to a McKinsey report (2025), around 78% of the companies analyzed use AI algorithms regularly, and 71% adopt Generative AI techniques, particularly in the Marketing and Sales domain.

## Organizations' use of AI has accelerated markedly in the past year, after years of little meaningful change.

Organizations that use AI in at least 1 business function,<sup>1</sup> % of respondents



<sup>1</sup>In 2017, the definition for AI use was using AI in a core part of the organization's business or at scale. In 2018–2019, the definition was embedding at least 1 AI capability in business processes or products. Since 2020, the definition has been that the organization has adopted AI in at least 1 function.

Source: McKinsey Global Surveys on the state of AI

**Figure 1. Organizations' Use of AI. McKinsey (2025).**

However, while the benefits of Artificial Intelligence use in business decision making are extensively discussed both in scholarly and managerial debates, a critical gap persists: much less attention has been devoted to understanding how AI should actually be integrated into decision-making processes. The discussion rarely moves beyond a generic recognition of AI's

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potential toward a structured analysis of how human and machine inputs can be combined in a way that is sensitive to context, organizational conditions, and decision characteristics.

This gap is precisely where the present thesis positions itself. The central research question driving the work is: How can a contingent approach guide the integration of AI into organizational decision-making processes? By contingent approach, this thesis refers to the idea that there is no universal, optimal configuration for human–AI collaboration. Instead, the effectiveness of AI integration depends on a variety of contextual factors, or contingencies, such as the type of decision (strategic vs. operational, familiar vs. unfamiliar), the characteristics of the information involved (explicit vs. implicit, external vs. internal), the maturity of the organization’s data and analytics capabilities, the oversight requirements of the decision, and the ethical or legal implications at stake.

The first chapter of this thesis establishes the theoretical foundation of organizational decision-making processes, reviewing the principal models that scholars have developed over time. The starting point is the traditional, sequential view of decision making, where decision makers move linearly from problem identification to evaluation of the outcomes. While historically influential, this approach has severe limitations in today’s uncertain and dynamic environments, as it assumes perfect information, rational actors, and stability.

Building on the concept of bounded rationality, more contemporary perspectives emphasize the variety and contingency of decision processes. Rousseau (2018) distinguishes between routine, non-routine, and novel decisions, stressing that each type requires a different process, and that the quality of decisions is strongly linked to the appropriateness of the underlying process. Mintzberg (1973) complements this view by identifying three modes of strategic decision making (entrepreneurial, adaptive, and planning) later expanded by Quinn’s (1978) notion of logical incrementalism, which stresses flexibility and staged progression in the face of uncertainty. Mintzberg, Raisinghani, & Théorêt (1976) further conceptualize decision making as unstructured processes, characterized by high complexity, non-linearity, and fragmentation. Their seven process configurations, ranging from simple search to dynamic design, illustrate how strategic decisions evolve through iterative phases of identification, development, and selection, influenced by contextual stimuli, solution availability, and organizational dynamics.

The chapter also examines differences between individual and group decision making, as Artificial Intelligence could be conceptualized as a “cybernetic teammate” (Dell’Acqua, et al., 2025), potentially offsetting human cognitive biases and inefficiencies while introducing new challenges of integration and oversight.

Each process studied reveals multiple configurations suited to different circumstances, reinforcing the centrality of a contingent perspective. Importantly, the growing involvement of AI adds yet another variable to this landscape, amplifying the need to adapt decision-making processes dynamically to context, data availability, organizational structure, and task complexity.

The second chapter examines different categories of AI models and evaluates their suitability for specific decision-making contexts. The analysis shows that while each model offers unique strengths, none provides a universally optimal solution; rather, their effectiveness depends on contextual contingencies such as the type of decision, the nature of available data, the degree of environmental stability, and the required balance between speed, accuracy, and interpretability.

Constraint Satisfaction Problems (CSPs) represent one of the most structured and rule-based approaches to AI. They are highly effective in domains such as resource allocation or workforce planning, where rules and constraints are clearly defined. However, their rigidity limits adaptability, making them ill-suited for dynamic environments where constraints evolve or remain uncertain. CSPs are best aligned with Rousseau’s (2018) non-routine and novel decisions or Mintzberg’s (1973) planning mode, where predefined structures guide the process. Machine Learning (ML), in contrast, provides greater adaptability. The chapter discusses the main ML paradigms: supervised learning for predictive tasks (e.g., customer churn prediction, sales forecasting), unsupervised learning for pattern recognition and segmentation, semi-supervised learning when labeled data is scarce, and reinforcement learning for dynamic trial-and-error contexts such as logistics. Different algorithms, including linear and logistic regression, clustering, decision trees, random forests, and neural networks, illustrate how ML can flexibly support decision making across domains like pricing, M&A, and sentiment analysis.

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Generative AI (GenAI) has rapidly emerged as a powerful tool for decision support and creativity. Recent evidence from the 2025 Global M&A Report by Bain & Company highlights its use in M&A strategies, with one in five companies already adopting it (Haxer, et al., 2025). GenAI's effectiveness also lies in its potential to act as a teammate rather than merely a tool (Dell'Acqua, et al., 2025), augmenting human decision-making capabilities through scenario generation, language-based reasoning, and adaptive support.

Agentic AI represents the next frontier: autonomous, goal-oriented systems capable of planning, adapting, and executing tasks in complex environments while interacting with existing tools. According to the Top Strategic Technology Trends for 2025 Gartner report, one-third of organizations will implement Agentic AI by 2028 (Coshov, et al., 2025). The chapter distinguishes between five agentic types: simple reflex, model-based reflex, goal-based, utility-based, and learning agents. Each is suitable for different business tasks ranging from routine maintenance to strategic M&A. Case studies from PwC (2024), including Siemens, Unilever, and Salesforce, demonstrate the potential of these systems to democratize AI use and enable broad organizational impact.

The comparative analysis in the final section highlights that the choice of AI model should not be driven by technological hype or availability alone. Instead, it must be guided by the characteristics of the decision at hand, the quality and structure of the data, the time horizon and speed requirements, the need for transparency and human oversight, and the broader organizational context.

The third chapter constitutes the core of the thesis, addressing the critical gap in the literature on how AI can be effectively integrated into organizational decision-making processes. While recent contributions (primarily between 2023 and 2025) highlight the potential of AI in business, most works remain conceptual, offering theoretical arguments and limited exploratory evidence. By systematically reviewing academic studies complemented by practitioners' reports, this chapter demonstrates the emerging consensus that a contingent approach is necessary to unlock AI's value in decision making.

The literature review reveals three interdependent clusters of analysis. The first examines organizational alignment and design, stressing that leadership styles, structures, and decision rights must adapt to accommodate AI. The second focuses on human-AI collaboration,

considering how task division, trust, and role clarity shape outcomes. The third addresses contextual contingencies, highlighting how the nature of the decision (its novelty, complexity, or operational repeatability) determines the appropriate role of AI. Far from being separate perspectives, these clusters intersect: organizational choices define the conditions for collaboration, which in turn condition the effectiveness of AI in different decision environments. Together, they converge on a central insight: there can be no universal model of AI adoption; instead, integration must be contingent on organizational, human, and contextual factors.

Building on this insight, the chapter reviews four existing frameworks emerged from the literature review that explicitly consider process configurations. Trunk, Birkel, and Hartmann (2020) propose a conceptual framework linking information types, decision categories, AI models, organizational design, AI literacy, transparency, and ethics to the decision-making process. Jain, Garg, & Khera (2023) revisit Puranam's (2021) six human-AI task division configurations, showing how they influence speed, trust, efficiency, and role clarity. Shrestha, Ben-Menahem, & Von Krogh (2019) define four configurations of the decision-making process and evaluate them across five criteria: the decision search space, the interpretability of the process, the size of the alternatives set, the speed, and the replicability. Finally, Yablonsky (2019) emphasizes how the maturity of employees' data analytics capabilities conditions the allocation of tasks between humans and AI. Collectively, these frameworks demonstrate the range of possible process designs but also underscore the novelty of the field, as few models explicitly integrate all organizational, human, and contextual dimensions simultaneously.

The chapter then applies these insights to seven business scenarios, ranging from highly strategic decisions such as M&A to operational ones like dynamic pricing. The analysis shows that strategic, unfamiliar, and oversight-intensive decisions align best with dynamic or political process designs (Mintzberg, Raisinghani, & Théorêt, 1976) where AI supports but humans dominate. Conversely, repetitive and efficiency-driven decisions call for basic or modified search processes (Mintzberg, Raisinghani, & Théorêt, 1976) in which AI takes the lead. Finally, complex strategic decisions with vast search spaces require dynamic designs that combine human judgment and AI's analytical capabilities in close collaboration.

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This thesis shows that both traditional and AI-enabled decision-making processes are characterized by multiple possible configurations, whose effectiveness depends on the context in which they are applied. In traditional processes, the most relevant contingency has historically been the distinction between strategic and operational decisions, with different modes or processes adapted to each. Once AI is integrated, however, the range of contingencies broadens considerably. Factors such as data availability and quality, the speed and accuracy required, interpretability and transparency, ethical considerations, and employees' skills and literacy all play a critical role in determining how the process should be configured, and, ultimately, how responsibilities should be distributed between humans and machines.

AI-based processes also display important differences in structure compared to traditional ones. They tend to follow a more linear and structured logic, resembling the assumptions of perfect rationality that underlie classical decision-making theories. This highlights an important paradox: AI can reduce the impact of human cognitive limitations and biases, bringing decisions closer to the ideal of rational choice, while at the same time introducing new forms of complexity. In other words, AI streamlines decision making but does not simplify it; instead, it shifts the locus of complexity from the cognitive domain to the organizational and contextual one.

For managers, this implies the need to adopt a deliberate and structured approach when configuring human-AI collaboration. The first step is to clarify the nature of the decision: strategic or operational, familiar or unfamiliar, short-term or long-term. Next, they must assess the type of information involved (explicit or implicit, internal or external), alongside the organization's capabilities (AI literacy, data analytics expertise, oversight capacity). Only after systematically analyzing these contingencies can managers identify the most appropriate human-AI configuration. AI adoption should therefore not be seen as a binary decision, that is whether to rely on humans or machines, but rather as a design challenge: aligning decision processes, technologies, and organizational structures with the specific contingencies of the decision at hand.

Ultimately, competitive advantage does not stem from adopting AI in itself, since the technology is increasingly commoditized and widely available. Instead, it lies in a firm's ability

to design fit-for-purpose decision-making processes, tailored to the interplay between strategic context, organizational structures, and human-AI collaboration. This requires moving beyond benchmarking and best-practice imitation, toward a more nuanced and context-sensitive analysis of contingencies. Organizations that succeed in this task will be able to leverage AI not just as a technological asset but as an enabler of differentiated, adaptive, and more effective decision making.



# CHAPTER ONE.

## Traditional Decision Making in Organizations.

### 1.1. Introduction

Decision making is a central activity in every organization, influencing not only daily operations but also long-term strategies and performance. However, the complexity of organizational contexts makes these decisions fundamentally different from those taken by individuals alone. This chapter begins exploring the distinctive characteristics of organizational decision making, starting from the framework proposed by Rousseau (2018), who identifies key differences such as the nature of work, the role of political dynamics, accountability structures, and the presence of diverse stakeholders.

The chapter first examines the traditional concept of decision making, a strictly sequential process moving from problem identification to evaluation of the outcomes. However, this model now reveals significant limitations in uncertain and fast-changing environments, especially because it assumes perfect information and rationality on the part of the decision maker.

The concept of bounded rationality, introduced by Simon (1955), is discussed as a more realistic alternative. As a matter of fact, decision makers tend to *satisfice*, rather than maximize (Simon, 1957). This perspective is further reinforced by Aumann (1997) five arguments, which support the notion that human rationality is inherently limited.

Building on the concept of bounded rationality, the chapter moves to an overview of contemporary models of decision making.

Rousseau (2018) proposes four types of decision processes: routine, non-routine, novel, and multi-type. Each of these processes are suited to different organizational contexts.

Mintzberg (1973) outlines three modes of strategic decision making: the entrepreneurial mode (focused on vision and authority), the adaptive mode (characterized by reactivity and compromise), and the planning mode (which follows a structured analytical process).

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Quinn (1978) introduces logical incrementalism, a model that emphasizes gradual, adaptive decision making as a response to complexity and uncertainty.

Mintzberg, Raisinghani, & Théorêt (1976) conducted a seminal study on unstructured decision-making processes, that is strategic, non-routine decision processes. They identified three iterative core phases (identification, development, and selection) supported by political, communication, and control routines, and influenced by six dynamic factors, such as delays, interruptions, and recycles. The authors also categorize decisions based on their stimulus (problem, opportunity, or crisis), the type of solution (ready-made, modified, or custom-made), and the process, identifying seven distinct decision process configurations.

These configurations demonstrate that decision-making processes, even without the integration of Artificial Intelligence, need to adapt to specific contingencies.

The final part of the chapter analyzed the differences between individual and group decision making, since AI could be seen as a cybernetic teammate (Dell'Acqua, et al., 2025).

Groups tend to be more rational and cognitively sophisticated, more self-controlled, and more productive than individuals. However, they can sometimes prioritize self-interest and potentially reduce welfare (Charness & Sutter, 2012).

Groups exhibit also different risk-attitudes than individuals. Evidence shows that individuals perform better under risk, while groups have an advantage in uncertain environments (Carbone, Georgalos, & Infante, 2019). Groups may also introduce risk biases in uncertain conditions (Marquis & Reitz, 1969).

Possible risks of group decision making include increased time requirements, groupthink, social loafing, conformity effects, and group polarization. These dynamics, if not properly managed and contained, can undermine the potential benefits of collaborative decision making and lead to suboptimal or even damaging organizational outcomes.

Understanding the traditional views and limits of organizational decision making is essential to appreciate the role of Artificial Intelligence in reshaping these processes. In fact, AI can extend the boundaries of bounded rationality by processing large datasets and discovering patterns which could go unnoticed, moving decision making closer to a form of “perfect” rationality.

## 1.2. Organizational Decision Making vs. Individual Decision Making

According to Rousseau (2018) “organizational decisions are similar to but different from other decisions”. In particular, organizational decisions lead to challenges linked to the structure and the environment of that particular organization. *Figure 2* summarizes the differences between organizational decision making and individual decision making.

Qualities	Organizational decision makers (managers, teams, work groups)	Individual decision makers (homelife, private professional practice)
Nature of work	Work with and through others	Personal choices/solo practitioners
Political influences	Strong political pressures can block or constrain decisions	Some but fewer political pressures
Accountability	Accountable for decisions by self and others	Accountable for own decisions
Decision types	Make many kinds of decisions, often concurrently	Make fewer kinds of decisions
Stakeholder diversity	Many stakeholders affect and affected by decisions	Fewer stakeholders affect and affected by decisions
Levels of uncertainty	Greater uncertainty due to missing information, difficulty interpreting situations, and environmental change	Uncertainty can vary, often low to moderate
Decision supports	Typically few decision supports and protocols	Professionals often have decision supports and protocols (e.g., checklists)

**Figure 2. Organizational Decisions Differ from Individual Decisions. Rousseau (2018).**

Organizational decision making, by definition, involves more than one individual working together to arrive at a decision. Thus, this type of process, in contrast with individual decision making, adds complexity due to the need for coordination and alignment between different actors. As Herbert Simon (1955, p. 161) explained, “a theory of organizational rationality must treat the phenomena of goal conflict, while a theory of individual rationality need not”.

In an organizational setting political influences are to be taken into consideration. This is because power dynamics in hierarchical structures and competing interests can render decision making processes slower, block them altogether or add unnecessary constraints. Moreover, this type of process poses accountability issues: decision makers in organizations are not only responsible for their own actions but are also held accountable for the decisions made collectively or by their subordinates (if any). In individual decision making, on the other hand, the process is generally more autonomous and subject to fewer political pressures, as an individual is accountable for their own choices.

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Often in organizations multiple kinds of decisions are to be dealt with simultaneously, and the presence of a diversity of stakeholders involved in the process, both directly and indirectly, further complicates the issue. All these kinds of stakeholders (managers, employees, customers, shareholders, etc.) may have conflicting priorities and expectations, and this adds to the level of uncertainty organizations need to face, which is already aggravated by factors such as limited or ambiguous information, constant environmental changes, and organizational complexity. For these reasons, decision makers could avoid dealing with decisions regarding stakeholders on whom they have less information or are more complicated to deal with (Rousseau, 2018).

Unlike individual decision makers, organizations often lack formal decision supports such as standardized protocols or checklists, therefore decision makers need to rely more heavily on their own judgement and experience.

Rousseau (2018) highlights that “organizational decision makers tend to pay attention to certain information because it fits their role and avoid other information if it seems irrelevant or exposes them to risks”. These biases, while sometimes necessary to focus efforts and make the process more efficient, may ultimately affect the quality of the decisions, and this is why task forces with individuals from different roles and backgrounds are essential.

### **1.3. Traditional Concept of Decision Making**

In the traditional concept of decision making the process is linear:

1. Identification of the problem;
2. Collection of information;
3. Identification of alternatives;
4. Evaluation of alternatives;
5. Choice of the best alternative;
6. Implementation of the decision;
7. Monitoring and evaluation.

The issue is that this kind of process has some limitations, especially in fast-changing environments. It assumes that decisions are made logically and are based on complete

information, while most of the time cognitive biases and lack of information come into play. Moreover, following these steps thoroughly may be time-consuming in a context requiring agility and fast responses. And finally, whenever a decision is taken, the alternative selected may ultimately not be the optimal choice; however, there may be resistance to revisiting or adjusting the decision.

The biggest problem with the traditional concept of decision making is that it assumes perfect rationality of the decision maker. However, the concepts of *homo economicus* and his perfect rationality have long been outdated, since Herbert Simon's contribution in "A Behavioral Model of Rational Choice" in which he introduced the term *bounded rationality* (Simon, 1955). Simon defines bounded rationality as the set of "theories that incorporate constraints on the information-processing capacities of the actor" (Simon, 1955, p. 162).

Possible constraints on rationality may be:

- Risk and uncertainty;
- Incomplete information about the alternatives;
- Complexity;
- "Other environmental constraints so great as to prevent the actor from calculating the best course of action" (Simon, 1955, p. 164).

This concept stands in stark contrast to the assumptions embedded in the traditional decision-making process, described as a linear and rational sequence of steps. Bounded rationality emphasizes that individuals and organizations operate under constraints that limit their ability to make fully rational choices. In fact, instead of optimizing, decision makers tend to *satisfice*: they search for a solution that is good enough given the limitations they face. As Simon (1957, p. xxiv) wryly states, "human beings [...] *satisfice* because they have not the wits to *maximize*".

For instance, consider a product development team in a large consumer goods company that needs to choose a market to launch a new product. According to the traditional concept of decision making, the team would begin by clearly defining the problem, collecting all relevant market data, identifying all possible entry strategies, then evaluating each alternative and finally

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selecting the one with the highest expected return. However, in reality the team may face several constraints, such as incomplete or ambiguous market research, time pressure from upper management, internal disagreements, and constraints on budget. These limitations prevent the team from conducting a fully rational and complete evaluation, and as a result they engage in *satisficing* behavior: rather than identifying and choosing the optimal solution they settle for the first alternative that seems “good enough” to meet performance thresholds and management expectations.

The concept of bounded rationality is defended by Robert J. Aumann’s five arguments (Aumann, 1997):

1. In most decisions, even simple ones, individuals are not maximizers. This hypothesis is in accordance with Simon’s concept of satisficing behavior.
2. Even if an individual wanted to maximize their decision, maximization is typically difficult, and most people would be unable to achieve it. For instance, when a chess player is faced with the choice of the best next move or sequence of moves, he can choose from thirty moves at any point in the game, with an average of  $10^3$  possible continuations and  $10^{120}$  possible games. Clearly chess players do not consider all of these moves but a small subset of possibilities, and finally they pick the one that *satisfices* them (Simon, 1955).
3. Observations show that most assumptions for rational decision theory are not satisfied. The sole assumption of perfect information and knowledge is naturally and physiologically unobtainable.
4. Observations show that the outcomes of rational analysis differ from reality. Individuals often deviate from the solutions proposed by utility maximization models (e.g., expected utility theory). For instance, suppose subjects “are asked to choose the prospect of winning €300 with probability 0.25 or the prospect of winning €400 with probability 0.2. Here, subjects are given a numerical description of probabilities, are typically asked to make one-shot decisions without feedback, and their responses are found to deviate from the expected utility hypothesis” (Wheeler, 2024, par. 7.3);

5. Some of the outcomes of rational analysis appear to be unreasonable. In fact, when rational models are followed, they may lead to choices that seem ethically questionable or simply unrealistic, such as ignoring sunk costs or preferring a choice based merely on utilitarianism regardless of social or emotional factors. For instance, going back to the example of a product development team deciding the best market to launch a new product, a rational analysis based solely on expected ROI could suggest a market where demand is high but local regulations allow for lower product safety standards, poor working conditions or unfairly low wages. The team therefore disregards the rational economic choice, feeling it would be ethically questionable.

## **1.4. Decision-Making Processes**

As Rousseau (2018, p. 141) highlighted, “decision processes matter and different processes are suited for different kinds of decisions” and “the process behind a decision provides a reasonable indicator of the likely quality of its outcomes”. As discussed in the previous section, the traditional decision-making process, based on a linear sequence of steps and the assumption of perfect rationality, is not fit to adapt to complexity, uncertainty, and time constraints faced by modern organizations. This is why the literature has been proposing alternative models of decision making that better reflect today’s business environment.

### **1.4.1. Rousseau’s Decision-Making Processes**

Rousseau (2018) proposes three (plus one) evidence-based decision-making processes.

The first type of process is for routine decisions.

These kinds of decisions are made in stable environments where the cause-effect relationships are well understood and observable. They happen regularly, and this allows organizations to develop and refine standardized procedures over time. Because the context remains consistent, best practices can be identified and continuously improved. There are advantages to creating standard procedures for decisions that happen regularly, but one possible problem is not searching for ways to improve. The key for effective routine decisions is “to gather facts on

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how the decision is currently being made, evaluate its outcomes, and then redesign the process periodically to get good outcomes more consistently” (Rousseau, 2018, p. 143).

It is crucial to note that for the same routine decision there is not a one-size-fits-all standard procedure. The process needs to adapt to the specific context.

Rousseau (2018) suggests that looking at what managers typically do and at the results of their routine decisions is important to create a benchmark on a standard decision protocol, avoiding however oversimplification and overstandardization, since the procedure needs to be agile to adapt to the specific context. Then, the protocols need to be reviewed periodically and if necessary improved to make sure they continue to be effective.

The second type of process is for non-routine decisions.

In these situations, no one involved in the process has all the necessary information, although such information may be available somewhere. These decisions require the collaboration with individuals with relevant expertise to collect evidence and evaluate options.

In this case, the traditional decision-making process comes to mind. The first thing to do is understand the problem to be able to collect relevant information. Then, all possible alternatives need to be evaluated against some key goals or metrics. When the best alternative is chosen, if possible, it would be better to test the decision. One way to monitor the effectiveness of a decision is to conduct an after-action review (AAR), which involves analyzing the decision's objective, the actual outcome and the reasons for that outcome, as well as what should be done next time (Rousseau, 2018).

The third type of process is for truly novel decisions.

Here information is unavailable because there is no historical precedent. In these cases, decision makers must generate new knowledge through experimentation and trial-and-error. Various types of uncertainty are involved, like technical, market, or political uncertainties. This process is the one that differs the most from the traditional, linear model. In fact, the problem cannot be understood, or even if it is, it may be unclear what needs to be done.

There could be two situations: a situation where the uncertainty and ambiguity reflect the new environment, context, or conditions, or a situation where “there may be more unknowables” (Rousseau, 2018, p. 144). The first situation needs a process of trial-and-error and learning,

gaining small wins on the way. The second situation, on the other hand, is too chaotic to allow for effective learning, so the key to these decisions is resilience. It is important to train people (managers or employees) to be able to take fast decisions in crisis situations, and when the crisis actually happens, create multiple independent experiments, so that if one fails there are little to no consequences.

The last type of process is for multi-type decisions, a combination of the first three types.

### **1.4.2. Mintzberg's Modes of Strategic Decision Making**

Mintzberg (1973) proposes three modes of strategic decision making: the entrepreneurial mode, the adaptive mode, and the planning mode.

In the entrepreneurial mode, the focus is on opportunity, not problems, therefore the approach is more active than passive. As the name suggests, here “power rests with one man capable of committing the organization to bold course of action” (Mintzberg, 1973, p. 45).

The bold entrepreneur is not afraid of uncertainty, since he/she knows that in that situation the organization can gain much more. The main goal of all decisions taken by the entrepreneur is the growth of the organization.

The conditions for this type of mode, such as the authority to be in the hands of one individual and the organization to be oriented to growth, are mostly typical of small enterprises. These organizations can afford to act boldly because they have little to lose. However, they are not the only ones: organizations in a deep state of crisis have little to lose, too, and acting boldly may be the only chance of survival.

The adaptive mode accepts the view that objectives may not be clearly defined. This is because there are multiple agents involved (what are now called stakeholders), each with his own goal. The complex environment is analyzed, and the decisions taken never aim to disrupt it. Here uncertainty is avoided, at least tentatively, and most of the time urgent problems are solved without thinking about the long-term strategy.

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Since here there are multiple interests to be taken into account (unlike in the previous mode where the only relevant interest is the entrepreneur's) the decision maker needs to reduce conflicts, and he does so sequentially. The decision ultimately taken does not maximize any goal, but rather *satisfices* the constraints, with each stakeholder involved both gaining and losing something.

If the previous mode was active in its nature, the adaptive mode is reactive. Since the environment is too complex and poses a variety of problems, the organization has to deal with them, and little time is left to search for opportunities. Even if there was time, since the organization cannot prioritize any goal then opportunities would be hard to identify.

The decision-making process focuses on a series of incremental steps, the outcome of which never differs much from the status quo. Feedback is crucial in this process, as it allows to adjust the course of action.

Finally, since there is a variety of demands from various stakeholders, the decision maker pays little to no attention to coordination, and as a result decisions appear to be disjointed, but able to adapt to emerging needs (Mintzberg, 1973).

This situation is typical of large and established organizations.

Ackoff (1970, pp. 2-5) describes the planning mode as “anticipatory decision making” involving “a system of decisions”. The goal is precise, there is a clear view of what the desired outcome is, and this outcome cannot create itself: action is needed. This mode is the one that almost overlaps with the traditional concept of decision making. However, Mintzberg (1973, p. 47) states that before the beginning of the process, three studies need to be conducted: “(1) fundamental organizational socioeconomic purpose, (2) value of top management, and (3) evaluation of external and internal opportunities and problems, and company strengths and weaknesses [i.e., a SWOT analysis]”.

These decisions have to be taken with the help of an analyst, who plays a major role in the process, especially when designing long-term strategies.

As in the traditional concept of decision making, the process is always linear and fixed, and alternatives are evaluated through a cost-benefit analysis. However, contrary to the adaptive mode, planning allows to take multiple decisions at once, each interrelated with the other, to create a global strategy that *satisfices* more than one goal.

This situation presents itself in large companies that can afford to spend resources on formal analytics, operating in an environment fairly stable and predictable. As has been said before when talking about the traditional concept of decision making, this mode is limited in its vision of reality; as Mintzberg (1973, p. 53) points out “it must be recognized that good planning is expensive, it often requires unrealistic stability in the environment, and, above all, it is the least flexible of the strategy-making modes. All this is not to conclude that planning is useless; rather, it suggests that the planner must become more realistic about the limitations of his science”. Plans need to be flexible enough to adapt to changing environments, and planners need to prepare a series of contingency plans.

Figure 3 summarizes the main characteristics and conditions of each decision-making mode.

	Entrepreneurial Mode	Adaptive Mode	Planning Mode
Characteristic			
Motive for Decisions	Proactive	Reactive	Proactive & Reactive
Goals of Organization	Growth	Indeterminate	Efficiency & Growth
Evaluation of Proposals	Judgmental	Judgmental	Analytical
Choices made by	Entrepreneur	Bargaining	Management
Decision Horizon	Long Term	Short Term	Long Term
Preferred Environment	Uncertainty	Certainty	Risk
Decision Linkages	Loosely Coupled	Disjointed	Integrated
Flexibility of Mode	Flexible	Adaptive	Constrained
Size of Moves	Bold Decisions	Incremental Steps	Global Strategies
Vision of Direction	General	None	Specific
Condition for Use			
Source of Power	Entrepreneur	Divided	Management
Objectives of Organization	Operational	Non-Operational	Operational

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Organizational Environment	Yielding	Complex, Dynamic	Predictable, Stable
Status of Organization	Young, Small or Strong Leadership	Established	Large

**Figure 3. Characteristics and Conditions of the Three Modes. Adapted from Mintzberg (1973, p. 49).**

Clearly, in reality these three modes are hardly found in their pure form, but rather in combinations that reflect the firm's own needs. For instance, an entrepreneur could adopt an adaptive mode, or a plan could be flexible enough to adapt to different scenarios.

Moreover, in the same organization different functions could use different modes. The marketing function could act in an entrepreneurial fashion, while the HR function could be more adaptive.

A parent company and a subunit (which could be a division, a subsidiary, or an agency) may use different modes. It has been found that "the adaptive mode is [...] always an acceptable one for the subunit, no matter what the mode of the parent" (Mintzberg, 1973, p. 51), while the situation where both parent and subunit use the entrepreneurial mode is the worst possible one, as it would be only a matter of time before one of the two entrepreneurial figures makes a move which interferes with the other. Finally, planning on part of the subunit works only if the parent plans too and if the two plans are effectively coordinated.

As one would expect, different modes are used in different stages of the organization's life cycle. As has been said before, small, young enterprises use the entrepreneurial mode since they committed few resources and need to grow. Then, as more resources are committed, and specific strategies set, the adaptive mode prevails. Here, the organization is at the end of the maturity stage. One possible way to regenerate growth is to return to an entrepreneurial mode, taking bold decisions. Most organizations, in fact, show a cyclical pattern where periods of growth with an entrepreneurial mode are followed by periods of stability with an adaptive mode, followed again by periods of growth, and so on. Large companies in periods of stability could also choose to use a planning mode, since they have significant resources to spend (Mintzberg, 1973).

### 1.4.3. Quinn's Logical Incrementalism

James Brian Quinn, in his article for the *Sloan Management Review* in 1978, adds the concept of “logical incrementalism” to Mintzberg’s view. This concept stands in stark contrast to the idea of planning, as in most organizations decisions are taken in a typically “fragmented, evolutionary, and largely intuitive” fashion (Quinn, 1978, p. 7). Planning is especially unrealistic in contexts where the so-called power-behavioral factors are present: variety of different goals, politics, bargaining and negotiation, *satisficing* (once again), and management coalitions, among others (Quinn, 1978). Moreover, planning is rendered unhelpful where what Quinn calls “precipitating events” occur, that is unforeseeable and urgent events for which planning *ex ante* is impossible.

Precipitating events are dealt with logical incrementalism, that is “a purposeful, effective, proactive management technique for improving and integrating *both* the analytical and behavioral aspects” (Quinn, 1978, p. 8). Quinn observes that top executives tend to respond to precipitating events in a gradual, adaptive way. They keep early commitments wide enough that they can be reevaluated as new information emerges. This approach is particularly valuable in contexts characterized by high uncertainty, where the implications of decisions taken are not clearly understandable or predictable. For instance, companies like Xerox or IBM implement a “phase program planning” system, in which the decision-making process is structured into phases, allowing for testing and feedback. Moreover, by breaking down complex decisions into manageable phases, logical incrementalism allows organizations to deal more effectively with cognitive and procedural limits.

Logical incrementalism also considers the political and organizational dynamics involved in decision making. It has been observed that executives often delay or vaguely define early decisions to allow time for building internal consensus, sharing information, and creating commitment from lower-level employees. In fact, “logic dictates that one proceeds flexibly and experimentally from broad concepts toward specific commitments, making the latter concrete as late as possible in order to narrow the bands of uncertainty and to benefit from the best available information. This is the process of logical incrementalism” (Quinn, 1978, p. 19).

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While Quinn's logical incrementalism and Mintzberg's adaptive mode may seem similar, since they both include concepts of adaptation, feedbacks, and uncertainty, they differ in some key respects.

The adaptive mode is largely reactive, where decisions emerge in response to complex environments and stakeholder pressures. It tends to lack clear objectives and coordination from the beginning, and it often produces disjointed decisions aimed to resolve urgent issues without thinking about the long-term direction.

In contrast, logical incrementalism is more proactive, as it involves planning through phases, with a clear strategic vision in mind, even though that vision may be revisited over time.

### **1.4.4. Unstructured Decision-Making Processes**

In his paper "The Structure of Unstructured Decision Processes" Mintzberg, together with Raisinghani and Théorêt, focused on the processes underlying strategic non-routine decisions, the so-called "unstructured processes", that is "decision processes that have not been encountered in quite the same form and for which no predetermined and explicit set of ordered responses exists in the organization" (Mintzberg, Raisinghani, & Théorêt, 1976, p. 246). The authors studied 25 unstructured decision-making processes and reviewed the empirical studies on this matter, and they found a basic framework underlying these apparently random processes. The latter are characterized by unfamiliarity, high level of complexity, and a lack of clear boundaries. Organizations enter these processes with uncertainty about the nature of the problem and the path to its resolution, having only a vague idea of the possible solution or even of the criteria to evaluate said solution. The final decision is ultimately reached through a non-linear and fragmented sequence of actions. Unlike decision making under uncertainty, where the possible alternatives are known but the outcomes are not, this process is more of a decision making under ambiguity, in which neither the possible choices nor their implications are clearly established or understood from the start (Mintzberg, Raisinghani, & Théorêt, 1976).

The first thing the authors found is that when faced with unstructured, non-routine decisions, decision makers tend to simplify the complexity of the situation by breaking it down into more familiar and manageable problems, in a decomposition process. Decision makers, in these

situations, also tend to *satisfice* instead of maximizing, reflecting Simon's take on decision making under uncertainty and bounded rationality. Mintzberg's discussion here reflects the core principles of his own adaptive mode.

The authors cite the work of Witte, Joost, & Thimm (1972) which by empirical analysis found that the traditional process of decision making (see Section 1.3), described as a linear sequence of steps progressing from problem definition to choice of the best alternative, was not supported by evidence. Therefore, the decision-making process is characterized by different phases (identification, development, and selection) but these phases are not sequential, but rather iterative.

The first distinction Mintzberg, Raisinghani and Théorêt (1976) make is characterizing decisions by the stimulus, the solution, and the process to reach them.

When talking about decisions by stimulus, one should imagine a continuum. At one end of the continuum there are opportunity decisions, while at the other there are crisis decisions. Everything that falls in between is problem decisions. Opportunity decisions are not reactions to an event, they are instead purely discretionary and are often made to improve the situation, like the introduction of a new product for an already established company. On the other hand, crisis decisions, as implied by the term itself, are reactions to some urgent issue. Problem decisions are less urgent than crisis decisions and could be originated from the outcomes of other decisions. The authors also include decisions that could be a mix of these three, such as opportunity-problem decisions or problem-crisis decisions. This is because during the development of the process, one decision could change its position along the continuum. For instance, "an ignored opportunity can later emerge as a problem or even a crisis, and a manager may convert a crisis to a problem by seeking a temporary solution, or he may use a crisis or problem situation as an opportunity to innovate" (Mintzberg, Raisinghani, & Théorêt, 1976, p. 251).

Regarding decisions by solution, there are four categories: solutions can be given, ready-made, custom-made, or modified. Given solutions are completely available and formulated at the start of the process. Ready-made solutions become completely available and formulated as the process moves forward. Custom-made solutions are context-specific and developed on the spot

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for the specific decision. Finally, modified solutions are a combination of ready-made and custom-made solutions, they are modified to tailor a specific decision context.

The third category, decision by process, will be discussed more in detail later in this section, as it requires a more thorough explanation.

Mintzberg, Raisinghani, & Théorêt (1976) identified twelve basic elements of a strategic decision-making process: three central phases, three supporting routines, and six dynamic factors.

The identification phase involves two routines: decision recognition and diagnosis.

The decision recognition routine reflects a situation where problems arise and the need for a decision to change the status quo is perceived. As the authors state, “the need for a decision is identified as a difference between information on some actual situation and some expected standard” (Mintzberg, Raisinghani, & Théorêt, 1976, p. 253). This routine helps to categorize decisions as problem decisions, crisis decisions, or opportunity decisions. The latter are prompted by an idea in the mind of the individual; crisis decisions, on the other hand, follow an urgent issue, a situation that requires fixing. Finally, problem decisions are taken after more than one stimulus since decision makers may choose not to react to a single stimulus unless there is an opportunity behind it. Action is taken depending on where the stimulus originates, how relevant or important the decision is to the decision maker, the expected benefits of acting, the level of ambiguity, and the likelihood of a successful conclusion of the decision.

The diagnosis routine comes after the recognition of the need for a decision to be taken. The decision maker needs to deal with unstructured data within an unfamiliar context. He/she must therefore gather or generate information to better understand and delineate the problem. According to Drucker (1971), Japanese decision makers engage in careful diagnosis, whereas American decision makers tend not to. Evidence points to the fact that in opportunity decisions there seldom is a process of diagnosis, and in crisis decisions there hardly ever is enough time to conduct a proper diagnosis. The literature around decision making almost never mentions a process of diagnosis, even though there are few exceptions (e.g., Bonge, 1972, Emory & Niland, 1966, pp. 50-66, and Drucker, 1971) (Mintzberg, Raisinghani, & Théorêt, 1976).

In the development phase, the decision maker conducts a series of activities to reach one or more solutions to a problem or a crisis, or to elaborate an opportunity. This phase requires the greatest number of resources in the process.

The development phase involves two routines: search and design.

Search routines find ready-made solutions through a process of convergent thinking. Four distinct types of search behavior can be identified (Mintzberg, Raisinghani, & Théorêt, 1976, p. 255):

1. Memory search refers to the examination of the organization's internal knowledge base, whether stored in an individual's memories or documented records.
2. Passive search involves being receptive to alternatives that may arise on their own, without actively searching for them. As Cyert & March (1963, p. 80) observe, "not only are organizations looking for alternatives; alternatives are also looking for organizations".
3. Trap search entails triggering mechanisms that encourage the emergence of alternatives. For instance, a company might publish a request for proposals (RFP) to signal its interest in a new software solution, thereby prompting vendors to submit proposals (alternatives).
4. Active search consists of the deliberate and targeted pursuit of alternatives, either by scanning the whole environment or by focusing attention on specific areas.

Evidence supports the idea that search is a sequential process: decision makers begin by consulting internal knowledge, then they engage in passive search, sometimes employing simple forms of trap search. The authors once again cite Cyert & March (1963, pp. 120-122), who suggest that search activities tend to start in the local environment, close and familiar to the organization, therefore immediately accessible. When these activities fail, organizations are likely to move to more active search strategies and involve more distant or unfamiliar sources of information. Finally, if these efforts to find ready-made solutions are unsuccessful, it is reasonable to assume that the organization will attempt to develop a custom-made solution.

Design routines create custom-made or modified solutions through a process of divergent thinking. When modified solutions are necessary, the search routine is useful to identify those

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ready-made solutions suitable for modification. The development of a custom-made solution is a complex and iterative process. It often begins with a loosely defined vision of an ideal outcome. Decision makers approach the task by breaking it down into a series of interconnected design and search cycles, navigating a decision tree in which each successive choice (a node in the tree) is more specific and well-defined. If a particular path of the tree proves to be unsuccessful, the process moves back to a previous stage for reconsideration. In this way, the solution is gradually defined, often without a clear picture of the result, in a process that recalls Quinn's logical incrementalism.

The selection phase is logically the last one, but since decisions are broken down into many subdecisions, each decision-making process involves more than one selection phase, according to how many subdecisions are taken.

This phase involves three sequential routines: screen, evaluation-choice, and authorization.

The screen routine is useful to identify the most fit and feasible ready-made solutions. In this case, the search routine has produced more ready-made solutions than it is possible to analyze thoroughly. This routine rules out solutions that are impracticable or unsuitable through successive elimination until only appropriate ones are left.

Once the alternatives are identified in the screen routine, the evaluation-choice routine selects the appropriate plan. This routine operates in three ways: judgement, bargaining, and analysis. In the judgement mode, an individual decides based on their own reasoning, that he/she may not be able to explain. Bargaining involves a group of decision makers with different and conflicting goals, and each of them applies personal judgement to negotiate on an outcome. In the analysis mode, technical experts conduct an assessment, but the final decision is made by managers, either through individual judgement or group bargaining. The evidence shows that "judgment seems to be the favored mode of selection, perhaps because it is the fastest, most convenient, and least stressful of the three; it is especially suited to the kinds of data found in strategic decision making. Bargaining appears in more than half of the decision processes - typically where there was some kind of outside control or extensive participation within the organization and the issues were contentious" (Mintzberg, Raisinghani, & Théorêt, 1976, p. 258). The analysis mode, however, was not supported by evidence.

The selection of strategic alternatives involves the consideration of many factors, the majority of which are more qualitative than quantitative, such as emotions, organizational politics, power dynamics, and so on. This complexity is further amplified by an ever-changing environment and uncertainty. Therefore, the evaluation-choice routine tends to be rather imprecise, because of both cognitive limitations and voluntary or involuntary biases.

Soelberg (1967) presents a detailed framework for understanding how the evaluation process is actually conducted. Organizations identify primary goals and secondary constraints, trying to reach a balance between maximizing and satisficing. Each alternative is assessed separately and independently from the others. During the screen routine, the secondary constraints are used to eliminate unsuitable alternatives. The remaining ones are then classified as acceptable, marginal or unacceptable based on how they relate to the primary goals of the organization. Acceptable options are then evaluated through a paired-comparison process, unless an alternative that seems to be the best overall is found. The ideal outcome is to identify a dominant alternative, one that outperforms all the others across every primary goal. If this alternative does not exist or cannot be found, the decision maker uses their own judgement to choose an alternative that is simply better than the others in some respects.

Finally, authorization serves to formally approve the selected course of action at a higher level within the organization's hierarchy, in a case where the decision maker does not have the authority to implement the decision. Sometimes, the decision must be approved even at the stakeholders' level if they have power to block it. Evidence points to a binary outcome in an authorization routine: either the decision is approved, or it is not. Only in a few cases the decision was only partially approved (Mintzberg, Raisinghani, & Théorêt, 1976).

Mintzberg, Raisinghani, & Théorêt (1976) identified three sets of supporting routines: decision control routines, communication routines, and political routines.

Decision control routines supervise the decision-making process. These routines are hard to study as they are seldom written down or formalized, since they happen prevalently in the mind of the decision maker. However, the authors found references to these routines in their empirical study.

Decision control routines consist of two main components: decision planning and switching.

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Decision planning involves all those activities aimed to set the boundaries of the decision space, such as outlining a tentative timeline, formulating a development approach, and estimating the level of resources needed for the process. In these activities there may be also an evaluation of constraints, and the development of a vision for an ideal outcome. However, these initial plans tend to be informal and rather adaptable, often evolving and becoming more defined as the process advances.

After the planning, concrete actions follow through the switching routine, where the decision maker selects the appropriate routine (through diagnosis or search), decides which resources to allocate and when, and effectively starts the process. Then, he/she monitors the development to revise the decision plan if needed (Mintzberg, Raisinghani, & Théorêt, 1976).

Communication routines control the flow of information necessary to the process. These activities appear in each stage of unstructured decision making (Witte, Joost, & Thimm, 1972). Communication routines consist of three main components: exploration, investigation, and dissemination.

Exploration routines involve the gathering of broad and often passive information, through scanning or passive searching. This is useful to build a general knowledge base to support decision making.

Investigation routines involve targeted efforts to obtain specific information. These routines are present during diagnosis, search, and evaluation-choice routines, either to collect new data or to verify the existing one. However, it is reasonable to assume that investigation is mostly conducted during the initial stages of diagnosis and development, as well as the initial stages of evaluation. In fact, Witte, Joost, & Thimm (1972) observed a U-shaped pattern of communication activity, peaking at the beginning and at the end of the decision-making process.

Dissemination routines are aimed at spreading the information gathered through previous routines. This effectively improves buy-in and facilitates acceptance. Evidence suggests that the more individuals are involved in or affected by a decision, the more time is spent to share information. This is particularly evident in the authorization routine of the selection phase. Moreover, as the process advances the likelihood of communicating information increases (Mintzberg, Raisinghani, & Théorêt, 1976).

Political routines help the decision maker manage supporting and contrasting external or internal forces. These activities are generally present in bargaining routines, and they may be present at the beginning of the process (i.e., identification phase), in the middle (i.e., development phase), and at the end (i.e., selection phase).

The authors found evidence of six dynamic factors, that is factors that cause the process to stop and restart or delay the decision. The dynamic factors mentioned in Mintzberg, Raisinghani, & Théorêt (1976) are the following:

1. Interrupts. These factors may be unexpected constraints presenting themselves in the final stages of the selection phase and causing the process to move back to development, political pressures causing delays (the most significant delays) or to move back to development, or unexpected new alternatives causing delays or speedups if the alternative was regarded to be outstanding. Interrupts are more common in crisis and problem-crisis decisions.
2. Scheduling delays. These are voluntary delays between stages caused by decision makers to better manage the process.
3. Feedback delays. These are systemic and structural delays due to the fact that before moving to the next phase the decision maker needs to wait for feedback on the previous phase.
4. Timing delays and speedups. These are caused by managers who may want to delay or speed up the process to wait for favorable circumstances or to gain advantages. This is particularly evident in highly competitive environments.
5. Comprehension cycles. These are factors inherent in the process that cause it to cycle back to a previous stage, helping the decision maker to better comprehend the situation at hand.
6. Failure recycles. These happen when a decision is ultimately rejected, for whichever reason, causing the decision maker to reevaluate the solution and propose a modified or entirely new one.

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Mintzberg, Raisinghani, & Théorêt (1976) developed a general model of the strategic decision process, illustrated in *Figure 4*.

The line at the center of the image depicts the two essential routines for any kind of decision-making process: the decision recognition routine and the evaluation-choice routine (with its three modes: judgement, analysis, and bargaining). This central line, therefore, shows a basic decision-making process, with merely the essential phases. In reality, this is hardly the case. This is why the model includes several deviations from the central line. For instance, some processes might require a development phase involving both search and screen routines to develop a ready-made solution or a design routine to create a custom-made or modified solution. Another deviation is the authorization routine, which may not be necessary in every process.

The model also comprises loops, as the process is seldom linear and sequential. For instance, comprehension cycles appear within the evaluation-choice routine, or the process moves back to development after authorization.

The three most common types of interrupts are shown in the model. The internal (or political) interrupts arise in the identification phase when there is disagreement about whether action is necessary. These interrupts may cause the process to move back to the recognition routine or to delay. New option interrupts typically emerge in the later stages of development or during evaluation and can cause the process to cycle back to design to better define the new option or move directly to evaluation to immediately decide on acceptance or rejection of said option.

Lastly, external interrupts may occur in the selection phase if external forces obstruct the implementation of the solution. In this case, the organization may address external concerns changing the design or engaging in bargaining.

Delays are shown as broken lines at the end of each routine, signaling that scheduling, feedback, and timing delays present themselves between each stage of the process. Supporting routines are not shown in the model (except for bargaining) as they are pervasive throughout the process.

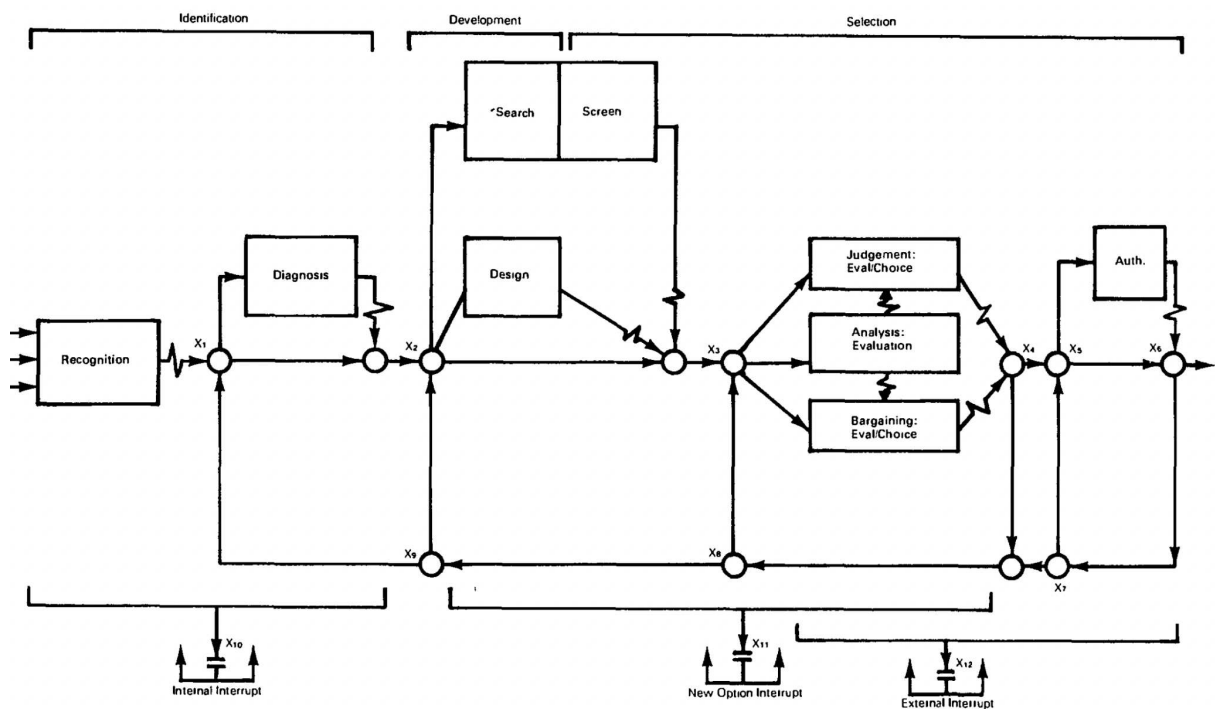


Figure 4. *General Model of the Strategic Decision Process.* Mintzberg, Raisinghani, & Théorêt (1976).

Mintzberg, Raisinghani, & Théorêt (1976) studied 25 different decision processes and identified seven configurations of this model, mostly depending on the type of solutions and dynamic factors:

1. Simple impasse decision processes. They almost follow exactly the central line of the model, involving no development activity and some interrupts.
2. Political design decision processes. They are somewhat more difficult than the previous ones since the interrupts are harder to overcome and political design (a development activity) is substantial.
3. Basic search decision processes. Here the decision maker searches for the best ready-made solutions in the development phase. These processes have few interrupts and last one or two years.
4. Modified search decision processes. Search activity finds suitable ready-made solutions that are then modified through design activity. Authorization is necessary and cycles in development are quite a lot. This situation is most common in decisions regarding the choice of new equipment.

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5. Basic design decision processes. Substantial design activities develop a complex and innovative custom-made solution. This situation typically arises with opportunities or moderate problems and does not last for a very long time, partly because there are usually few interrupts. Every marketing decision the authors analyzed was a case of this kind of process.
6. Blocked design decision processes. These are identical to the fifth type except for the selection phase, in which the chosen solution was rejected by outside forces.
7. Dynamic design decision processes. These are the most complex ones in terms of paths followed since the processes meet numerous interrupts. As a result, these processes are also those which take the longest (up to more than four years). Usually, they emerge from problems or problem-crises and involve a decision regarding new facilities. The authors conclude that “the dynamic nature of these facilities decisions reflects (a) the relatively large investment needed, (b) the complex design activity involved in such facilities, and, paradoxically, (c) the likelihood of new option interrupts because of the availability of ready-made structures” (Mintzberg, Raisinghani, & Théorêt, 1976, p. 272).

### 1.5. Individual vs. Group Decision Making

After exploring the various models for decision-making processes in the last section, it is essential to consider who makes these decisions. In particular, a key distinction lies between decisions made by individuals and those made by groups. Each approach has its own advantages and challenges, and its effectiveness depends on factors such as the type of the decision, the complexity, the time available, and the overall organizational context.

Charness & Sutter (2012) identified the main differences between group decision making and individual decision making.

The first difference is that “groups are more cognitively sophisticated” (Charness & Sutter, 2012, p. 159). The authors reach this conclusion analyzing a specific setting: the beauty-contest game. In this game, individuals are asked to choose a number from zero to one hundred, and

the winner is the individual whose number is closest to  $p$  times the average number chosen, where  $p$  is a number less than 1. This effectively means predicting what the average number will be.

The rational equilibrium in this case, since  $p$  is less than 1, would be zero. For instance, given  $2/3$  as the common value for  $p$ , if players assume that others are picking numbers randomly between zero and one hundred, then the average would be around 50 and  $33.3$  (i.e., two thirds of 50) would be the best response. However, an individual may assume that every other player will choose the best response, leading to a new expected average of  $33.3$ , and thus a best response of  $22.2$ . Repeating this logic, ultimately the best response converges to zero.

Citing the results of Kocher & Sutter (2005), Charness & Sutter (2012) affirm that groups get to the rational equilibrium choice a lot quicker than individuals, suggesting that groups reason “more deeply about the strategy of the game and are expecting the other parties to reason more deeply as well” (Charness & Sutter, 2012, p. 160). Therefore, groups outperform individuals significantly.

The authors also analyze the differences in deviations from rational behavior between individuals and groups, drawing from the results of Charness, Karni, & Levin (2007), who designed an experiment with two urns (left and right) and two states of the world (up or down), each fixed for two rounds. A participant is asked to draw one ball at a time with replacement and to observe its color. In the “up” state of the world the left urn contains four black balls and two white balls, whereas in the “down” state the proportions are reversed. The right urn has six black balls in the “up” state and six white balls in the “down” state. If the participant has to draw the first ball from the left urn and is given a payoff only for black balls and not white ones, in case he draws a black ball (favorable outcome), the rational strategy is to switch to the right urn. On the contrary, if a white ball is drawn, he should continue to draw from the left urn. However, psychology supports a “win-stay, lose-shift” behavior in individuals. Persistent refusal to switch urns highlights systematic errors in individual judgement, whereas group decisions achieved perfect rationality.

A famous example to support differences in errors is the Linda paradox, where the following question is asked (Charness, Karni, & Levin, 2010):

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“Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations. Which is more probable:

(a) Linda is a bank teller.

(b) Linda is a bank teller and is active in the feminist movement.”

Since the second option introduces an additional constraint with respect to the first, it is quite unlikely that it is the most probable. However, the majority of individuals chose the second option. On the other hand, groups succeeded in choosing the right answer, and error rates declined as the number of people in a group increased.

Lastly, one example focused on limited cognitive capabilities. Cooper & Kagel (2005) investigate the “limit-pricing game”, in which one player represents a market incumbent with either high or low production costs and chooses an output level before a second player, acting as a potential entrant, decides whether to enter the market or not. Game theory predicts that the incumbent should adopt a limit-pricing strategy, producing a higher output and lowering prices to discourage entry. Cooper & Kagel (2005) find that groups of two people behave more strategically than individuals, choosing the limit-pricing strategy more often. Moreover, groups adapt more quickly to a shift in market conditions, such as a change in cost structure.

These examples provide strong evidence that in decision-making contexts characterized by cognitive limitations (and therefore bounded rationality) group choices tend to align more closely to theoretical predictions. In fact, these findings support the conclusion that groups exhibit more rational behavior than individuals (Charness & Sutter, 2012).

The second difference between groups and individuals is that groups are more self-controlled and productive, although the evidence is limited. Charness & Sutter (2012) cite the work of Falk & Ichino (2006), who found that average productivity was 16 percent higher when individuals worked in groups compared to working in isolation, suggesting that peer control within groups positively influences performance.

The presence of others encourages members to justify their decisions and consider alternatives more carefully. For instance, going back to the example of a product development team deciding where to launch a new product, a team composed of individuals coming from different functions and having different backgrounds can brainstorm ideas, challenge each other and

contribute with different insights, improving the quality of the final decision. On the contrary, if a single manager were to take the decision by themselves, they might rely on personal experience or overlook data, rendering the decision suboptimal.

The third and last difference is that “groups may decrease welfare because of stronger self-interested preferences” (Charness & Sutter, 2012, p. 166). In fact, there are cases in which groups are detrimental for social welfare, and cases where they are beneficial.

One example for the former case is the classic prisoner’s dilemma, where each of the two players has a dominant strategy, but collaboration would lead to higher payoffs. Charness & Sutter (2012) cite Charness, Rigotti, & Rustichini (2007), who investigate this game in a group context, where individuals decide for their group and therefore affect everyone in their group. Their findings show that collaboration rates drop significantly when individuals play in these conditions. Therefore, group affiliation increases the likelihood of non-cooperation, thus reducing social welfare. This behavior is mainly caused by the fact that groups show very little trust in others.

However, in the so-called coordination games, where multiple pure-strategy equilibria exist, groups facilitate efficient coordination and enhance social welfare. For instance, Feri, Irlenbusch, & Sutter (2010) examined the “weakest link” game that shows how group decision making can improve coordination. Five players (who can be either individuals or groups of three persons) select an effort level from one to seven, briefly discussing beforehand if they are in groups. Payoffs increase with higher effort levels, but they are ultimately determined by the lowest effort chosen among all players (that is, the weakest link). Any case in which all the players select the same effort level constitutes an equilibrium, therefore the highest collective payoff possible is the case in which players coordinate on a high effort level. The authors find that groups are not only more likely to reach efficient, high-effort equilibria, but also more inclined to avoid miscoordination (selecting different effort levels).

Evidence suggests that groups tend to make more rational decisions, and this can reduce social welfare in games with a unique pure-strategy equilibrium (see the prisoner’s dilemma), while increasing social welfare when games consider multiple equilibria, as they are more effective in coordination. A possible reason for this behavior is that groups tend to place greater emphasis on their own payoffs compared to individuals (Charness & Sutter, 2012).

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Charness & Sutter (2012) attribute the higher rationality of groups with respect to individuals to three main reasons:

1. The aggregation of multiple minds may improve problem-solving capabilities, as collective reasoning can lead to better-informed decisions. This is also supported by evidence from psychology.
2. Groups may be more effective at predicting the actions of others, thereby improving strategic coordination.
3. Group decisions may place greater emphasis on monetary payoffs, reducing the influence of non-economic factors such as fairness or emotional biases. As a matter of fact, groups are more competitive and act more selfishly than individuals, a behavior that social psychology calls “discontinuity effect” (Schopler & Insko, 1992).

The main conclusion of Charness & Sutter (2012) is that groups are more likely to make choices aligned with standard game theory, whereas individuals are more sensitive to biases, limited cognitive capabilities, and social pressures. This implies that decisions taken by individuals are not good predictors of group decisions. However, group decisions do not always lead to better social outcomes. They tend to be most effective when the group is diverse and operates in a collaborative and open environment that encourages the exchange of ideas. Diversity increases the likelihood that a single member could offer a critical insight that the rest of the group oversaw, highlighting the importance of having a broad base. However, the effectiveness also depends on maintaining a manageable group size, as overly large groups can suffer from coordination difficulties and a tendency for social loafing (see Section 1.5.2.).

### **1.5.1. Individual and Group Decisions under Risk and Uncertainty**

The evidence on differences between risk attitude in groups and in individuals is conflicting. Some authors support the theory that groups tend to be risk averse (e.g., Masclet, et al., 2009), others support lower risk aversion (e.g., Shupp & Williams, 2008), and others find risk neutral preferences (e.g., Baker, Laury, & Williams, 2008).

Carbone, Georgalos, & Infante (2019) conducted an experiment to investigate risk attitude differences in group and individual decision making, in an intertemporal consumption framework. They also added contexts of ambiguity, a form of uncertainty, to the test.

The experiment simulated a lifecycle decision-making environment, structured into fifteen time periods. In each period individuals or groups were given an income in tokens which could be either high or low, and this was determined by a draw from an urn. Participants (either individuals or groups) were required in each period to decide how many of their tokens to consume (converting them into points) and consequently how many to save. Interest rates were fixed at 20% per period. Each participant completed this task twice across two independent 15-period sequences.

The instructions given to the participants described the structure of the experiment and briefly explained the utility function (“conversion function” in this case) and its properties (such as the diminishing marginal returns). In the risk setting of the experiment the urn contained ten balls, five black (representing high income) and five white (representing low income). In the ambiguity setting, the participants did not know the composition of the urn. In both settings the draws were made with replacement. The participants were also made aware that in each new period the amount of tokens they could convert into points would include the given income plus their accumulated savings and interests, and that any savings left at the end of the final period would have no value.

Individuals were given one minute for each decision during which they could try different consumption-savings allocations using a calculator. They were not allowed to confirm their choice until the full minute had passed. This restriction was designed to encourage individuals to carefully consider their strategy and to minimize random noise in the data. The system provided the participants with simulated outcomes of their choices in terms of savings, interests, and utility, to evaluate different alternatives before finalizing their decision.

On the other hand, groups of couples were paired randomly after each sequence, however it was ensured that no participants were paired together more than once. Each pair had three minutes to make their decision, and in this case they could confirm their choice after at least one minute. If no decision was confirmed at the end of the three minutes, the system randomly selected between the group’s last two tried alternatives.

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A random incentive system was used to determine the final payoff: one of the two 15-period sequences was randomly chosen and participants were paid according to their utility in that sequence. Said utility was converted into real money at a fixed exchange rate of €2 for every 100 points. This conversion rule was clearly explained in the instructions. For what regards groups, both individuals in the pair received the same monetary amount, calculated according to this method. In this way, the incentive structures were the same between both individuals and groups.

Furthermore, to avoid influencing the participants' strategic decisions, no rules for dividing the payoff between participants were imposed, nor were they allowed to engage in bargaining or negotiations about how to split the reward (Carbone, Georgalos, & Infante, 2019).

Carbone, Georgalos, & Infante (2019) considered two definitions of optimality: the unconditional and the conditional optimalities. The unconditional optimality refers to the optimal consumption determined based on assumptions about the agent's preferences, specific parameter values, the given income, and the optimal wealth level. The conditional definition of optimality is less rigid and is calculated based on the actual cash available at the start of each period, that is the sum of the gross returns from previous savings and the current given income. This method also allows for learning effects and improvements in decision making over the lifecycle and gives a result that is subject-specific. The authors chose to follow this definition of optimality in their findings.

The authors present six findings in their conclusions (Carbone, Georgalos, & Infante, 2019):

1. In both risk and ambiguity settings, both individuals and groups over-consume with respect to the predicted level of optimality.
2. Both individuals and groups show significant deviations from the predicted level of optimality, in both risk and ambiguity settings. All deviations have positive signs, and this is consistent with the first finding. In the risk setting, individuals deviate significantly more from the optimal consumption level than groups during the first sequence, while in the second sequence this result is reversed. In the ambiguity setting,

groups significantly decrease their deviation towards the end of the lifecycle, while individuals continue to increase theirs.

3. Deviations tend to increase with higher levels of wealth and income but decrease as participants progress through the lifecycle. Group decision making improves under risk, while individual performance declines under ambiguity. In addition, gender plays a role: male and mixed-gender groups deviate less from optimality.
4. Within the same decision environment, significant differences emerge between settings: individuals outperform groups under conditions of risk, while groups achieve better performance than individuals when facing ambiguity.
5. Individuals show smaller deviations when making decisions under risk than under ambiguity. On the contrary, groups tend to deviate less in the ambiguity setting rather than in the risk one.
6. Most participants, both individuals and groups, show myopic (short-term) planning, and no significant differences are observed between risk and ambiguity settings.

These findings argue that group decision making can be advantageous or not depending on the nature of uncertainty and the stage of decision making. While individuals excel under risk, groups provide a relative benefit when ambiguity (uncertainty) is present. However, both individuals and groups tend to show short-term planning.

A contribution from Marquis & Reitz (1969) analyzed the effect of uncertainty on risk taking in individual and group decisions. They set an experiment with gambling problems, and the participants had to choose between nine alternatives for each problem. The problems were set in uncertain or certain environments where the stakes, chances of winning, and the prize were given to the participants. In the uncertain environment, one of the characteristics of the alternative was indicated in a range. The decisions under the assumptions of zero, positive, or negative expected value were tested.

Regarding individual decisions, the authors found that uncertain environments made individuals more risk-averse, regardless of the expected value (positive, negative, or zero). This effect increased as uncertainty increased. In fact, individuals bet smaller amounts of money where uncertainty was present in a higher degree.

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On the other hand, group discussion after individual choices does not affect decisions in problems with a zero expected value. However, when dealing with positive expected value problems group discussion leads to significantly riskier choices, while for negative expected value problems, groups become more cautious. This means that, if uncertainty is not involved, group discussion helps align decisions to the expected value rather than introducing a general risk bias. When uncertainty is introduced, group discussion tends to produce “risky shifts” in both zero and positive expected value problems. The risk-taking attitude in zero expected value problems may be caused by risk biases triggered by uncertainty, whereas the one (much more significant) in positive expected value problems may reflect both this risk bias and a better understanding of expected value through discussion. The “cautious shift” observed for negative expected value problems under uncertainty may suggest that the maximization of the expected value outweighs the tendency to take risks (Marquis & Reitz, 1969).

The authors concluded that group discussion seems to clarify the expected value of choices, which then guides decisions toward either more risky or more cautious choices, depending on what the expected value implies. Since individuals tend to respond to uncertainty with more cautious decisions, group discussion may reduce this perceived uncertainty through the exchange of opinions (although new information is not introduced).

Consequently, the findings support two main hypotheses: (1) group discussion tends to amplify attention to expected value, and (2) it introduces a risk bias only in situations where uncertainty is present. Therefore, while uncertainty causes individuals to act cautiously, group discussion can counterbalance this effect, encouraging more confident (but sometimes riskier) decisions (Marquis & Reitz, 1969).

### **1.5.2. Risks of Group Decision Making**

While group decision making offers a broader knowledge base and more rational decisions (as seen before in this chapter), it may cause some substantial risks. These risks can compromise both the efficiency and the quality of the decisions taken, especially in contexts that require speed and clarity, or in fast-changing, uncertain environments.

The first problem arising is the time taken to reach a group decision, as group processes often involve extended discussions to reconcile different points of view, which can be particularly problematic in time-sensitive situations. In fact, conflict among group members may arise when diverging opinions or personal biases dominate the discussion, and this could lengthen the process even further.

Sometimes groups composed of highly qualified and competent individuals still end up taking wrong decisions, or sticking to the wrong decisions even when it is evident that they are working out badly (Janis, 1971). This may be caused by the presence of *groupthink*, that is “the mode of thinking that persons engage in when concurrence-seeking becomes so dominant in a cohesive ingroup that it tends to override realistic appraisal of alternative courses of action” (Janis, 1971, p. 43). According to Janis (1971) symptoms of groupthink include:

- Illusion of invulnerability, which leads members to take excessive risks.
- A belief in the inherent morality of the group, which blinds members to ethical considerations.
- Collective rationalizations, where warning signs or contradictory evidence are dismissed.
- Stereotypes of outsiders with opposing views, further reinforcing internal biases.
- Self-censorship by dissenting members.
- Direct pressure to conform.
- The illusion of unanimity, which can suppress productive discussions.
- The emergence of self-appointed mindguards to block dissenting information, effectively shielding the group from contrary evidence or opinions.

Janis (1971) also discussed some possible consequences of groupthink. In these situations, only two or few more alternatives are discussed, and reevaluation of the decision selected by the majority is improbable, even when drawbacks arise. Little time is spent discussing the possible benefits of alternatives that were immediately disregarded, and experts on the matter are hardly consulted. Members of the group are almost blind to dissenting information, while they hold in high regard every piece of information that confirms or supports their view. Lastly, groups tend

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to fail to prepare themselves for possible negative consequences of their decisions, for instance by creating contingency plans.

To mitigate groupthink, leaders should promote open criticism and avoid stating their preferences early in the process. Moreover, encouraging input from external, independent sources, and holding follow-up meetings to reevaluate important decisions are all proven techniques to preserve critical evaluation in group decisions (Janis, 1971).

Another issue is *social loafing*, that is the tendency for individuals to exert less effort when working in a group compared to when working alone. This phenomenon occurs when the link between individual input and group outcomes is unclear, causing members to feel like their personal contributions are insignificant. This dynamic is further aggravated the larger the group is, as it becomes more difficult to identify and assess each member's efforts. In some cases, this leads to the so-called *sucker effect*, where team members reduce their efforts to avoid being exploited or fooled by less committed colleagues. Organizations can reduce social loafing by keeping groups as small as possible, clarifying each member's contributions and making them visible, encouraging peer evaluation, and reinforcing the value of each person's role.

Conformity effects are another complication of group dynamics. Experiments by Asch (1951) and Milgram (1963) demonstrated how individuals often align their views with the majority or blindly agree with authority figures, even when doing so contradicts their own opinions, views, or beliefs. This can further suppress innovation and critical thought, especially when members are already reluctant to voice their dissenting opinions.

Lastly, groups may be susceptible to group polarization, which is the tendency to adopt more extreme positions than individuals would. This was an underlying dynamic present in the experiments investigating risk taking introduced in the previous section. Polarization occurs because responsibility is shared across members, and this reduces individual accountability; moreover, members (especially those higher in the hierarchy) often persuade others into believing their opinions. As a result, group decisions may lean toward riskier or more conservative extremes.

## 1.6. Conclusions

This chapter examines the characteristics of decision making within organizations, highlighting the complexity and high contextuality of these processes. The differences between organizational decisions and individual ones were outlined, showing how a pure linear approach is inadequate in an organizational context.

The limitation of traditional concepts of decision making, which assume perfect rationality and complete information, have been addressed through the lens of bounded rationality (Simon, 1955) and supported by arguments from Aumann (1997).

Recognizing these constraints, the chapter explored alternative models to better reflect how decisions are actually made in organization, especially under conditions of uncertainty, time pressure, and limited cognitive resources.

Evidence-based models proposed by Rousseau (2018), the strategic modes of Mintzberg (1973), and the logical incrementalism of Quinn (1978), provide insights into the diversity of decision-making strategies that organizations could adopt depending on the situation.

In particular, the work of Mintzberg, Raisinghani, & Théorêt (1976) highlights how real decision processes are often unstructured, influenced by dynamic forces that cannot be foreseen and political routines.

However, despite their contributions, each of these models presents limitations that reinforce the need for more advanced support systems (i.e., Artificial Intelligence) to complement human judgement. For instance, Rousseau's (2018) categorization of routine, non-routine, and novel decisions rightly accounts for varying degrees of uncertainty and information availability, but it still assumes that humans can efficiently access, filter, and process vast amounts of data, a task where AI could offer significant advantages, especially for non-routine and novel decisions, where information is fragmented or unknown. Mintzberg's (1973) strategic decision-making modes also reflect real organizational behaviors, but they tend to be either overly centralized (entrepreneurial mode), overly reactive and fragmented (adaptive mode) or overly rigid (planning mode). Each of them struggles to cope with rapidly changing environments and information overload, where AI tools could introduce structure, coordination, and data-driven insights. Quinn's (1978) logical incrementalism is adaptive and flexible, but its reliance on

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gradual learning and managerial intuition can delay responses and make it difficult to process real-time data, again highlighting a role for AI in accelerating feedback loops and identifying patterns that might not be visible through human observation alone. Finally, the unstructured decision-making framework by Mintzberg, Raisinghani, & Théorêt (1976), while valuable in describing the complexity and non-linearity of real-world decisions, offers limited practical guidance for navigating such complexity. Its iterative nature, influenced by dynamic and often unpredictable factors, makes it difficult for organizations to plan and scale decisions. Here, AI can play a critical role by detecting patterns across unstructured factors, simulating possible outcomes, and supporting decision makers in coordinating processes that are otherwise fragmented and contingent.

The final section of this chapter focused on the comparison between individual and group decision making, discussing both the cognitive advantage of groups and the potential risks, including social loafing, conformity effects, and groupthink. While groups tend to perform better in conditions of uncertainty due to their diverse perspective, they can exhibit risk biases. As organizations consider integrating Artificial Intelligence into decision making, it becomes important to differentiate between the challenges linked to individual cognitive constraints and those emerging from group interactions. AI may offer different types of support in each context: helping individuals manage complexity and avoid bounded rationality, or mitigating group-level failures such as conformity and groupthink by providing objective, data-driven input.

The discussion of this chapter has shown that decision making in organizations is a contingent process, one that cannot be captured by a single model or approach. It is influenced by the type of decision, the environment, the stakeholders involved, and other unpredictable factors. In fact, improving the quality of organizational decisions often means balancing between standardized processes and flexibility, speed and accuracy, individual judgement and group discussions. However, even when more people are involved in the process, the human capacity to process information is limited (Lawrence, 1991; Fiori, 2011; Trunk, Birkel, & Hartmann, 2020). This is why human decision makers tend to simplify the processes and break down complex problems into sequential steps, more manageable for the human computation capacity (Trunk, Birkel, & Hartmann, 2020).

These limitations invite a deeper exploration of how Artificial Intelligence can complement and improve decision making in organizational contexts. The next chapter will examine the different models of Artificial Intelligence organizations are using for this reason.



## **CHAPTER TWO.**

### **Artificial Intelligence in Organizational Decision Making**

#### **2.1. Introduction**

Artificial Intelligence (AI) has become a central driver of digital transformation. Specifically, it offers multiple opportunities to enhance decision-making processes across every business function, from operations to strategy. However, the impact of AI varies significantly depending on the context in which it is used. This chapter explores different AI models, each characterized by their own strengths, limitations, and suitability for different types of business decisions.

The first model explored in this chapter is Constraint Satisfaction Problem (CSP) algorithms, which represent one of the most structured and rule-based forms of AI. In fact, CSPs aim to identify solutions based on defined constraints. These models are valuable in problems of resource allocation or workforce planning. The different types of CSPs (binary, non-binary, dynamic, or over-constrained) have different levels of complexity, but algorithms like backtracking, forward checking, and constraint propagation explore possible solutions efficiently.

However, CSPs lack adaptability and are not suited for dynamic environments where constraints evolve or are simply not known.

In contrast, Machine Learning (ML) represents a more adaptive approach, as these models do not operate on fixed rules but instead they learn patterns and make predictions by analyzing large datasets.

This chapter distinguishes between the different types of ML: supervised, unsupervised, semi-supervised, and reinforcement learning. Each of them is suitable for different decision contexts. Supervised learning, for instance, excels in customer churn prediction or lead scoring, as seen in platforms like Salesforce. Unsupervised learning, on the other hand, is better suited for pattern discovery and segmentation, such as in AWS's product Amazon Redshift. Semi-

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supervised learning can be valuable when labeled data is insufficient, while reinforcement learning is applicable in dynamic contexts requiring a process of trial and error.

Several key ML algorithms are also presented, from linear regression to neural networks, highlighting their business applications.

The chapter then examines the use of Generative AI (GenAI) to enhance decision making. There is substantial proof that GenAI is now used by many companies, up to 71% of businesses according to Singla *et al.* (2025).

One possible use case relates to M&A strategies; in fact, according to the 2025 Global M&A Report by Bain & Company, by 2027 one in two companies will leverage GenAI in their M&A activities.

Moreover, an experiment involving Procter & Gamble product development teams (Dell'Acqua, et al., 2025) validates GenAI's effectiveness as a teammate, suggesting that when paired with human judgement, these systems can significantly enhance the quality and efficiency of complex decision-making tasks.

The last model explored in this chapter is Agentic AI, which offers autonomous, goal-oriented systems capable of planning, adapting, and acting, in complex environments. These models are powered by foundation models like Large Language Models (LLMs), but they are further improved by memory, planning capabilities, and the possibility to use other tools and collaborate among each other.

Although these technologies are still emergent, PwC (2024) presents some success stories, such those of Siemens, Unilever, and Salesforce.

The final section of the chapter presents a comparison across the different models, highlighting key contingencies (such as speed, accuracy, required competences), showing how each AI model excels in certain conditions but falls short in others.

### **2.2. Main AI Models Used in Businesses**

As Artificial Intelligence becomes growingly embedded in business operations, it is essential to understand the different types of AI models currently in use. Each model has its own level

of autonomy, learning mechanisms, and functional applications, varying widely from more traditional models, such as Machine Learning systems used to identify patterns in data, to more complicated and advanced models such as Generative AI or Agentic AI, which could in theory operate as an autonomous party in the process.

### **2.2.1. Constraint Satisfaction Problem Algorithms**

Constraint Satisfaction Problems (CSPs) represent a core methodology in Artificial Intelligence for solving complex problems by systematically applying a set of constraints to identify possible solutions. Rather than searching through all possible outcomes, CSPs work by narrowing the solution space, using logical rules to exclude invalid options. This makes them especially powerful in domains where precision and efficiency are critical, such as scheduling, planning, and resource management. Consider, for instance, a product development team that is preparing to launch a new product and must decide which markets to enter, considering a variety of constraints:

- Budget limitations restrict the number of markets that can be entered simultaneously.
- Each market has different levels of regulatory complexity, competitive environment, and consumer readiness.
- The company may want to prioritize markets that align with strategic goals (e.g., expansion in emerging economies or where the existing brand presence is strong).
- There are timing constraints related to when product launch or certifications can be completed.

The CSP-based AI system evaluates combinations of markets based on these constraints and suggests an optimal portfolio of markets to enter, ensuring that all factors are balanced.

At their core, CSPs are defined by three fundamental components: variables, which denote unknowns to be resolved; domains, which specify the possible values each variable can take; and constraints, which establish the conditions that valid combinations of variables must satisfy. In our example, the variables are the potential markets under consideration; the domains are the

possible decisions for each market (e.g., enter now, delay entry, or exclude); and the constraints are budget caps, strategic priorities, regulatory readiness, and launch timelines.

The true strength of CSPs lies in their ability to break complex real-world problems down into a structured, algorithm-friendly format. Rather than solving problems through trial and error, CSPs enable AI systems to systematically evaluate and eliminate unviable options, accelerating the path to an optimal or at least valid solution (Singh, 2024).

This structured approach resonates with many of the decision-making models explored in the previous chapter. For instance, CSPs offer a formalized way to support Rousseau's non-routine and novel decisions, where information is dispersed or uncertain, by helping decision makers navigate constraints systematically rather than relying solely on intuition. They also complement Mintzberg's planning mode, where strategic decisions must be coordinated across interdependent goals and resources, a context where CSPs can optimize trade-offs across competing constraints.

There are four types of Constraint Satisfaction Problems (Singh, 2024):

1. Binary CSPs.

These are the most basic form, where constraints involve exactly two variables at a time. This simplicity makes them easier to model and solve using graphical representations, where variables are nodes and constraints are edges. In a business context, consider assigning two employees to shifts in such a way that prevents an overlap in availability while also considering constraints such as incompatible skill sets or interpersonal tensions.

2. Non-binary CSPs.

These involve constraints among three or more variables, capturing more complex interdependencies. These problems require advanced modeling techniques or conversion into binary equivalents to be solved effectively. For instance, in product launch planning, a constraint might require that marketing, logistics, and product development all complete their tasks in non-overlapping time frames to avoid resource contention. These interdependencies among multiple departments and tasks create a non-binary structure that cannot be solved by evaluating pairs alone.

3. Dynamic CSPs.

These account for scenarios where variables, domains, or constraints can evolve over time, reflecting real-world conditions where change is constant. These problems demand adaptive algorithms capable of updating solutions as new information emerges. For instance, in a retail supply chain real-time changes in inventory levels, supplier delays, or sudden shifts in demand may alter delivery times, and here a dynamic CSP can help to continuously optimize the plan in response to these fluctuations.

4. Over-Constrained CSPs.

These occur when it is impossible to satisfy all constraints simultaneously. Therefore, instead of seeking a perfect solution, the objective becomes finding the most acceptable trade-offs, such as prioritizing certain constraints over others or relaxing some requirements. These demonstrates that machines may exhibit *satisficing* behavior, just as humans do. A possible example is a company that may not have enough skilled personnel to meet all project needs within the desired timeline. Therefore, an over-constrained CSP would help the firm allocate the best-fit employees to the most critical tasks while delaying or de-prioritizing less urgent initiatives.

The resolution of these problems relies on a variety of algorithms. Each algorithm offers trade-offs between efficiency, complexity, and scalability.

Backtracking is a fundamental *depth-first search* technique. This means that the algorithm begins at the root node of the tree and explores as far as possible along each branch before backtracking, prioritizing the deepest nodes (the farthest from the root). Backtracking incrementally builds candidate solutions and abandons them as soon as a constraint is violated. In practice, the algorithm selects an unassigned variable and assigns it a value from its domain; then, it attempts to assign values to the remaining variables. If it meets a variable for which no valid value can be assigned, it backtracks to the previous variable and tries a different value. This process continues until a solution is found or all possible combinations have been tried out. Backtracking may become computationally expensive as the number of variables and constraints grows, despite being quite straightforward and intuitive.

Forward checking is an improvement over basic backtracking that reduces the search space by enforcing partial consistency after each assignment. After assigning a value to a variable, the

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algorithm moves to the next variable and removes all possible values for that variable that would violate the constraints. If then the domain of any future variable becomes empty, the algorithm backtracks. This is an improvement over simple backtracking because the algorithm detects conflicts early in the process and reduces redundant computations.

The last possible algorithm is constraint propagation. This goes beyond forward checking by actively enforcing consistency across the entire problem, rather than only between two consecutive variables. The algorithm assigns a value to a variable and automatically updates the domains of all other variables. This effectively accelerates the process (GeeksforGeeks, 2025).

Consider a company that needs to assign employees to different shifts across a week. Each employee may have preferences (for instance, they may be unavailable on Sundays), and obviously every shift must be covered. This company could use a backtracking algorithm to create the shifts. It would start by assigning employees to shifts one by one. If it reaches a shift where no employee is available, it backtracks and reassigns the previous shift with different choices. Backtracking here is possible because the problem is not huge (supposing there are few employees and few shifts), and employees' preferences are relatively easy to manage manually.

However, if we consider a product development team that wants to select a set of features to include in a new product, with features having dependencies between them, backtracking is not possible anymore, because of the interdependencies between choices that would render backtracking too resource intensive and time consuming. The team may instead use a forward checking algorithm based on which as soon as a feature is selected, all incompatible features from the available options are removed.

Finally, imagine a multinational company that needs to decide which international market or markets to enter as part of its expansion strategy. This kind of decision must consider multiple interdependent constraints, such as regulatory issues, market readiness, local partnerships, and logistical complexities, among others. Additionally, each potential market is affected by others, as entering one market may reduce the benefits of entering another. In this context, a constraint propagation algorithm would work best. This is because due to the high interdependencies between markets, assigning "yes" to Market A automatically and immediately affects the value

of Market B. Moreover, this algorithm does not just look one step ahead (as the forward checking algorithm would) but it updates all related variables (markets) to ensure the solution aligns with the overall strategy. Backtracking here would assign values to markets one at a time, not anticipating side effects and exploring many infeasible combinations before finding a valid one.

One of the key advantages of CSPs in AI lies in their structured approach to modeling and solving complex issues, decomposing a problem into variables, domains and a set of constraints, making it possible to manage and navigate intricate problems more efficiently. Moreover, CSPs are highly versatile and applicable across diverse domains, ranging from scheduling and resource planning to automated reasoning.

A significant strength of CSPs is their ability to handle multiple, often conflicting, constraints simultaneously, an essential feature for tackling real-world problems. In fact, in the previous chapter it was discussed how one of the main problems in organizational decision making is the presence of multiple stakeholders, having different and conflicting goals (e.g., see Mintzberg's adaptive mode).

However, the application of CSPs is not without challenges. A major limitation is scalability: as the number of variables and constraints increases, the problem space expands exponentially, making computation increasingly resource intensive. Additionally, over-constrained problems may end up failing to find a perfect solution.

To overcome these limitations, researchers and practitioners have developed heuristic strategies and hybrid approaches that combine CSP methods with optimization algorithms or Machine Learning techniques (Singh, 2024).

### **2.2.2. Machine Learning**

According to Flower (2023) in an article for Forbes, “the machine learning market—which brought in \$15.44 billion in 2021—is expected to reach almost \$210 billion by 2030, ballooning 38.8% annually”.

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Machine Learning is a branch of Artificial Intelligence that allows computer systems to learn and improve from data without being explicitly programmed. These systems adapt their algorithms based on patterns and insights extracted from the data they process.

According to Marr (2016) for Forbes, the origin of Machine Learning dates back to 1950, when Alan Turing created the Turing Test to see if a machine was able to fool a human into thinking it was a human itself. Two years later, in 1952, Arthur Samuel created the first self-learning program that taught an IBM computer how to play checkers and improve through experience. In 1957, Frank Rosenblatt introduced the perceptron, the first neural network that mimicked basic human cognitive functions.

Developing an effective Machine Learning model involves several key phases, illustrated in *Figure 5* (Chen, 2024):

1. Data collection and compilation.
2. Choosing the right algorithm, such as a decision tree or a logistic regression (explained in detail below). The algorithm selected should align with the complexity of the task and the nature of the data.
3. Data preparation. The data collected is rarely ready for training as it is. It must be cleaned and structured through processes like handling missing values, standardizing formats, or deleting duplicated records. This process not only ensures that the dataset is accurate, but it also ensures compatibility with the algorithm.
4. Training the model. The dataset is used to train the algorithm. This process involves feeding the model examples from which it learns to recognize patterns. The learning process may require adjustments to the parameters or even a change of the algorithm.
5. Evaluating model performance. After training, the model is tested on new, unseen data to assess its generalizability.
6. Refinement and optimization. Further *fine-tuning* ensures the model performs well in its specific context.
7. Deployment and monitoring.

Machine Learning can be categorized into four main types, each with its own advantages, limitations, and ideal applications.

Supervised learning is the most widely used and straightforward approach. It relies on labeled datasets and the algorithm learns to associate specific inputs with corresponding outputs by identifying patterns in the training data. For instance, in fraud detection, a model trained with transactions labeled as fraudulent or not can learn to classify future transactions. Here a human expert is required to teach the algorithm the right answers. However, supervised learning requires a significant amount of labeled data, which can be costly and time-consuming to generate.

Moreover, not having sufficient data could cause *overfitting*, which means that the model excels at predicting patterns when using the training data but fails to do so when using real data (Chen, 2024).

Unsupervised learning, on the other hand, works without labeled data. This allows the model to independently explore patterns and structures in the data. One of the most common techniques in unsupervised learning is *clustering*, where the algorithm identifies natural groupings in the dataset. This is often used in market segmentation or recommendation systems, such as suggesting products based on similar customer behaviors. However, although it offers greater flexibility in discovering hidden patterns, the lack of predefined labels can make results harder to interpret and validate.

Semi-supervised learning mixes techniques of supervised and unsupervised learning. This is especially useful when large volumes of data are available, but only a small portion of them is labeled. The process begins with training the model on the labeled portion of the dataset, and as confidence grows, the model starts assigning *pseudo-labels* to the unlabeled data, and adds them to the labeled dataset, re-starting the training with more labeled data. This iterative process ensures that the model improves using both types of data. Semi-supervised learning, therefore, can significantly reduce labeling costs while still achieving robust performance (Chen, 2024).

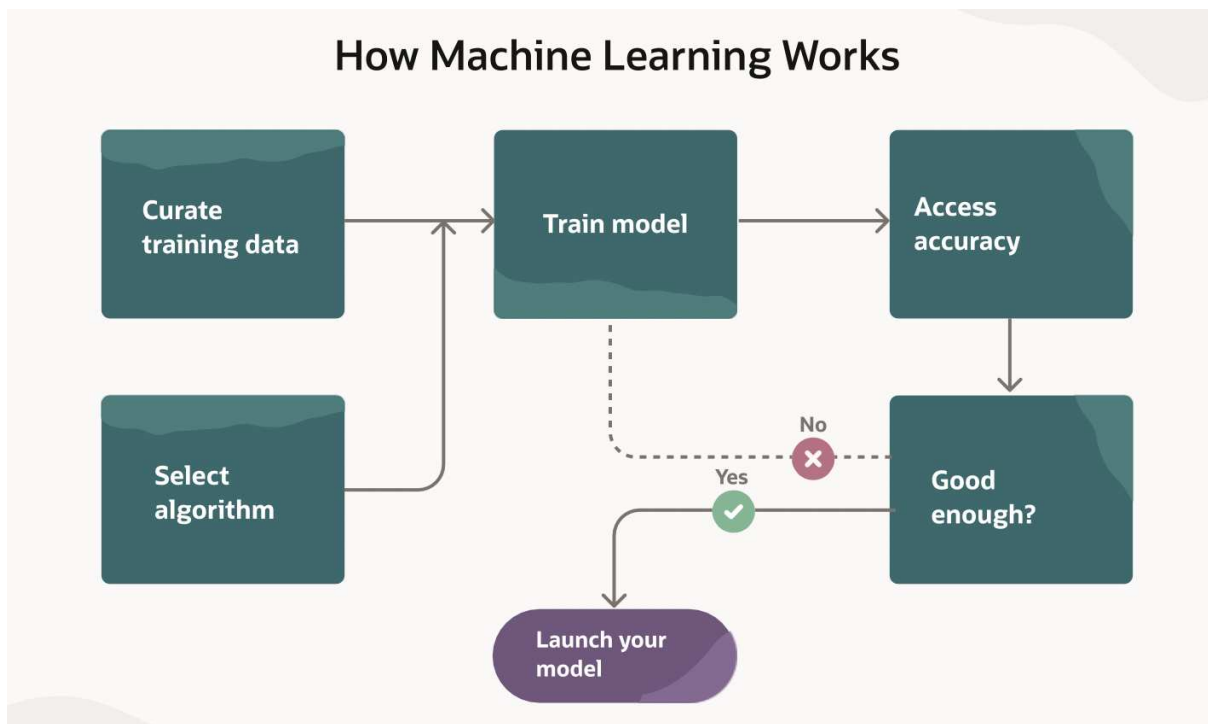


Figure 5. *How Machine Learning Works*. Chen (2024).

The last type of Machine Learning, reinforcement learning, is fundamentally different. It involves a process of trial and error, where the algorithm receives feedback in the form of rewards or penalties and learns to optimize its actions over time. Unlike supervised learning, in which the algorithm is not given a specific direction, reinforcement learning is goal oriented. This method excels in complex, dynamic environments where decisions have long-term consequences, such as supply chain logistics, as it is suitable for tasks where adaptability and strategic planning are critical (Chen, 2024).

Selecting the right type of Machine Learning depends on various factors, including the availability of labeled data, the budget, the timeline for development, and the specific use case. For instance, supervised learning could be used in lead scoring, which is the likelihood that a sales lead will convert into a customer. In this case, the historical CRM data is used as the training dataset and labeled as “converted” or “not converted”. The algorithm learns from these labeled examples and assigns a score to new leads, thereby helping sales to prioritize their work. Salesforce, the most widely used CRM, uses supervised learning in its Einstein Lead Scoring system, which analyzes data from converted past leads to see which new leads have most in

common with them (Salesforce, 2025). In this case unsupervised learning would not work because the algorithm needs to predict a specific outcome (i.e., conversion) based on past labeled data. Semi-supervised learning might be useful if the labeled data were insufficient, but this is hardly the case in CRM systems. Finally, reinforcement learning would be unnecessary, since this is not a dynamic environment with real-time feedback, it is a one-shot classification task.

Amazon Web Services (AWS) offers the possibility to use unsupervised learning, especially through clustering, with its product Amazon Redshift (Bates, et al., 2021). This unsupervised Machine Learning model can be used to segment customers based on behaviors like purchase history, browsing patterns, or frequency of visits. In this case, supervised learning would require pre-defined labels which may not exist a priori, and reinforcement learning does not fit since there is no sequential decision-making process or goal-oriented interaction, only pattern discovery. Again, semi-supervised learning could be used if partial labeled data were available.

A case where semi-supervised learning could be useful is sentiment analysis (Shan Lee, et al., 2019). Sentiment analysis is used to detect the emotional tone (positive, negative, or neutral) expressed in text, such as social media posts, online reviews, and news articles. Labeling all this data manually would be expensive and time-consuming, therefore with semi-supervised learning analysts label only a small portion of the data to train an initial sentiment model, which then labels itself the remaining texts. Unsupervised learning here is inapplicable because it would not provide a sentiment classification, but rather some clusters with unclear meaning, and reinforcement learning is not appropriate, as there is no feedback loop or reward mechanism.

Reinforcement learning is appropriate, for instance, in inventory management, as this problem requires sequential decision making. This algorithm interacts with the environment, seeing changes in demand, supply delays, or seasonal patterns, receives feedback in the form of stockouts or excess inventory, and learns to make better restocking decisions over time (Boute, et al., 2022). In this case, supervised learning does not adapt well to changing environments and cannot optimize over time, while unsupervised learning alone would not suffice, since it

## Artificial Intelligence in Organizational Decision Making

only detects patterns in data. Finally, semi-supervised learning lacks the trial-and-error, feedback-driven structure needed for dynamic inventory decisions.

Having explored the different types of Machine Learning, it is now essential to examine some of the most common algorithms that operationalize these methods.

Linear regression is a foundational algorithm used to model the relationships between one or more independent variables and a continuous dependent variable. By identifying the “line of best fit” this algorithm helps estimate outcomes and trends. Linear regressions could be used in sales forecasting, allowing decision makers to allocate budgets more effectively or plan inventory levels in advance.

Logistic regression, on the other hand, is designed to handle problems with binary outcomes. It is particularly useful in scenarios of lead scoring, where the company wants to predict if a lead will become a customer or not.

Clustering, mentioned before, is an unsupervised learning method that identifies natural groupings within data by examining similarities and differences. As has been said before, this is particularly useful when there are no predefined labels or outcomes. In business, clustering is often applied to segmentation, analyzing purchasing behaviors, demographics, or browsing histories to identify distinct customer groups.

Decision trees are algorithms used in supervised learning. They structure the decision-making process into a series of “if-then” rules. This is particularly helpful where the decision needs to be transparent and interpretable. Decision trees may be helpful in decisions regarding M&A, as the tree could structure the decision-making process based on key criteria, such as strategic fit, cultural alignment, and synergies, among others. Each node would represent a decision point, helping managers to visualize trade-offs and consequences of different acquisition scenarios.

While decision trees are useful, they can be sensitive to small variations in data. Random forest algorithms address this by aggregating the predictions of multiple decision trees trained on different subsets of the data, reducing variance and improving accuracy. For instance, if a company wants to determine the optimal pricing strategy across different markets, random forests can integrate a variety of interrelated criteria (e.g., local demand elasticity, competitor pricing, or taxes) to provide more robust and generalizable insights.

Neural networks are inspired by the structure and the functioning of the human brain and consist of layers of interconnected nodes (the “neurons”) that process and transmit data. Each node analyzes inputs and passes outputs to the next layer, allowing the network to detect complex patterns in large datasets. This algorithm is particularly useful in decision-making contexts that require pattern recognition and prediction based on unstructured data. For instance, it could be used for customer sentiment analysis, helping marketing teams to fine-tune product positioning and ad targeting (Chen, 2024).

A subset of Machine Learning, and specifically of neural networks, that is gaining traction in recent years is Deep Learning.

What differentiates Deep Learning from traditional Machine Learning is the fact that the latter uses simple neural networks with one or two layers, whereas the former uses three or more layers, usually in the range of hundreds or thousands of layers. Because of this huge amount of data and layers, Deep Learning is not ideal in contexts where interpretability of the decision is important (Holdsworth & Scapicchio, 2024).

Deep Learning-augmented decision making is used across various sectors to enhance organizational performance. For instance, Deep Learning has significantly influenced decision making in the financial sector, as it is now widely used to analyze complex and high-dimensional financial data, supporting tasks such as stock market forecasting, fraud detection, credit scoring, and algorithmic trading. In fact, these models help identify patterns and anomalies that traditional methods may overlook, by processing vast and intricately datasets in real time (Taherdoost, 2023). JPMorgan Chase & Co. effectively uses Deep Learning-augmented decision making for fraud detection (Lydon, 2023) and algorithmic trading (J.P. Morgan, 2023).

Decision-making processes can benefit from Machine Learning, as they rely on timely and accurate data analysis. This process, when performed manually, can be both time-consuming and resource-intensive, and often leads to limited or poor insights. Machine Learning addresses this challenge by automatically analyzing vast amounts of data to uncover patterns, trends, and correlations that may not be immediately apparent. Therefore, instead of dedicating time to manually handle data, decision makers can focus on interpreting results and implementing

actions. However, Machine Learning may cause issues regarding data quality, biases, and data security and privacy (Chen, 2024).

### 2.2.3. Generative AI

Generative AI (GenAI) is a branch of Artificial Intelligence that can generate content, such as text, images, videos, and so on. These models rely on Deep Learning, explained in the previous section.

In recent years, Generative AI has gained more attention particularly with the introduction of ChatGPT in 2022. According to Singla *et al.* (2025) for McKinsey, 71% of businesses use Generative AI regularly in their processes, and 21% of these report that GenAI use caused at least some workflows to be redesigned.

Unlike traditional AI, such as Machine Learning, which focuses primarily on the recognition of patterns, Generative AI goes further and identifies underlying themes and trends, revealing organizational strengths and weaknesses, or uncovering hidden market opportunities. For instance, in finance, GenAI helps CFOs navigate complex risk environments, make data-driven investment decisions, enhance productivity, reduce costs, and ultimately generate new sources of business value (IBM Institute for Business Value, 2024).

A Generative AI model is developed in three phases: training, tuning, and generation, evaluation and retuning.

The process begins with a foundation model, a Deep Learning model.

Large Language Models (LLMs) are currently the most common foundation models. These are trained on massive volumes of unstructured and unlabeled data.

During training the model undergoes a series of prediction tasks, such as completing sentences or anticipating the next line of a code. Through a process of iterative adjustments, the model minimizes the gap between predictions and the actual data, learning the underlying structures and patterns.

The outcome is a neural network consisting of billions of parameters that capture the statistical relationships within the data. Once trained, the model can generate coherent and contextually relevant content in response to the user prompts (Stryker & Scapicchio, 2024).

After being trained, the model is proficient across many domains but not specialized in any one in particular. Therefore, to achieve higher accuracy and relevance in specific applications, the model requires tuning. This can be done through several techniques; the two most common ones are explained below.

Fine-tuning is the process of adapting a trained model to a particular task by feeding it with a context-specific, labeled dataset. For instance, if a company wants to develop a customer service chatbot, the model needs to be fine-tuned on a dataset of frequently asked questions and ideal responses in the appropriate tone and format. In this way the model learns to recognize not just content, but also the intent, structure, and style relevant to the use case. Fine-tuning can be resource-intensive and time-consuming, since it may require labeling large amounts of data. Therefore, companies are increasingly outsourcing the labeling process to specialized workforces.

Another possible technique is reinforcement learning, already seen in the previous section. This is a more dynamic approach, where human agents assess the quality of the outputs generated by the trained model and provide feedback that helps the model learn which responses are more appropriate, accurate, and useful. This can be done ranking the outputs for a specific prompt or giving corrections in real time as in a conversation (Stryker & Scapicchio, 2024).

Generative AI models are not static; developers and users frequently evaluate their outputs and implement updates to improve accuracy, relevance, and alignment with evolving user needs. In many cases, tuning is carried out on a weekly basis to adapt to possible changes. The foundational models behind the GenAI models, on the other hand, are updated or re-trained much less frequently due to the high costs and complexity involved.

An increasingly used approach for improving the performance of GenAI applications without re-training or updating the core model is *retrieval augmented generation (RAG)*. RAG retrieves data from external knowledge sources to incorporate up-to-date information in real time. This process is also useful for transparency since RAG allows the user to trace back the source from which the model generated a specific output. This is particularly important in high-stake decision-making contexts (Stryker & Scapicchio, 2024).

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Figure 6 lists the perceived benefits of Generative AI implementation in businesses, from the point of view of CIOs.

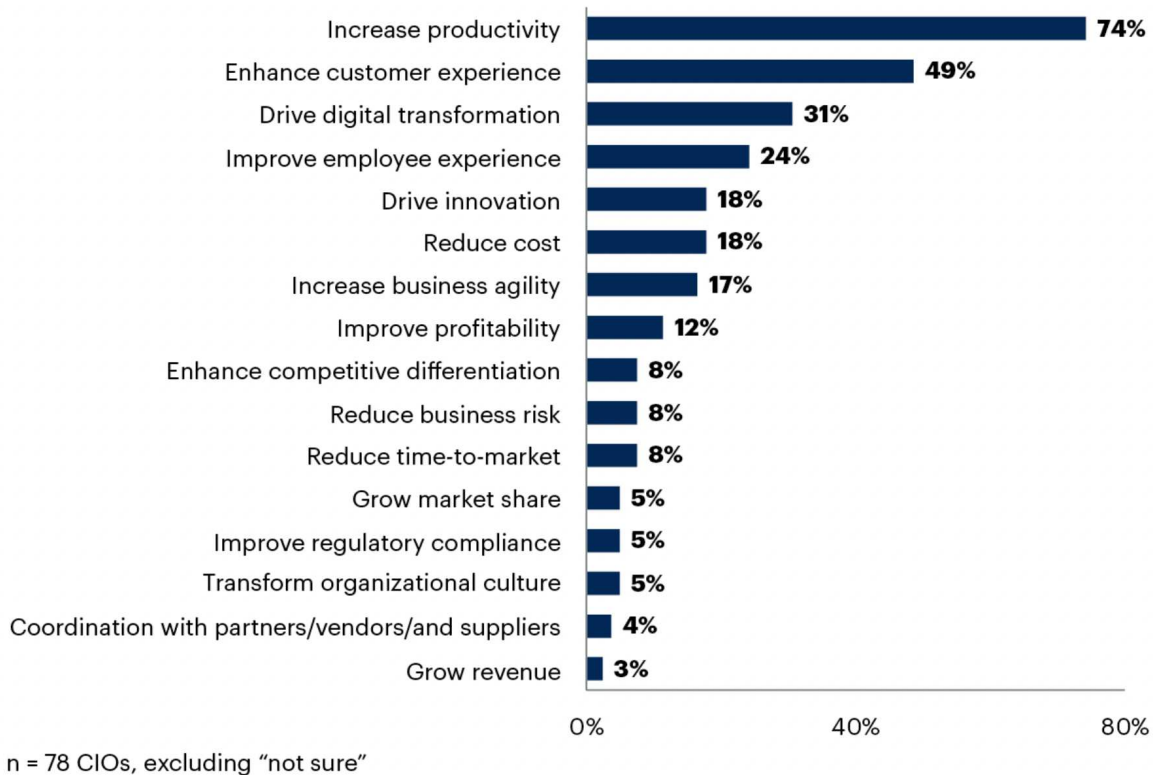


Figure 6. *Top Types of Business Value from Applying Generative AI. Gartner CIO Generative AI Survey (2024).*

One of the most obvious advantages of Generative AI lies in its ability to significantly boost operational efficiency, with the automatic and (almost) immediate creation of content, summaries, reports, and responses. These models effectively reduce the burden of repetitive, time-consuming tasks, allowing organizations to reallocate human resources to higher-value, strategic work.

But beyond this, GenAI plays a transformative role in decision making. Its capacity to process and analyze vast volumes of data allows it to uncover patterns and hidden insights and generate data-driven hypotheses and recommendations in real time. This empowers executives, analysts, and professionals across functions to make faster, more informed decisions.

For instance, Chuma & de Oliveira (2023) analyzed the use of ChatGPT as a tool for business decision making, in particular for decisions regarding M&As and customer behavior.

The authors submitted ChatGPT three questions:

1. What is the impact of a merger between ICA and COOP Swedish supermarkets?
2. What are the risks of investing in Petrobras (a state-controlled oil and gas company in Brazil) company shares?
3. What are the factors influencing online buying behavior?

The first question was answered by ChatGPT in this way (Chuma & de Oliveira, 2023, p. 7):

“A merger between ICA and Coop, two of the largest supermarket chains in Sweden, would likely have a significant impact on the Swedish retail market. The combined company would likely become one of the largest retailers in Sweden, with a significant market share in the grocery and consumer goods market. This would likely lead to increased competition for other retailers and suppliers, as the combined company would have more negotiating power when it comes to pricing and product offerings. Customers could also potentially see changes in product availability and prices.

Additionally, the merger could also lead to job losses as the company may look to cut costs by reducing redundancies in the company.

However, it should be noted that the merger would also have to go through regulatory scrutiny and be approved by the competition authorities, to ensure that the merger would not harm competition in the market.”

The information presented by ChatGPT may be important or relevant for a student or an ordinary person but are quite obvious for an expert.

To the second question, regarding investment in a company, ChatGPT answered in this way (Chuma & de Oliveira, 2023, p. 8):

“Petrobras is a state-controlled oil and gas company in Brazil, and investing in its shares may carry certain risks. Some of the key risks to consider when investing in Petrobras include:

Political risk: As a state-controlled company, Petrobras is subject to significant political influence and changes in government policies could impact the company’s operations and financial performance.

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**Operational risk:** The company's operations are primarily focused in Brazil, which poses a range of operational risks such as environmental, social and safety risks, along with the challenges of operating in deep-water and other technically demanding areas.

**Corruption risk:** In the past, Petrobras has been involved in significant corruption scandals. These have led to significant fines, legal proceedings and reputational risks, which may negatively impact the company's financial performance and share price.

**Financial risk:** Petrobras is heavily leveraged, and its credit rating is lower than investment grade, so the company's high debt levels and cash flow volatility could make it more vulnerable to economic downturns or unexpected changes in commodity prices.

**Currency risk:** A significant portion of Petrobras' revenue is generated in U.S. dollars, while its debt is primarily denominated in Brazilian reals. Changes in the exchange rate between these two currencies could impact the company's financial performance and share price.

It's important to note that past performance of the company or sector is not a guarantee of future performance and that the risks mentioned above are not exhaustive and should be considered along with other factors such as the overall market conditions and your personal investment profile.”

In this case ChatGPT's contribution influenced the time spent when researching information. In fact, ChatGPT summarized the main risks for this investment, effectively saving time. However, the authors noted that the CNN Business website offered much more detailed information than ChatGPT.

The last ChatGPT answer regarding customer online behavior follows (Chuma & de Oliveira, 2023, p. 9):

“There are several factors that can influence online buying behavior, including:

1. Convenience: The ease and convenience of shopping online can be a major factor in influencing buying behavior.
2. Price: Online shoppers can easily compare prices and find deals, which can influence their buying behavior.
3. Product reviews and ratings: The ability to read reviews and ratings from other shoppers can influence a person's decision to buy a product.
4. Product selection: Online retailers often have a wider selection of products than brick-and-mortar stores, which can influence buying behavior.
5. Social influence: Social media and online communities can influence buying behavior by highlighting popular products and trends.

6. Personalization: Many e-commerce sites now offer personalized recommendations based on a shopper's browsing and buying history, which can influence buying behavior.
7. Trust and security: Trust in the online retailer and security of the website can also play a role in influencing online buying behavior.
8. Marketing and advertising: Online marketing and advertising can also influence buying behavior by showcasing products, offering discounts and promotions.”

Again, this answer is quite superficial and obvious to experts.

The authors concluded that ChatGPT could not, in its 2023 version, substitute an expert in the decision-making process, but it was a helpful supporting tool.

The analysis made by Chuma & de Oliveira (2023) used a nowadays outdated version of ChatGPT. It is therefore necessary, for the sake of completeness and accuracy, to pose these questions to the current version of ChatGPT, which underwent several updates.

For the first question, this prompt was used: “Based on your knowledge as an M&A expert, what is the impact of a merger between ICA and COOP Swedish supermarkets? Be as specific and as technical as possible.”

This is ChatGPT's answer (ChatGPT, 2025):

“A hypothetical merger between ICA Gruppen and Coop Sverige, the two largest Swedish grocery retail chains, would represent a major consolidation in Sweden's food retail sector. Such a merger would have far-reaching strategic, financial, operational, competitive, and regulatory implications, particularly due to the high market concentration in the country. Below is a detailed and technical breakdown of the potential impacts:

1. Market Structure and Competition

Herfindahl-Hirschman Index (HHI) Impact

- Pre-merger: ICA has ~50% market share, Coop ~20%.

- Post-merger HHI increase:

Pre-merger HHI =  $(50^2 + 20^2 + \text{other competitors}) \approx 2500 + 400 = 2900+$

Post-merger HHI =  $(70^2 + \text{others}) = 4900+$

- Change in HHI > 1000, signaling highly anti-competitive concentration per EC/US DoJ thresholds.

Antitrust Scrutiny

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- The Swedish Konkurrensverket (Competition Authority) and the European Commission DG COMP would almost certainly challenge the deal.
  - Remedies (e.g., divestitures, store closures) would be complex, given limited overlap in some rural vs. urban areas but dense overlap in cities.
2. Operational and Supply Chain Synergies  
Procurement & Supply Chain Integration
- Both ICA and Coop operate their own distribution centers (DCs), logistics networks, and private label lines.
  - Expected economies of scale in:
    - Joint procurement → Higher negotiation power with global FMCG suppliers (e.g., Nestlé, Unilever)
    - DC consolidation → Reduced warehousing and transport costs
    - Unified inventory management systems
- Challenges:
- Coop is a cooperative structure (owned by consumers), while ICA is a publicly listed company with franchised stores → cultural and governance clashes
  - IT systems (e.g., POS, ERP) differ → Costly systems integration
3. Financial implications  
Valuation and Deal Structure
- ICA's 2024 revenue: ~SEK 130 billion
  - Coop's 2024 revenue: ~SEK 40 billion
  - Deal likely structured as stock plus cash, potentially with earn-out provisions due to Coop's variable profitability.
- Synergy Estimates (typical M&A assumption in retail)
- Revenue synergies: 1-3% via cross-selling, brand leverage
  - Cost synergies: 3-5% of combined operating expenses, especially in logistics and procurement
  - NPV of synergies discounted at WACC (ICA's ~6-8%) could drive substantial deal premium justification
- Debt & Leverage
- ICA would likely finance part of the deal through debt issuance → Potential rating impact (currently BBB+)
  - Coop's financials would need to be adjusted to match IFRS if under local GAAP → Potential surprises in due diligence
4. Customer Impact and Branding  
Private Label Rationalization
- Coop: "Änglamark," "X-tra"
  - ICA: "ICA Basic", "ICA Gott Liv"
  - Expect brand rationalization → reduction in SKU duplication and clearer brand hierarchy
  - Risk of consumer backlash due to perceived monopoly pricing or loss of co-op identity

### 5. Labor and Employment

#### Union and Employee Relations

- Coop has strong union presence (Coop is owned by consumer co-operatives, many of which have close union ties)
- Potential layoffs in overlapping HQ/warehousing functions could spark public backlash or require job guarantees as deal conditions

### 6. Sustainability and ESG Considerations

#### ESG Impacts

- Both chains emphasize sustainability, but Coop has a stronger ethical brand identity
- Merger could:
  - Increase ESG reporting obligations
  - Require harmonizing carbon footprint tracking, sustainable sourcing standards
  - Face public concerns over greenwashing or dilution of Coop's values

### 7. Regulatory and Legal Hurdles

- Swedish competition law (under the Swedish Competition Act) prohibits mergers that significantly impede effective competition, especially in oligopolistic markets
- Divestitures likely:
  - Certain city-level store clusters may be sold to Axfood (Willys, Hemköp) or Lidl
- May trigger EU-level review if market share thresholds or cross-border impacts are triggered under EC Merger Regulation (ECMR)

### 8. Strategic Rationale

- Facing increased pressure from discounters (Lidl) and e-commerce entrants (e.g., Amazon, Mathem), consolidation can:
  - Improve digital transformation capabilities
  - Share data analytics infrastructure
  - Strengthen position vs. emerging omni-channel players

### Conclusion

A merger between ICA and Coop would fundamentally reshape the Swedish grocery market, creating a near-monopoly with enhanced operational efficiencies but enormous antitrust concerns. While it could unlock substantial synergies, especially in logistics and procurement, the regulatory, cultural, and structural obstacles are likely to make such a deal extremely difficult to approve without significant concessions.”

This answer is evidently more technical and precise than the one presented in Chuma & de Oliveira (2023). However, some of the given data are not correct. For instance, according to ICA Gruppen's website, ICA Sweden in 2024 had a market share of approximately 33%, not

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50% (its market share in 2023 according to Statista (2025)), and its 2024 revenue was SEK 110,241 million, not 130,000 million (ICA Gruppen, 2024).

Apart from the incorrect data, probably due to a failure to update, the answer provides an initial orientation and helps to identify the possible red flags (regarding regulations, culture, or labor), understand the synergies and limitations and anticipate communication and branding challenges. However, it does not replace financial due diligence, planning, or legal considerations, although it could be a valuable briefing in the early stages of consideration, useful for internal discussions.

Generative AI in M&A has been investigated by Bain & Company in its 2025 Global M&A Report. In fact, currently one in five companies already uses GenAI for M&A strategies, and this number is expected to rise to one in two by 2027 (Haxer, et al., 2025).

*Figure 7* describes the perceived advantages of using Generative AI in a firm's M&A strategy. Companies that effectively harness Generative AI in M&As over the next five years are likely to gain a significant competitive edge, as they will be able to identify acquisition targets more rapidly, evaluate the value of a deal with greater confidence, and carry out due diligence and integration processes more efficiently, using fewer resources. As a result, these companies will generate superior total shareholder returns (TSRs). Moreover, the authors expect that over the next year early adopters will leverage GenAI to create integration workplans and transition service agreements (TSAs) in less than 20% of the time compared to traditional methods. Following that, these tools will be increasingly used to analyze company-specific data to estimate more accurately cost and revenue synergies and to develop value creation strategies informed by data on the performance of past acquisitions. Within five years, GenAI is expected to support and improve each and every stage of the M&A process (Haxer, et al., 2025).

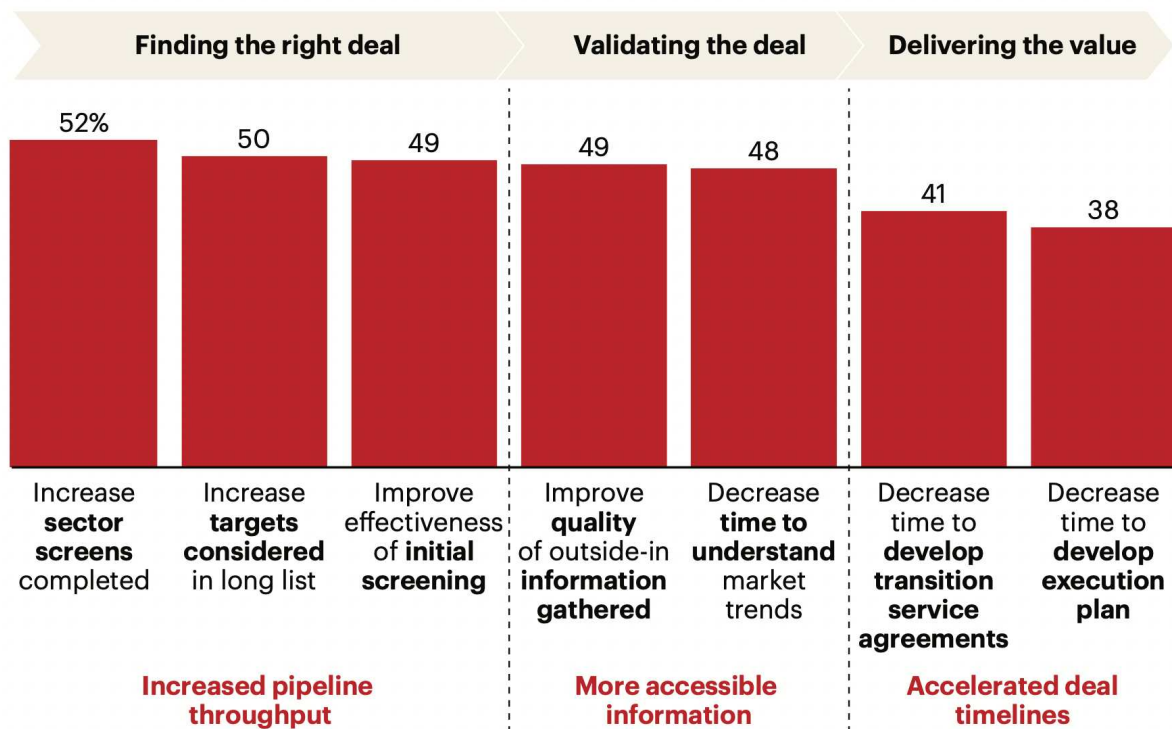


Figure 7. *Expected Enhancements to M&A Strategy and Process from the Use of Generative AI.* Haxer et al. (2025).

Hao, Demir, & Eysers (2024) investigated the possible usefulness of Generative AI in group decision making, specifically for decisions regarding market launches, logistics optimization, market penetration, and strategic digital marketing. They found that the intervention of AI improved creativity, efficiency and strategic execution. This was particularly evident in unfamiliar contexts where humans could not rely on past experience and were therefore more prone to cognitive biases and the use of heuristics. Moreover, GenAI demonstrated to be flexible enough to adapt its responses in dynamic contexts.

However, the collaboration between humans and the machine highlighted the risk of dependence on AI, which could lead to the erosion of human capabilities and amplify biases embedded in the data. Additionally, it was evident that humans relied more on intuition, while the Generative AI had a data-driven logic, and this can at times lead to friction or misalignment in the decision-making process. This is why a strategic task allocation between humans and AI is essential.

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Another experiment regarding group decision making was discussed in Dell'Acqua *et al.* (2025) in collaboration with Procter & Gamble, specifically involving cross-functional product development teams. The first finding was that individuals using AI and groups not using AI both outperformed the control group; this means that GenAI was effectively comparable to a teammate and brought the same advantages (see Section 1.5.). Additionally, the AI allowed less experienced employees to get task-related information without consulting other employees with greater expertise. The second finding was a large productivity improvement when using AI in groups, as the time spent searching for a solution significantly dropped. Finally, the use of GenAI improved cross-functional collaboration, while in teams working without AI professional silos emerged.

According to Singla *et al.* (2025) for McKinsey, C-level executives use Generative AI more than anyone in organizations. In fact, as Korst, Puntoni, & Toubia (2025) noted that GenAI can be used to brainstorm concepts and co-create and test strategies.

For instance, Marc Benioff, CEO of Salesforce, has integrated Generative AI into his executive decision-making process through an unreleased version of Einstein, Salesforce AI model, called Einstein Guidance. Benioff consults Einstein in every executive meeting, after hearing the progress of Salesforce executives. Einstein Guidance provides an unbiased, data-driven evaluation of the company's performance, and helps identifying strengths and weaknesses across regions, products, and teams. Benioff even goes as far as calling Einstein another executive at the table (Bort, 2017).

However, Generative AI does not come without important challenges. The main issue is hallucinations, that is false outputs, but besides these the model could also offer inconsistent outputs. Biases are another risk since the trained model could have picked up some societal prejudices from training data or even from feedback. Finally, relevant especially in contexts that require decision making to be transparent, the black box nature of many of these models reduces trust.

#### 2.2.4. Agentic AI

Agentic AI represents a new significant evolution in Artificial Intelligence, moving beyond predictive analytics and task automation. An agent effectively becomes another coworker, capable of autonomous planning and adaptive decision making. It can analyze complex scenarios, generate strategic options, and even simulate long-term impacts.

Understanding the advantages and risks of Agentic AI now is essential, as in the *Top Strategic Technology Trends for 2025* Gartner Report it is predicted that by 2028 33% of organizations will implement Agentic AI (Coshow, et al., 2025).

According to Yee *et al.* (2024) for McKinsey Quarterly, agents can bring value to businesses in three ways:

1. Agents manage complex, unpredictable business processes that traditional automation could not handle. Many workflows, in fact, involve ambiguity and uncertainty, and are not well-suited for automation. Agentic AI is built on foundation models with the capacity to adapt in real time and to complete processes with considerable flexibility and resilience.
2. Agents can interact with natural language. Traditionally, workflows have been automated using lines of code, a task that required technical expertise and often a lot of time. Agentic AI, on the other hand, allows users to describe tasks as in a conversation with another coworker, and this significantly reduces the effort and cost of implementation. Additionally, this also democratizes AI use, as the involvement of technical professionals in the process is not required anymore.
3. Agents are able to interact with existing digital tools and platforms, therefore they can query existing databases, generate reports, search the web, or use other AI models for specific tasks. Traditional systems would require manual integration to do this, for instance using APIs.

The foundation of an AI agent is a Large Language Model (LLM), an AI model specifically developed to understand the natural language. This foundation model, useful for generating

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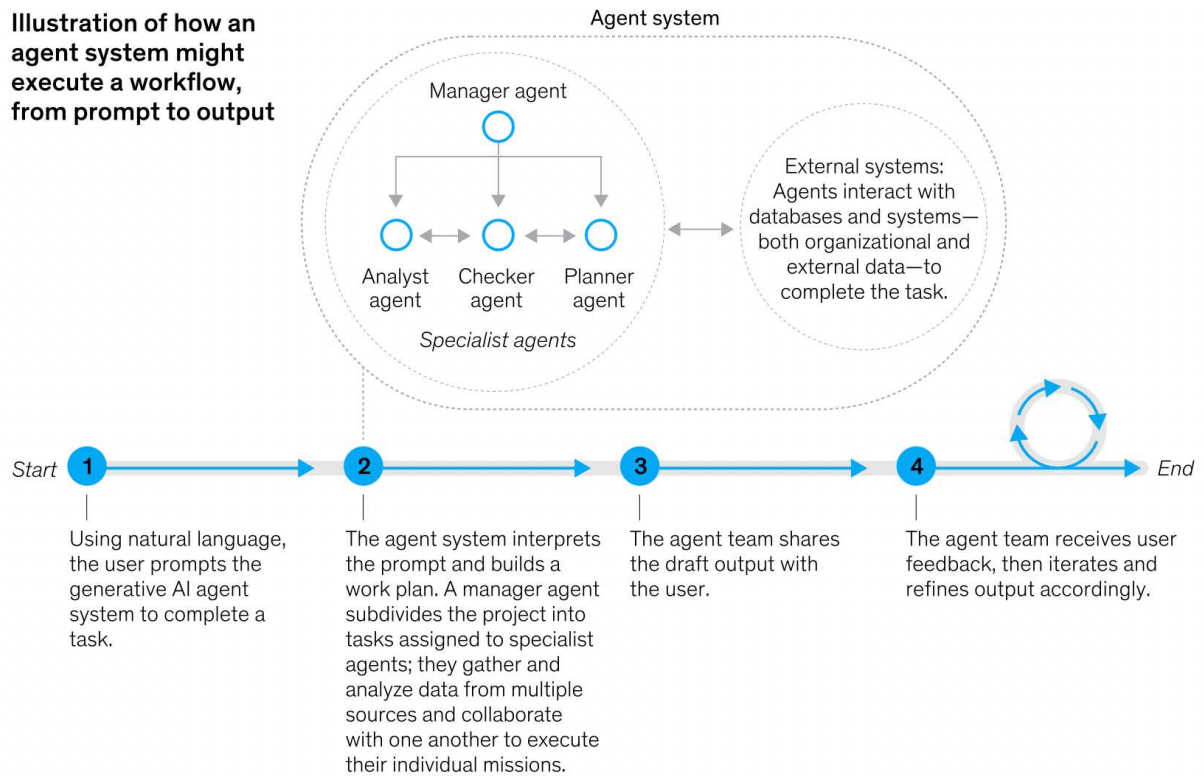
responses based on the data it was trained on, is further enhanced with the capacity of tool integration, which allows the system to retrieve real-time information. Agentic AI is also dynamic, as it learns from feedbacks and interactions with users stored in its memory (Gutowska, 2024).

An Agentic AI process is illustrated in *Figure 8*. Typically, four phases are present (Yee, et al., 2024):

1. Instructions are given using natural language by the user, similar to how an employee might give instructions to a colleague. The agent interprets the intent behind the prompt and requests clarification if needed.
2. The system then creates a structured plan by identifying objectives and translating them into tasks and subtasks. A central “manager” agent delegates each of these tasks to specialized sub-agents, each of them having context- and task-specific knowledge, along with access to relevant tools and organizational data. These agents are not independent from each other, they collaborate and coordinate through *AI orchestration*. It is important to note that different use cases require different agentic architecture. This means that in some contexts, it is better for the agents to work as equals in a decentralized way, although this process is slower than a vertical hierarchy (Stryker, 2025).
3. As the sub-agents work, often the system may ask for further input from the user to fine-tune the results. This causes an iterative refinement based on feedback.
4. Once all the tasks are completed, the agent executes actions if required by the user. Actions could include sending reports to managers, updating dashboards, or triggering workflows.

**Agents enabled by generative AI soon could function as hyperefficient virtual coworkers.**

Illustration of how an agent system might execute a workflow, from prompt to output



**Figure 8. A Possible Agentic AI Workflow. Yee et al. (2024).**

There are five main types of AI agents that can vary significantly in their capabilities and are suited to different decision-making contexts.

Simple Reflex Agents operate on condition-action rules, reacting immediately to input without having memory or contextual awareness. In a business context, they are well suited to automated quality control systems in manufacturing, such as a visual inspection system that detects defective products.

Model-Based Reflex Agents, on the other hand, have memory and can handle partially observable and changing conditions. For instance, a customer-facing chatbot used in online sales collects and processes user inputs and stores this information to build a profile of the lead.

Goal-Based Agents act based on a defined goal, and plan actions to achieve it. These systems could use internal data (sales, costs, resources) and external data (market growth, competitor

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presence) to evaluate and recommend the best region for expansion, simulating different scenarios and recommending actions that achieve a defined business goal.

Utility-Based Agents evaluate outcomes against a utility function, choosing the most beneficial solution. These could be dynamic pricing engines, like the ones used by Amazon or most airline companies, which adjust prices in real time based on supply, demand, customer behavior, and competitor activity.

Learning Agents are the most advanced, capable of adapting and improving over time. These agents could provide an AI-driven M&A analysis learning from historical deal data, market conditions, and business performance metrics and suggest potential acquisition targets (Gutowska, 2024).

Although Agentic AI is quite new, there are already some real-world success stories of companies efficiently employing agents in their businesses.

Siemens revolutionized its maintenance strategy by implementing Agentic AI systems capable of analyzing real-time data from sensors in industrial machinery. These models predict potential equipment failures and automatically schedule maintenance activities before disruptions occur. Siemens achieved a 20% reduction in maintenance expenses and improved production uptime by 15%, while enhancing operational reliability and improving safety conditions for workers. Unilever has integrated Agentic AI into its recruitment process to analyze video interviews and candidate responses. This technology enables the system to assess key traits and competences and help recruiters efficiently identify top candidates. Unilever saved over one million dollars annually in recruitment expenses and reduced its hiring time by 75%, while increasing diversity and improving candidate experience.

Coca-Cola uses agents to improve its marketing strategy by generating content, analyzing customer behavior, and personalizing advertisement. This use of Agentic AI allows to create quickly targeted, data-driven campaigns that resonate with specific segments. Coca-Cola cut content creation time by 50% and improved campaign ROI by 20%, while implementing more innovative and dynamic marketing strategies and strengthening customer engagement.

Salesforce's Agentforce analyzes customer interactions, market trends, and sales data to deliver real-time insights that help sales teams prioritize leads and close deals more efficiently. Salesforce boosted sales performance by 15% and shortened sales cycle times by 25%, while

strengthening customer relationships and enabling more informed and data-driven sales decisions (PwC, 2024).

Nestlé uses Outset Agentic AI to accelerate and improve its product innovation process. The agent autonomously conducts customer research by moderating interviews, interacting with customer responses and summarizing results into quantitative and qualitative analyses. Nestlé found that participants shared over twice as much with the agent compared to a human interviewer; moreover, while with traditional methods Nestlé could not involve more than twenty to thirty participants per project, now thanks to the use of the agent more than 200 participants can be involved (Cannon, 2025).

However, Agentic AI, as with every AI model, poses certain challenges and risks.

Because these agents operate using Large Language Models, any hallucination of these foundation models can trigger a series of faulty decisions. Given their autonomous nature, these systems require oversight and accountability.

One key risk is the generation of harmful outputs. In fact, since GenAI can occasionally provide incorrect or misleading information, agents using this data could, for instance, approve high-risk loans or take actions that have negative financial consequences. Transparency and traceability are essential to help users understand how decisions are made and to catch potential issues early in the process.

Trust dynamics between humans and agents present an additional challenge. In fact, if users do not trust the AI, they may withhold valuable input and limit the agent's effectiveness. On the other hand, as the agent becomes more and more humanlike, there is a risk of anthropomorphism which could lead users to trust the AI too much, causing them to follow faulty recommendations. Organizations should train employees on the responsible use of agents.

Value alignment is another critical point since agents are effectively a coworker and must reflect the organization's values and standards.

A human-in-the-loop (HITL) approach offers a first solution for these risks, as it places human judgement at key points in the decision-making process (Yee, et al., 2024).

### **2.3. Comparison Between the Main AI Models**

The discussion of this chapter highlights that there is no universally optimal AI approach for decision making. Instead, the most effective solution depends on a series of contingencies, such as the level of accuracy needed, the availability of data, the complexity of the environment, and the required oversight of a human.

Constraint Satisfaction Problem algorithms are best suited for decision-making contexts characterized by well-defined variables, clear rules, and a limited set of possible outcomes. They are highly accurate and interpretable, as every decision is fully traceable to a specific rule or constraint, making them ideal, for instance, for supply chain optimization or resource allocation. However, they lack the adaptability and the learning capabilities of other AI models and therefore perform poorly in uncertain or dynamic environments. Moreover, they require a technical expert to define rules and constraints. For these reasons, CSPs are not suited for ambiguous, high-volume problems or tasks involving unstructured data.

Machine Learning models are a flexible and powerful tool for decision making; however, their performance and applicability are highly contingent on the nature of the task, data availability, and the desired outcomes.

Supervised learning is an accurate and powerful tool for prediction tasks (such as forecasting customer churn or scoring sales leads) when large volumes of labeled data are available, but it requires extensive data preparation and human oversight to avoid biases.

Unsupervised learning is better suited for discovering patterns in unlabeled data, useful, for instance, for market segmentation, but it offers less control over outcomes and lacks clear interpretability.

Semi-supervised learning addresses the time-consuming process of labeling data, unifying the advantages but also the risks of both supervised and unsupervised learning.

Reinforcement learning is particularly effective in strategic, dynamic decision contexts like logistics optimization or dynamic pricing, where the model can learn the optimal actions through trial and error in an evolving environment. These models typically require longer training and substantial resources, but at the end they are highly adaptable.

Machine Learning models require data science and programming capabilities to be developed.

Generative AI expands the possibilities by enabling rapid content creation and hypothesis generation, such as creating marketing content or exploring M&A synergies, but it suffers from accuracy issues, caused by the possible emergence of hallucinations, and low explainability, as Large Language Models are black boxes, and it is not possible to trace an answer back to its source. These limitations become more critical when decisions have high stakes or legal implications, but GenAI effectively augments human decision making when speed and creativity are prioritized over transparency, such as in marketing strategy.

Developing these models requires technical competencies, but after that anyone can interact with them thanks to the natural language interface.

Agentic AI is capable of autonomously handling multi-step, adaptive decision processes, such as gathering market intelligence or planning a strategy. However, the effectiveness of agentic systems also depends on the type of agent.

Simple Reflex Agents are suitable only for rule-based, fully observable environments, such as automated quality control. They are not adaptable, as they do not have memory.

Model-Based Reflex Agents are slightly more adaptable, capable of handling partially observable scenarios like warehouse management, where the conditions might change but they still follow recognizable patterns.

Goal-Based Agents offer improved planning capabilities, making them effective for structured business planning or lead prioritization, as the system adapts to dynamic data and business goals.

Utility-Based Agents optimize the best outcome and are suited for environments where trade-offs must be evaluated, such as portfolio management.

Learning Agents build experience over time and represent the most advanced form, suitable for complex, dynamic contexts such as market expansion or M&A processes.

*Figure 9* summarizes the main differences between the AI models described in this chapter.

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<i>Contingency</i>	Constraint Satisfaction Problem (CSP)	Machine Learning (ML)	Generative AI (GenAI)	Agentic AI
<i>Type of problems best suited</i>	Well-defined, rule-based	Pattern recognition, predictions	Content generation, summarization, ideation	Multi-step, dynamic decisions requiring autonomy
<i>Accuracy</i>	Very high within defined constraints	High with sufficient training	Variable because of possible hallucinations	Depends on foundation model
<i>Speed</i>	Fast for small or medium problems but much slower for large-scale ones	Quite fast once trained, but training may be time-intensive	Quite fast once trained, but training may be time-intensive	Slower than the others due to planning, use of different tools, and orchestration
<i>Interpretability</i>	Very high because of transparent rules and constraints	Moderate to low, it depends on the complexity of the model	Low, outputs may lack rationale or transparency	Depends on the design
<i>Competences required</i>	Technical logic and programming skills	Data science, statistics, model fine-tuning	Prompt engineering, creative oversight	Multidisciplinary, prompt design, orchestration and architecture, governance

<i>Scalability</i>	Limited by complexity and constraints	Highly scalable	Highly scalable	Now difficult to scale reliably, but improving
<i>Adaptability to new conditions</i>	Low unless reprogrammed	Moderate to high with retraining and fine-tuning	Moderate, limited memory and reasoning	High, dynamic adaptability using external tools, feedback, and memory
<i>Use of real-time data</i>	Limited	Possible	Possible	Designed to interact with live data and tools
<i>Need for human oversight</i>	Low once verified	Moderate, requires monitoring of performance and fairness	High because of possible hallucinations	Very high, requires HITL
<i>Trust</i>	High because of predictable behavior	Moderate because of possible biases and lack of transparency	Low to moderate, depends on safeguards	Moderate

**Figure 9. Comparison Between the Main AI Models. Author’s elaboration.**

## 2.4. Conclusions

This chapter has offered a comprehensive analysis of the main Artificial Intelligence models currently used in business contexts, with a focus on their applicability to decision making.

## Artificial Intelligence in Organizational Decision Making

The analysis highlights that there is no universally optimal AI model, and the effectiveness of each approach is contingent on a combination of specific factors, including the accuracy and the flexibility of the model, among others.

Structured, rule-based models like CSPs excel in static environments with well-defined parameters, such as scheduling or allocation. The strength of these models lies in their transparency, accuracy, and efficiency. However, their rigidity and lack of adaptability render them unsuited in dynamic environments.

Machine Learning in its various forms has been demonstrating immense potential for enhancing data-driven decision making, allowing organizations to discover patterns and forecast outcomes. However, its effectiveness depends on the availability of labeled data and the accuracy of this data, as the model could present biases inherent in the data it was trained on. The success of these models depends on the availability of quality data and on the organization's capacity to continuously train and monitor the models.

Generative AI goes one step beyond and contributes not only to analysis but also to content and insight creation. It allows decision makers to explore multiple scenarios rapidly. As demonstrated by Bain & Company's projections and Procter & Gamble's use in product development teams, GenAI acts as an assistant capable of producing hypotheses, generating alternatives, and accelerating analytical tasks.

However, the black-box nature of these models limits their explainability and could reduce trust in high-stake decisions.

Finally, Agentic AI introduces the capability to make autonomous decisions and actions, as they are designed to plan, act, and learn. They can orchestrate workflows, access internal and external data to stay up-to-date, and act autonomously on behalf of decision makers. While Simple Reflex Agents are well-suited for real-time monitoring of rule-based decision making in fully observable environments, Goal-Based Agents support strategic decisions with target outcomes. Learning Agents, the most advanced form, are capable of adapting to unfamiliar environments and evolving goals, which could make them valuable in areas like M&A analysis.

As the last section of this chapter demonstrated, variables like speed, accuracy, interpretability, and scalability, among others, play critical roles in determining the most appropriate AI model. For instance, a fast-moving marketing campaign requiring creativity and customer personalization might benefit from GenAI or Learning Agents. On the other hand, a highly regulated compliance decision might be better supported by supervised learning or even CSPs because of the need for transparency and interpretability.

The choice of the AI model should not be guided by technological trends alone, but instead by a careful consideration of the nature of the decision, the structure and quality of data, the required speed and accuracy, the need for interpretability, and generally the organizational context in which the model will be used.



# **CHAPTER THREE.**

## **Contingent Views on AI Adoption in Organizational Decision Making.**

### **3.1. Introduction**

While the advantages of integrating Artificial Intelligence into organizational decision making have been extensively discussed, a critical gap in the literature emerges when it comes to how AI should effectively be integrated in the process.

The first section of this chapter, however, collects some references that support the need for a contingent approach to the use of AI in business decision making, which demonstrate that AI cannot be applied in the same way across organizations or even across decisions in the same organization.

The second section presents four frameworks, emerged from the literature review, that contribute to understanding how different process configurations are influenced and influence key factors (contingencies).

Trunk, Birkel, & Hartmann (2020) provide a conceptual framework of the decision-making process supported by AI in contexts of uncertainty, emphasizing how the type of information available (external or internal, explicit or implicit), the decision type (strategic or operational), organizational structures, AI literacy, data transparency, and ethical perspectives influence this process.

Jain, Garg, & Khera (2023), building on the work of Puranam (2021), who proposed six human-AI task division configurations, demonstrate how each configuration influence efficiency, decision quality, trust, role clarity, and reliability.

Shrestha, Ben-Menahem, & Von Krogh (2019) propose four possible configurations: full delegation to AI, AI-to-human and human-to-AI sequential decision making, and aggregated human-AI decision making. Each configuration is evaluated based on five evaluation criteria: the decision search space, the interpretability of the process, the size of the alternatives set, the speed, and the replicability.

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Yablonsky (2019) emphasizes the role of data analytics capabilities as a determinant of how AI can be integrated in the process.

The final section of this chapter applies the information gathered from the literature review and the four frameworks presented, along with the work of Mintzberg, Raisinghani, & Théorêt (1976) (See Section 1.4.4.), to a series of business scenarios, illustrating how different decision contexts (from long-term strategic M&A decisions to highly operational ones like dynamic pricing) require not only different configurations of the human-AI decision-making process but also different AI models.

This section aims at demonstrating the practical relevance of a contingent perspective and highlights how organizations can align contingencies with the integration of AI to improve decision quality, efficiency, and trust in the outcomes.

### **3.2. The Need for a Contingent Approach: A Literature Review**

According to Jain, Garg, & Khera (2023) there is a critical gap in the current literature on the use of Artificial Intelligence in organizational decision making: the insufficient attention given to social and organizational factors when implementing AI. More particularly, work design, human-AI interaction dynamics, and contextual variables are often overlooked. The authors, therefore, call for the need to understand how context influences collaboration preferences and decision outcomes. This supports the motivation for a contingent approach to the use of AI in business decision making, since AI cannot be effectively integrated without considering the organizational and contextual environment.

Although the literature concerning this approach is limited, the following paragraphs present some references that support it.

#### **3.2.1. Methodology**

The literature review for this chapter was conducted with the objective of identifying both academic and practitioners' contributions that support a contingent approach to the use of Artificial Intelligence in organizational decision making.

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The primary search was conducted using Scopus, complemented by Google for direct search of practitioners' reports (i.e., Deloitte, McKinsey, and IBM). This dual approach ensured coverage of both academic insights and applied perspectives.

To ensure systematic coverage, multiple search strings were applied in Scopus.

The first search used the combination "AI" AND "Decision Making" AND "Contingent" OR "Contingency", searched in titles, abstracts, and keywords, limited to the subject area Business, Management, and Accounting. This yielded 6 documents (4 articles, 1 conference paper, 1 review), of which two were retained after reading the abstracts and the introductions for direct relevance. The other four were excluded because they either approached AI decision making from a purely technical or engineering perspective without organizational implications or addressed contingency theory in domains unrelated to managerial decision processes, like IT process management.

Seeing the limited number of results of the first search, the second search used the broader combination "Human AI Collaboration" AND "Decision Making", with the same filters, resulting in 164 documents (66 articles, 54 book chapters, 30 conference papers, 10 books, 2 reviews, and 2 editorials). After reading the abstracts, 14 were provisionally included. The remaining studies were excluded because of one or more of the following reasons:

- They did not apply a contingent approach (majority of the results);
- They addressed only technical aspects of AI;
- They did not focus on decision-making processes;
- They focused on AI performance without linking it to process characteristics;
- They analyzed contexts outside business (e.g., healthcare, psychology).

A full reading led to the exclusion of three papers, which either analyzed only one configuration of the process without comparative value or explored trust in autonomous agents in non-business contexts (firefighting). This left a smaller subset of papers (11) directly addressing the implications of different human-AI configurations.

Subsequent searches using combinations of "Contingency Theory" OR "Contingent Approach" AND "Task Allocation" OR "Task Division" AND "AI" AND "Decision Making" produced no results, while further refined searches either returned duplicates of already captured documents or studies irrelevant to the research objective. A final search using the broader terms

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“Contingent” AND “AI” AND “Decision Making” returned 9 results, however none of them was relevant to the scope of this thesis, as they:

- Focused on AI’s technical performance rather than its integration into organizational decision processes;
- Focused on stakeholders’ view on AI use;
- Analyzed AI adoption outside decision-making processes;
- Analyzed AI recommendation’s effect in streaming platforms;
- Or used the word “contingent” in other meanings (e.g., army contingent).

The process of refining search strings and systematically excluding irrelevant studies ensured that the final selection included only contributions that directly addressed the central research question. While the number of retained articles is limited, this outcome underscores a key finding of the review: the existing literature provides only partial and fragmented insights into how AI should be integrated into decision processes, and insufficient attention is given to a contingent perspective. This gap further justifies the relevance of this thesis, which builds on the available evidence while extending it through the application of a structured contingent approach.

In addition to the 13 references found through Scopus, 6 works were identified by reviewing the reference lists of the papers initially collected, 3 were originally identified in the previous chapters of the thesis but were revisited here since they presented some insights useful for the discussion of this chapter, and 5 are practitioners’ reports on Artificial Intelligence in the business context which provide marginal support to the thesis.

References were included if they addressed AI or automation in relation to decision-making processes, while explicitly or implicitly adopting a contingent or context-dependent approach, and/or if they provided frameworks or case studies that illustrate how AI implementation varies with organizational, task-related, or human factors.

In total, 27 references were collected, summarized in *Figure 12*. This number signals a critical gap in the literature, and the need for further research.

The following section presents the contributions of each of the references collected, in chronological order.

### 3.2.2. Literature Review

The integration of Artificial Intelligence in decision-making processes requires a strong leadership commitment. Evidence (McKinsey Analytics, 2018; Bernroider & Schmöllerl, 2013) highlights that initiatives are more likely to succeed when top management is actively engaged in the process. In fact, leaders provide resources, structure, and strategic alignment, but they also foster a culture of trust and openness in the technological change.

However, even leadership styles are affected by specific contingencies. Shao, Feng, & Hu (2015) demonstrated that one key factor influencing the type of leadership that is most effective when introducing an enterprise-wide technological change is the phase of the technology lifecycle: adoption, implementation, assimilation, and extension. Citing Bass (1985) the authors present two types of leadership style:

1. Transactional leadership: this is characterized by an approach based on efficiency that emphasizes stability and short-term objectives. Transactional leaders prioritize low-risk solutions, and they are primarily concerned with ensuring that current operations run smoothly, making changes only when it is strictly necessary. This approach is rather reactive than proactive.
2. Transformational leadership: this is more of a visionary approach that aims to inspire others by communicating shared goals and driving meaningful change, encouraging innovation, challenging the status quo, and motivating individuals to reach their full potential. Therefore, this approach is more proactive than the previous one, favoring radical innovations rather than incremental ones.

Shao, Feng, & Hu (2015) also cite Vera & Crossan (2004), who drew on Quinn (1984, 1988) leadership roles to link them with the leadership styles mentioned above. It was found that transactional leadership is connected to the roles of coordinator, monitor, producer, and director, whereas transformational leadership is connected to the roles of innovator, broker, facilitator, and mentor.

## Contingent Views on AI Adoption in Organizational Decision Making

Shao, Feng, & Hu (2015) found that in the adoption phase it is essential to define a clear strategy and create a vision to motivate the executive team. Therefore, a transformational leadership approach is the best fit to show support and increase the likelihood of success.

In the implementation phase, success depends on solving task-related conflicts among different stakeholders and effectively using project management capabilities. For this reason, a transactional leadership can deliver the necessary support and ensure successful implementation.

In the assimilation phase, effective training programs and reward mechanisms are needed, and to achieve this, the best approach is a blend of transformational and transactional leadership styles, as they combine motivational support and structured guidance.

Finally, in the extension phase, where the technology is spread across the organization, success depends on the ability to communicate a long-term vision and foster collaboration across both internal and external stakeholders. Therefore, as in the previous phase, a combination of transactional and transformational leadership is best (Shao, Feng, & Hu, 2015).

As demonstrated in the previous chapter, the choice of the most suited AI model to be used for a specific decision is in itself not universal. Each model comes with its own strengths and limitations in terms of accuracy, interpretability, required data, speed, and necessary competences (See *Figure 9*).

McKinsey Analytics (2018) note that there is no one-size-fits-all AI solution and that, “for example, the AI techniques implemented to improve customer-call-center performance could be very different from the technology used to identify credit-card-payments fraud” (McKinsey Analytics, 2018, p. 53). Therefore, selecting the right AI tool for each context and each stage of the company’s digital transformation is essential.

This idea is also supported by IBM (2024) and Trunk, Birkel, & Hartmann (2020), who argue that this choice is influenced primarily by the quality and quantity of data available and the purpose of the model.

McKinsey Analytics (2018) also notes that the biggest problem when introducing a new technology is adapting organizational processes and managing the employees’ experience.

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In fact, according to Deloitte (2023), since access to AI and Generative AI in particular is widespread, competitive advantage stems not only from the technology itself, but from the way humans and AI interact within each organization. Leaders, therefore, need to find “unique ways for humans and AI to interact” (Deloitte, 2023, p. 9).

Fountainne, McCarthy, & Saleh (2019) found that most of the companies try to replicate what has worked elsewhere, creating central hubs, decentralized models, or hybrid models without a specific reason, but the effectiveness of each approach depends on the specific characteristics of the firm, such as its size, culture, strategic priorities, and other contingencies. Therefore, organizational models for AI implementation must be tailored to the specific internal and external context rather than following generic best practices. More specifically, this choice is affected by three contingency factors: the maturity of AI capabilities, the complexity of the business model, and the pace and level of technical innovation required. For instance, at the beginning of the AI journey, centralizing AI talent in a hub facilitates the creation of foundational capabilities and standards. Then, as the firm capabilities become more mature, these talents can be decentralized into business units. Furthermore, if the business model is complex, and/or AI is implemented in a variety of business functions or geographies, then AI experts would be better consolidated in a hub and assigned to different units when needed. Finally, when competition leads to the need to innovate rapidly, capabilities should be centralized in the hub to be able to quickly react to market changes (Fountainne, McCarthy, & Saleh, 2019).

Rudko, Bashirpour Bonab, & Bellini (2021) developed a theoretical model to analyze the interaction between Artificial Intelligence and organizational structures and the attitude of employees towards it, consequently attempting to theorize the best strategy of implementation given organizational inertia and employees' resistance. They affirm that organizations must align their internal organizational variables (i.e., job variety and job richness, span of control, decentralization and chain of command, and coordination mechanisms) and decision-making processes with contextual factors and the “AI contingency” to achieve competitive advantage. Therefore, the authors support the idea that there is no universally optimal way to structure an organization in response to AI, but the effectiveness of the integration depends on how well the

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algorithms fit within a firm's specific internal and external context. However, the authors note the literature gap in this matter and call for further research.

The theoretic contribution of Choudhary *et al.* (2023) to the use of AI in organizational decision making identifies when human-AI aggregation (which the authors call "ensemble") is useful in prediction tasks. The authors argue that contrary to general belief, algorithms do not always outperform humans at prediction. Therefore, full delegation of prediction tasks is not always optimal.

The authors propose three cases to compare where human-AI (H-AI), human-human (H-H), and AI-AI ensembles are best suited. In Case I, Data Type I (i.e., extrinsic, codified, adequate data for AI processing) is not available (meaning that it is insufficient to make accurate predictions), but Data Type II (i.e., intrinsic data, accessible only to human agents) is. In this case, the AI would make inefficient predictions, therefore H-AI ensembles are not suited. In Case II, the situation is reversed: Data Type I is available and Type II is not; the H-AI ensemble is not suited, again, because AI outperforms humans if it is given all the available data. Finally, in Case III, both types of data are available, so both AI and humans can add value to the process. Therefore, H-AI ensembles are suited in contexts where both AI-accessible and human-accessible data is available.

The authors also note that H-AI ensembles can be formed either by augmentation (i.e., AI supports human agents) or automation (i.e., AI replaces one human agent in a group of decision makers). Augmentation would be more useful than automation in cases where the errors made by humans are diverse: if the errors are similar, it would be inefficient to keep all the human agents in the group.

Hendriksen (2023) proposes a theoretical framework of analysis for the AI integration in supply chains, and its impact on possible disruptions (i.e., interruptions or delays), arguing that AI has more disruptive potential than humans and that different modes of integration will have different results. The framework is developed through two dimensions: the level of integration (partial or full) and the role of the AI in decision making (the amount of decision authority the machine has). *Figure 10* depicts Hendriksen's (2023) framework.

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	<b>Partial Integration</b>	<b>Full Integration</b>
<b>Assistive Role</b>	1. Human Sherlock, Robot Watson: AI provides insights for specific supply chain activities like inventory management, supporting human-led decision-making.	2. Robot Cartographer: AI provides end-to-end supply chain visibility and generates insights for decision-making, but strategic decisions are still made by humans.
<b>Autonomous Role</b>	3. Chess Grandmaster: AI takes charge of specific activities like supplier selection or inventory replenishment, but humans retain the final approval authority.	4. Artificial Ecosystem: AI takes charge of end-to-end supply chain management, from demand forecasting to delivery, with minimal human intervention.

**Figure 10. Theoretical Framework for AI Integration in Supply Chain Decisions. Hendriksen (2023).**

Hendriksen (2023) notes that the effects of AI are contingent not only on the mode of integration or on how much autonomy AI has, but also on the human perception of it. In fact, taking as an example Quadrant I of the framework, that is the case where AI is a supporting tool to human decisions, if the human agent is skeptical towards the AI disruptions are less likely because the human does not blindly trust AI outputs; if, on the other hand, the human agent regards the AI as a partner, disruptions are more likely, although they remain contingent on the practices already in place to avoid them.

Lupp (2023) focuses on entrepreneurial decision making and how, theoretically, Machine Learning can be useful to it. He mentions that different contexts and different types of ML lead to different outcomes. In fact, supervised ML can help discover opportunities in risk situations where options are highly defined and need to be compared to find the best one. In uncertain situations, rather than risky, where the set of possible options is not bounded, opportunities can be discovered through unsupervised ML.

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Lamarre *et al.* (2024), in an article for McKinsey, analyzed which are the six capabilities necessary to exploit the full (Gen)AI potential. The first capability is to understand in which areas of the business AI can give a real competitive advantage: the company should not blindly integrate AI in every decision. In fact, the excitement around it leads firms to experiment with it without a clear vision or a real reason, and that is why the majority of these experimentations are unsuccessful. The authors brought one example of a mistake that they often see in their work, which is when companies try to use AI in customer service, although for most of them it is not part of the core business and consequently will not create a competitive advantage. On the other hand, for some industrial companies maintenance is crucial for their business, therefore GenAI copilots in that domain could bring significant advantages. Therefore, companies need to analyze where the technology would have the most impact and evaluate their specific needs, capabilities, and strategic goals (Lamarre, et al., 2024).

Hao, Demir, & Evers (2024) used a quasi-experimental design to analyze how GenAI intervention in organizational decision making shaped the outcomes of the decisions. First, human agents were asked to discuss together, without the use of AI, a series of scenarios with related questions. The outcomes were compared with those of the discussions on the same set of scenarios and questions with the use of ChatGPT 4.0. An important variable for the results of the analysis is the familiarity of the scenarios. In familiar scenarios decision makers can rely on their own experience to take a decision, whereas in unfamiliar scenarios they rely more on intuition and heuristics. Therefore, AI in familiar contexts is a support tool, used in parallel with human expertise, as human agents rely on experience and not intuition, whereas in unfamiliar contexts it needs to be used to eliminate human cognitive biases by providing data-driven insights, and therefore it should dominate the decision-making process.

Ellencweig *et al.* (2024) in an article for McKinsey focus on the value of Generative AI in M&A strategy, identifying four areas where AI can improve the process: target identification, due diligence and negotiation, execution, and internal capability building. The relevance and impact of each use case depends on the firm's strategy. In fact, "if your M&A strategy is focused on acquiring dozens of very small players, GenAI will have the greatest impact on opportunity

scanning and assessment. Conversely, if you do one to two larger deals a year, GenAI may also help you streamline and accelerate the execution processes.” (Ellencweig, et al., 2024).

Schrage & Kiron (2025a), in an article for MIT Sloan Management Review, focus on Artificial Intelligence as a “choice architect”, since it influences the options presented to decision makers and in some cases even recommends or initiate action. In fact, AI can identify options or interdependencies that could be overlooked by human agents or suggest entirely new areas of improvement. This raises the questions of how much autonomy AI systems should have and under what conditions humans should step in. The degree of human oversight must be determined in relation to the criticality of the task, the risk, and organizational values. This is why leaders should adopt flexible and context-specific governance models, and “when weighing choice architecture options, [they] should explicitly consider how these systems would engage with users and connect them with the job or task for which they are best suited” (Schrage & Kiron, 2024).

Schrage & Kiron (2025b) challenge the traditional view of decision rights being fixed and centrally assigned; instead, they propose a context-dependent allocation of decision authority in environments where humans and AI systems interact. Decision rights must be fluid, “continuously allocated, contested, escalated, or deferred among humans and machines”, and they must “adjust dynamically to domain complexity and data asymmetry”.

Regarding human oversight, a report from McKinsey (Singla, et al., 2025) argues that the level of human oversight of GenAI outputs varies significantly across organizations and industries, with some firms reviewing all AI-generated content and others reviewing very little. In particular, firms in business, legal, and professional services tend to maintain higher levels of oversight. This means that the decision-making process depends on the industry standards and risk tolerance of the decision context, as high-stake decisions should always be supervised by a human agent.

Dell'Acqua, Kogut, & Perkowski (2025) designed an experiment to analyze the effects of AI on teamwork and found that the impact of automation is not uniform across organizations, and

## Contingent Views on AI Adoption in Organizational Decision Making

even within the same organization, as it depends, among other things, on the skill level of the employees involved. The authors found that high-skilled teams were better at collaborating with automated agents, while low- and medium-skilled teams exhibited decreases in performance. This means that if decision makers are low-skilled, augmentation (using AI as a support tool) should be preferred to automation (delegating the process entirely to AI).

Moreover, Maragno *et al.* (2023, p. 7), in their study on AI in the public sector, sustain that the “balance between automation and augmentation depends on the type of AI systems implemented: while chatbots serve more towards effective communication [augmenting communication], machine learning and computer vision systems work for increasing efficiency [automating repetitive, manual processes]”.

Dell'Acqua *et al.* (2025) support the idea that different organizations may choose between automation and augmentation differently, as some could prioritize efficiency while others could focus on the complementarity between humans and AI. For instance, if a firm prioritizes efficiency, AI could handle routine, repetitive decisions or decisions requiring extensive data analytics, and humans would be completely replaced in the process. If, on the contrary, a firm prioritizes human-AI collaboration, algorithms would be used as a support tool.

Moreover, the authors note that results from AI adoption are influenced by contextual factors like users' AI proficiency, the organizational environment, and knowledge transfer.

D'Amico *et al.* (2025) in an article for McKinsey concentrated on the possible roles Artificial Intelligence can have in the strategic decision-making process. AI can take on the role of researcher, interpreter, thought partner, simulator, or communicator. Each of these roles emerges in different parts of the process, as shown in *Figure 11*.

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		Researcher	Interpreter	Thought partner	Simulator	Communicator	
<b>Design the strategy</b>	Align on the strategic challenge	[Blue]		[Green]			
	Assess through multiple lenses	[Blue]		[Green]			
	Explore value-creating big moves	[Blue]					
	Commit to a bold strategy				[Blue]		
<b>Mobilize the organization</b>	Empower and engage					[Blue]	
	Translate strategy into concrete initiatives			[Green]	[Blue]		
	Prioritize and reallocate resources			[Green]	[Blue]		
	Govern and rewire plans and budgets			[Green]			

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		Researcher	Interpreter	Thought partner	Simulator	Communicator
<b>Execute, monitor, and review</b>	Force execution momentum					Green
	Drive and support performance	Blue	Blue	Blue	Green	Green
	Test assumptions and adapt	Blue	Blue	Blue	Blue	Green
	Launch the next S-curve				Green	Green

**Figure 11. The Possible Roles of AI in Different Stages of Strategy Making.** Adapted from D'Amico *et al.* (2025). Blue symbolizes a core use case, whether green symbolizes a supplementary use case.

When AI acts as a researcher, it gathers information from various sources. This can be used in M&A strategies to identify potential targets, a time-consuming process if done by a human.

When AI creates insights from the collected data, it acts as an interpreter, as it interprets how these insights are valuable for the specific goals of the strategy. For instance, AI is an interpreter when in the context of a growth strategy it helps to identify options from various data and to score them based on their fit with the strategy, effectively reducing the number of possible alternatives.

Thought partner means that AI is helpful in generating ideas and reducing cognitive biases when brainstorming. This is useful to test a possible strategy against a framework, with the AI acting as a devil's advocate.

After selecting a possible strategy, AI can help to create scenarios based on real-time data to test if that strategy can lead to positive outcomes, acting as a simulator. Simulations can also be useful when monitoring the execution of the strategy, as AI can detect early signals from the market and simulate possible outcomes.

To ensure buy-in from stakeholders, communication is essential. AI can take on the role of communicator to generate compelling narratives supporting the chosen strategy, tailoring the message for different stakeholders or geographies (D'Amico, et al., 2025).

This article supports the idea that the role of AI and consequently its use need to be tailored to the specific stage of strategy making. Therefore, companies need to analyze their specific needs to understand where AI can be useful and how to best use the AI models based on the specific role they should have.

Aal (2025) uses the social systems theory to analyze the use of Artificial Intelligence in organizational decision making. What is interesting is his review on the current applications of AI in business, where he draws on the work of Davenport & Ronanki (2023) and Gümüşay, Bohné, & Davenport (2022) to sustain that in structured decision-making processes (i.e., routine and operational), process automation, and therefore full delegation to AI, is preferred. In semi-structured processes, hybrid structures (i.e., sequential human-to-AI or AI-to-human decision making) are preferred. In unstructured processes, that is in infrequent, strategic decisions, aggregated human-AI structures are best. Moreover, the most suited AI model changes, too: predictive ML is best for structured decisions and semi-structured decisions, whereas GenAI is useful for semi-structured and unstructured decisions. Therefore, different models affect different situations and the human-AI interaction to be preferred.

Hao, Demir, & Evers (2025) conducted 28 interviews across leading firms to analyze the collaboration between humans and AI and how it can improve operational efficiency, which they found stems from the ability to continuous learning (both on the part of the AI and the human), to build trust and to ensure ethical oversight, but most importantly to adapt to changing situations. First, they distinguish between human-in-the-loop (HITL) configurations, where humans interact with AI, human-over-the-loop (HOTL), where humans supervise the process (routine tasks are handled by the AI, which refers to humans for complex decisions), and human-in-command (HIC) configurations, where the decisions are assured to remain under human control. HITL configurations are suited in cases where the learning process of the algorithm is essential, as the human agent ensures the optimization of its learning behavior. HOTL configurations are suited for high-stake decisions, where timely human intervention is

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needed. Finally, HIC configurations are suited for contexts involving possible ethical risks. However, they argue that these configurations assume fixed roles, but the relationship between humans and AI is more dynamic and contingent on organizational and institutional factors, as organizational rules, industry norms, and legal factors need to be taken into account, along with the risk involved and the type of data available. In fact, they sustain that “in the deployment phase [the actual implementation of the AI system in the process], the division of labor between AI and [humans] becomes functionally adaptive, reflecting the temporal and environmental contingencies of real-world operations” (Hao, Demir, & Eysers, 2025), although it is not clear how the adaptation works in practice.

Condé & Münch (2025) conducted 23 interviews with experts to analyze the use of Artificial Intelligence in supply chain decisions and specifically how it can improve supply chain resilience, recognizing however that actual implementation by firms remains limited. This article is supportive to the theory of a contingent approach in its future research directions section, in which the authors call for research on how the AI solutions should be tailored to the size of the firm, from small enterprises to multinationals, and to the operational contexts (i.e., procurement, distribution, or logistics).

Ngo (2025) analyzed data from experiments in marketing to understand if AI augmentation improves decision outcomes. The findings show that AI support reduces human errors, but genuine collaboration (synergy) is limited, and when humans and AI do collaborate, the performance is worse compared to AI performance alone. However, the success of the collaboration is contingent on the task type and contextual factors. In fact, if in analytical tasks collaboration is detrimental, in creative or ambiguous tasks it is actually advantageous, as it combines human creativity and AI computational power. Moreover, human capability matters: low-experienced human decision makers fail to capitalize on AI integration, a result consistent with that of Dell'Acqua, Kogut, & Perkowski (2025).

*Figure 12* summarizes the collected references and their contributions, in chronological order.

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Authors	Publication	Methodology	Focus	Contribution Theme	Contribution
Shao, Feng, & Hu, 2015	European Journal of Information Systems	Empirical multi-case study, qualitative methodology	Contingent fit between leadership styles and phases of technology lifecycle	Leadership styles	Leadership styles need to adapt to the stage of the technology lifecycle
McKinsey Analytics, 2018	McKinsey & Company	Practitioners' insights	How to successfully use AI in businesses	AI model choice	No AI model is optimal for every decision
Fontaine, McCarthy, & Saleh, 2019	Harvard Business Review	Theoretical study	Organizational and cultural barriers to AI implementation	Dynamic organizational models	Organizational models depend on the specific characteristics of the firm, the maturity of AI capabilities, the complexity of the business model, and the technical innovation required
Shrestha, Ben-Menahem, & Von Krogh, 2019	California Management Review	Theoretical study	How to evaluate human-AI configurations	Evaluation criteria	Different configurations of the decision-making process can be evaluated across five dimensions
Yablonsky, 2019	Technology Innovation Management Review	Theoretical study	Multidimensional Big Data-driven AI enterprise maturity framework	Data analytics capabilities	The process depends on the level of employees' data analytics capabilities
Trunk, Birkel, & Hartmann, 2020	Business Research	Theoretical study	Conceptual framework of decision-making processes under uncertainty	Configurations framework	The decision-making process is influenced by the type of information available, organizational structures, ethical considerations, and the type of AI application used

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Authors	Publication	Methodology	Focus	Contribution Theme	Contribution
Rudko, Bashirpour Bonab, & Bellini, 2021	Journal of Theoretical and Applied Electronic Commerce Research	Theoretical study	AI contingency and organizational structures fit	Organizational design	Structures and processes need to be aligned to specific internal and external contexts
Jain, Garg, & Khera, 2023	Kybernetes	Empirical study, quantitative methodology	Work design and division of labor between humans and AI	Critical gap in literature	Insufficient attention is given to social and organizational factors when implementing AI
Deloitte, 2023	Deloitte.com	Practitioners' insights	How to maximize GenAI value	Human-AI interaction	Competitive advantage comes from unique ways to configure the human-AI interaction
Maragno, et al., 2023	International Journal of Information Management	Empirical study, qualitative methodology	Contextual factors driving AI adoption	Automation vs. augmentation	The choice between automation or augmentation depends on the AI model
Choudhary, et al., 2023	Journal of Management	Theoretical study	When are human-AI ensembles beneficial in prediction tasks?	Type of accessible data	The appropriateness of H-AI ensembles depends on the types of data available: H-AI ensembles are suited when both AI- and human-accessible data are present
Hendriksen, 2023	Journal of Supply Chain Management	Theoretical study	Impact of AI on supply chain disruptions	Human-AI configurations	The effects of AI are contingent on the mode of integration, on the level of autonomy of AI, and on the human perception of it
Lupp, 2023	Journal of Business Venturing	Theoretical study	Machine Learning usefulness in entrepreneurial decision making	Risk vs. uncertainty	Supervised ML is useful in risk situations, unsupervised ML is useful in uncertain situations
IBM, 2024	IBM.com	Practitioners' insights	How to best implement AI in businesses	AI model choice	No AI model is optimal for every decision

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Authors	Publication	Methodology	Focus	Contribution Theme	Contribution
Lamarre, et al., 2024	McKinsey Quarterly	Practitioners' insights	How to best implement AI in businesses	Strategic integration	Companies need to analyze where there is the most impact and evaluate specific needs, capabilities, and strategic goals
Schrage & Kiron, 2024	MIT Sloan Management Review	Theoretical study	AI as a choice architect	User-centered design	The design of the process should consider users and tasks
Hao, Demir, & Evers, 2024	Technology in Society	Empirical study, qualitative methodology	Effects of GenAI in organizational decision making	Familiar vs. unfamiliar scenarios	In familiar scenarios decision makers rely on experience, in unfamiliar scenarios they rely on intuition and heuristics
Ellencweig, et al., 2024	McKinsey & Company	Theoretical study	GenAI use in M&A	GenAI in M&A strategy	The relevance and impact of each AI use case depends on the firm's strategy
Singla, et al., 2025	McKinsey & Company	Empirical study, qualitative methodology	Organizational changes driven by AI adoption	Human oversight	Human oversight depends on industry standards
Schrage & Kiron, 2025a	MIT Sloan Management Review	Theoretical study	Intelligence Choice Architectures	Human oversight	Human oversight must be determined in relation to the criticality of the task and the risks involved
Schrage & Kiron, 2025b	MIT Sloan Management Review	Theoretical study	AI effect on decision rights	Dynamic decision rights	Decision rights should continuously adjust to the context
Dell'Acqua, Kogut, & Perkowski, 2025	The Review of Economics and Statistics	Empirical study, quantitative methodology	Effects of AI in teams	Skill-dependent automation	The success of automation depends on the skills of the employees
Dell'Acqua, et al., 2025	Social Science Research Network	Empirical study, qualitative methodology	Effects of AI in teams	Efficiency vs. complementarity	Different organizations may choose between automation and augmentation differently because of a preference for either efficiency or complementarity

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Authors	Publication	Methodology	Focus	Contribution Theme	Contribution
D'Amico, et al., 2025	McKinsey & Company	Practitioners' insights	AI use in strategy development	AI role	The role of AI changes based on the stage in the process
Hao, Demir, & Evers, 2025	Sustainable Futures	Empirical study, qualitative methodology	Collaboration between humans and AI to improve operational efficiency	Human-AI configurations	Different human–AI collaboration models (HITL, HOTL, HIC) effectiveness is contingent on contextual factors such as organizational rules, industry norms, risk level, and data availability
Condé & Münch, 2025	Journal of Business Logistics	Empirical study, qualitative methodology	Use of AI in supply chain decisions and resilience	Tailored AI solutions	AI solutions should be tailored to firm size and operational contexts (procurement, distribution, or logistics)
Ngo, 2025	Marketing Letters	Empirical study, quantitative methodology	Does AI augmentation improve marketing decision outcomes?	Drivers of success of human-AI collaboration	Success of the collaboration is contingent on the task type and contextual factors

Figure 12. *Collected References and Their Contribution. Author's elaboration.*

### 3.2.3. Discussion

The analysis of the collected references reveals a body of literature that is both fragmented and emergent, with important implications for the study of AI integration through a contingent approach.

The temporal distribution of publications highlights the novelty of the topic. The first, few contributions date back to 2015 and 2018, followed by a small but steady increase between 2019 and 2021. However, the overwhelming majority of works were published between 2023 and 2025, confirming that the contingent approach to AI in decision making has only recently gained traction in both academic and practitioner debates. This explains the scarcity of comprehensive frameworks and the prevalence of exploratory or conceptual works, as the field is still in the process of establishing its theoretical foundations.

The diversity of places of publication further underscores the fragmented nature of the literature. References are dispersed across high-impact academic journals (e.g., *European Journal of Information Systems*, *International Journal of Information Management*, *Journal of Management*), practitioner-oriented platforms (e.g., McKinsey & Company, Deloitte.com, IBM.com), and interdisciplinary journals (e.g., *Sustainable Futures*, *Technology in Society*). This distribution indicates that this debate has not yet consolidated within a specific academic community but rather spans multiple domains of management, technology, and organizational studies. The significant presence of practitioner studies, particularly from McKinsey, suggests that the practical urgency of AI integration has outpaced theoretical elaboration.

The methodological breakdown confirms this duality between theory and practice. Out of 27 references, 12 are theoretical studies, while 7 are qualitative empirical studies, mostly based on interviews and case studies. Quantitative empirical contributions are rare (3), and mostly new (two of them are from 2025), indicating limited large-scale or statistically grounded validation of the proposed frameworks. Finally, 5 contributions derive from practitioners' insights, reflecting field experience and industry trends rather than systematic academic inquiry.

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Therefore, the literature is characterized by a predominance of conceptual arguments, enriched by some exploratory evidence but lacking robust empirical generalization.

An examination of the focus of the selected works reveals a wide heterogeneity, reflecting the still dispersed state of the literature. Early contributions concentrate on general guidance on how to successfully use AI in businesses, then gradually shifting toward more specific organizational questions such as cultural barriers, division of labor between humans and AI, and fit between AI contingencies and organizational structures. More recent works explore decision-making processes under uncertainty, the role of AI in shaping decision rights, and the conditions under which human-AI ensembles are beneficial, moving to a more structured contingent approach, rather than merely marginal. Sector-specific analyses, including supply chain resilience, M&A strategies, and marketing decisions, further highlight the growing interest in contextualized applications. Moreover, several practitioner-oriented contributions focus on how to maximize the value of GenAI and drive organizational changes.

The thematic breadth confirms the lack of a consolidated research stream: while many works converge on the idea that AI integration must be context-dependent, they approach the issue from diverse disciplinary and practical angles, and up to recent years only marginally during their discussions.

The thematic trajectory of the contributions to a contingent approach mirrors the evolution of the literature from broad concepts to increasingly specific contingency factors. These contributions can be grouped into three broad clusters.

A first group of studies focuses on organizational alignment and design, examining how leadership styles, organizational structures, and decision rights must adapt to AI adoption. Within this cluster, works emphasize the importance of dynamic organizational models, strategic integration, and tailored solutions, rejecting one-size-fits-all approaches and stressing the need to align AI with specific business contexts and lifecycles.

A second cluster centers on human-AI collaboration. Here, the literature discusses alternative configuration frameworks (e.g., human-in-the-loop vs. human-over-the-loop, sequential vs. parallel division of tasks), the balance between automation and augmentation, and the tension between efficiency and complementarity. These studies also highlight skill-dependent

outcomes, showing that the benefits of automation vary across employee groups, and identify critical success factors such as trust, oversight, and user-centered design.

Finally, a third group of contributions addresses the decision-making context contingencies. These works analyze how AI supports decisions under risk versus uncertainty, in familiar versus unfamiliar contexts, and in domain-specific applications such as M&A strategy or supply chain management.

These are not stand-alone clusters, there is a clear interdependence: organizational design decisions shape the conditions for human-AI collaboration, while both of these, in turn, determine the effectiveness of decision making in different contexts. Therefore, the contributions converge on a central insight: the integration of AI in organizational decision making cannot follow universal models but must be contingent on organizational structures, human factors, and contextual decision environments.

While many studies identify relevant contingencies, they are often limited in specifying how these factors interact dynamically and how they impact decision-making processes in practice. This leaves open the challenge of translating the contingent approach into actionable process configurations, a gap that this thesis seeks to address.

In the following sections, four papers will be analyzed in depth. These are the only ones from those emerged that focus entirely and solely on possible configurations of decision-making processes integrated with AI, each dependent on different contingencies:

- Trunk, Birkel, & Hartmann (2020) argue that the process is influenced by the type of information available, organizational structures, ethical considerations, and the type of AI application used.
- Jain, Garg, & Khera (2023) demonstrate that different configurations influence efficiency, decision quality, trust, role clarity, and reliability.
- Shrestha, Ben-Menahem, & Von Krogh (2019) propose four configurations influenced by the specificity of the decision search space, the interpretability of the decision-making process and outcome, the size of the alternatives set, the speed, and the replicability.

- Yablonsky (2019) argues that the process is influenced by the level of analytics capabilities.

### **3.3. Decision-making process n° 1: Trunk, Birkel, & Hartmann (2020)**

Trunk, Birkel, & Hartmann (2020) focus on strategic organizational decision making under uncertainty, being the latter a significant variable in this context, as seen in the first chapter of this thesis. The authors draw on a systematic literature review on traditional decision-making theory (Rousseau, 2018; Mintzberg, 1973; Charness & Sutter, 2012; Carbone, Georgalos, & Infante, 2019 – See Chapter One) and a content analysis to create a conceptual process framework that would improve decision quality in dynamic, complex, and uncertain environments.

The process defined by Trunk, Birkel, & Hartmann (2020) is divided into three phases: input, process, and output. The input phase is linked to perception, the process is linked to interpretation, and the output is linked to actions. *Figure 12* depicts the conceptual framework proposed by the authors.

The process begins with the definition of a goal, which is assumed to be a human-only task. Then, information needs to be collected. There are two types of information: external and internal. Internal information can be either explicit (ready-to-use data about products, inventories, or flows) or implicit (experiences, emotions, and so on). Implicit data is more difficult to gather since its sharing is dependent on trust or hidden agendas.

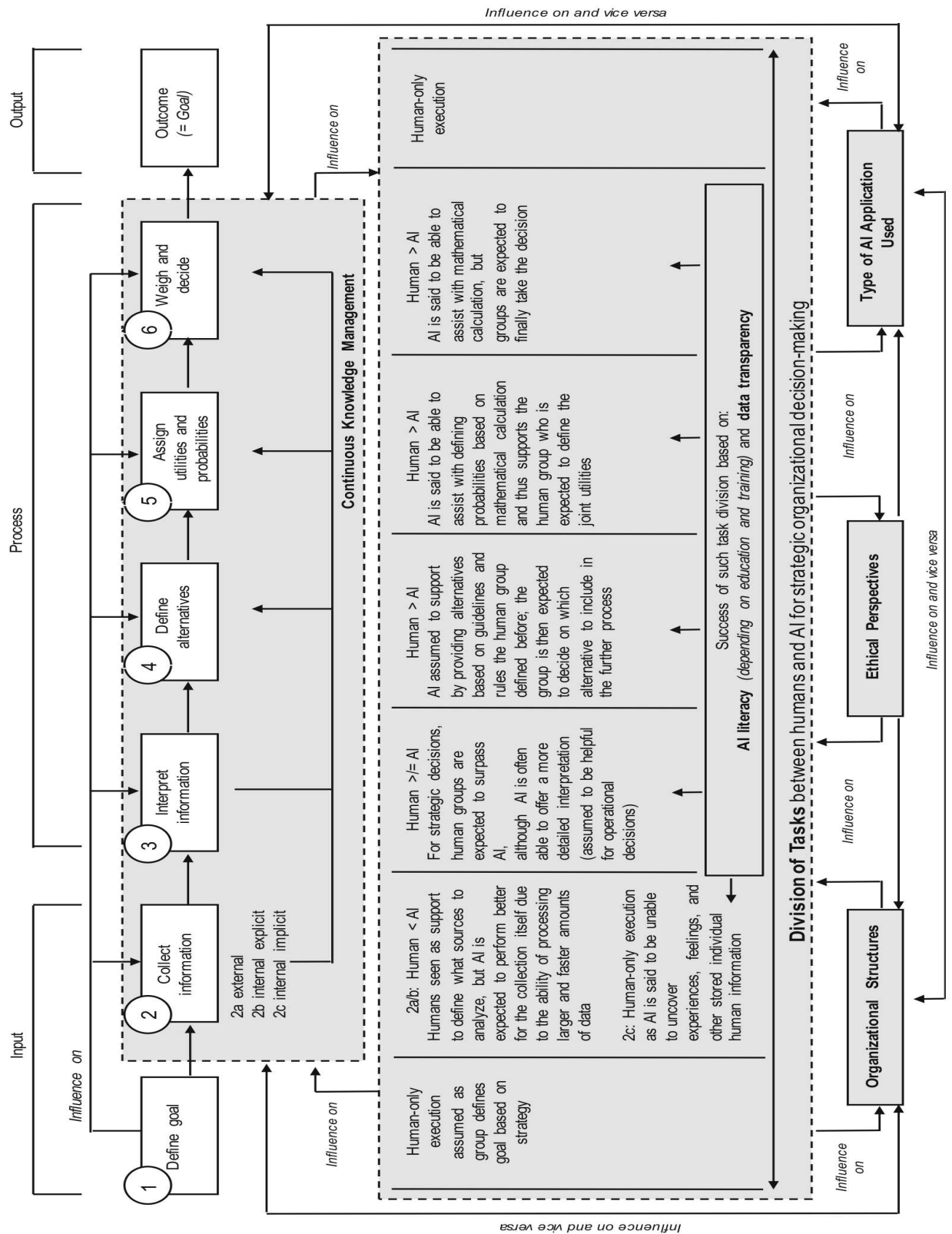


Figure 13. *Conceptual Framework for AI Integration into the Organizational Process for Decision Making Under Uncertainty.* Trunk, Birkel, & Hartmann (2020).

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For these reasons, if the information needed is external and/or internal explicit, the collection task is assigned to AI, which would perform better because of high computing and processing capabilities. However, if the information is implicit, only humans could gather it, since AI would be unable to correctly pick up on emotions and experiences, or people would not trust an algorithm with this type of personal information.

The information collected then needs to be interpreted. In this case, the authors note a difference between strategic decisions and operational decisions. In strategic decisions, information interpreting should be assigned to humans, who could however be supported by algorithms (as seen in the previous Chapter); in operational decisions, AI surpasses humans (Trunk, Birkel, & Hartmann, 2020).

When it comes to defining alternatives, AI can support humans providing the alternatives based on guidelines given by humans, but the human decision maker is ultimately expected to select the definitive alternatives.

The possible alternatives are then assigned utilities and probabilities. AI assigns utilities based on mathematical calculations, but humans define the final joint utilities. However, it has to be noted that this research was published in 2020, that is five years ago, and the computational capabilities of algorithms are now so powerful that it is arguable that AI could outperform humans in this phase.

The same is to be said for the final step, the ultimate decision.

The division of tasks in the process is also influenced by organizational structures, ethical perspectives, and the type of AI application used, although it is not clear how. These variables are influenced by and influence each other. The success of the chosen division of task is, however, dependent on AI literacy and data transparency (Trunk, Birkel, & Hartmann, 2020).

Consequently, this process is influenced by a series of contingencies, including:

- The type of information, if external or internal, and if explicit or implicit.

- The type of decision, if strategic or operational.
- The type of AI model and the data analytics skills of the human decision maker.
- Organizational structures.
- Ethical perspectives.
- AI literacy.
- Data transparency.

### **3.4. Decision-making process n° 2: Jain, Garg, & Khera (2023)**

Effective Human-AI Work Design for Collaborative Decision-Making by Jain, Garg, & Khera (2023) focuses on the division of labor between humans and AI in the decision-making process. They used situational response surveys to understand the effect of different task division configurations on trust, role clarity (understanding how the expectations of the human agent are different from those of AI), and preferred feedback style, since feedback is crucial for effective human-AI collaboration.

The authors draw on the work of Puranam (2021) who identified six possible configurations, depending on whether the human and AI tasks are parallel or sequential and whether there is specialization or not.

1. Parallel without specialization. In this case, human and AI perform the same task at the same time. The authors argue that this configuration produces the greater efficiency and effectiveness, besides providing validation to human decisions. However, this could be an inefficient use of resources.
2. Parallel with specialization. In this case, human and AI perform different tasks at the same time, each of them performing the task they are better at. For instance, the human decision maker could analyze qualitative data whether AI could analyze quantitative data. This configuration also demonstrates high speed, efficiency and effectiveness, but the AI decision is taken completely autonomously without giving a reason to the human.
3. Sequential without specialization (AH). In this case, AI first performs a task, then the decision is shared with the human, who performs again the same task, giving a second

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opinion on the AI decision. AI effectively supports the decision process, providing insights that humans could overlook. However, there is the risk of overreliance on the AI decision, which could stop humans from expanding the scope of the AI output or even lead to blindly accepting AI decisions.

4. Sequential with specialization (AH). In this case, humans and AI perform different tasks, but the human task comes after the AI task and uses the outputs of the algorithm as inputs. This leads to an increase in speed and humans have better control over the process, as they effectively take the final decision. However, also in this case humans do not know exactly why the algorithm took that decision.
5. Sequential without specialization (HA). In this case, humans and AI perform the same task, but sequentially, with the human task coming first. This process provides validation to the human decision, with AI integrating and, if necessary, correcting it. The authors cite Endsley (2017) to say that this configuration may be time consuming.
6. Sequential with specialization (HA). In this case, humans and AI perform different tasks sequentially, with the human task coming first, and the AI using its output as inputs. The advantages are similar to the other configurations with specialization; however, here humans can perceive a loss in control, since it is the AI that ultimately takes the decision (Jain, Garg, & Khera, 2023).

Jain, Garg, & Khera (2023) also note that the chosen configuration will influence the level of trust in the AI, the role clarity, and the preference of feedback by humans.

Configuration 3, sequential without specialization (AH), is the configuration in which the perceived level of trust is lowest. Configuration 2, parallel with specialization, is the configuration that produces the most clarity in the role of both AI and humans. Role clarity was high also in Configuration 4, sequential with specialization (AH). The authors found no difference for feedback preferences.

Interestingly enough, the level of trust and role clarity was higher when humans collaborated with AI with respect to collaborating with other human colleagues. This implicates that distrust in AI is not inherent but comes from the configuration of the human-AI collaboration.

Consequently, the presented configurations influence a series of factors, including:

- Speed.
- Efficiency and effectiveness.
- Decision quality.
- Level of trust.
- Role clarity.

### **3.5. Decision-making process n° 3: Shrestha, Ben-Menahem, & Von Krogh (2019)**

Shrestha, Ben-Menahem, & Von Krogh (2019, p. 67) recognize the “lacuna in the literature” on “how to design organizational structures that combine human and AI-based decision making so as to maximize its benefits and minimize risks” and provide five evaluation criteria for decision-making process configurations: specificity of the search space (i.e., how specific the definition of the characteristics of the possible alternatives to be considered needs to be), interpretability of the decision-making process and outcome (i.e., the understanding of how and why that specific decision was taken), size of the alternatives set, decision-making speed, and replicability (i.e., the possibility for the results to be replicated). The authors evaluate four different configurations against these criteria: full human to AI delegation, hybrid (human-to-AI and AI-to-human) sequential decision making, and aggregated human-AI decision making. *Figure 14* illustrates the authors’ framework.

According to the authors, “full delegation is particularly useful in decision-making scenarios where the decision search space is specific and restricted, interpretability of the decision-making process is less important than the accuracy of the prediction, the alternatives set is large, decision-making speed is critical, and replicability of decision outcomes is desirable” (Shrestha, Ben-Menahem, & Von Krogh, 2019, p. 72).

Organizational Structure	Specificity of the Decision Search Space	Interpretability	Size of the Alternative Set	Decision-Making Speed	Replicability	Examples
Full human to AI delegation	High (required for AI to function)	Low (due to absence of human involvement)	Large (not restricted by human capacity)	Fast (not restricted by human capacity)	High (computationally standardized)	Recommender systems, digital advertising, online fraud detection, dynamic pricing.
Hybrid 1: AI to human sequential decision making	High → Low (high in the first phase, low in the second phase)	High (due to human involvement in the final decision)	Large (due to involvement of AI in the first phase)	Slow (due to human decision-making as a bottleneck)	Low (vulnerable to human variability)	Idea evaluation, hiring.
Hybrid 2: Human to AI sequential decision making	Low → High (low in the first phase due to human involvement, and high in the second phase for AI)	Low (due to AI involvement in the final decision)	Small (due to human involvement in the first phase)	Slow (due to human decision-making as a bottleneck)	Low (vulnerable to human variability)	Sports analytics, health monitoring.
Aggregated human-AI decision making	Low (for decisions allocated to humans) High (for decisions allocated to AI)	High (for decisions allocated to AI) Low (for decisions allocated to humans)	Small (same set of alternatives are evaluated by both humans and AI)	Slow (due to human decision-making as a bottleneck)	Partial (replicability only guaranteed in decision elements allocated to AI)	Top management teams, boards.

Figure 14. *Decision-Making Process Configurations*. Shrestha et al. (2019).

Full delegation is used, for instance, in dynamic pricing and fraud detection, where an objective function can be accurately defined. However, speed and optimization are gained at the expense of human interpretability. This is why full delegation is used in contexts where speed is essential, and therefore the involvement of a human in the process would cause a critical delay.

The first hybrid structure considered by Shrestha, Ben-Menahem, & Von Krogh (2019) is comparable to Jain, Garg, & Khera's (2023) Configuration 3, sequential without specialization (AH). The human decides among the alternatives provided to them by the algorithm, which acts as a filter.

This is appropriate for contexts where the set of alternatives is large, and humans alone could not handle it. Here as well the specificity of the decision search space is required.

Again, the trade-off between speed and interpretability is present: the process becomes slower, but interpretability increases. Replicability is lower. However, there is the risk of not considering eligible alternatives because of the previous elimination on the part of the AI, which effectively conceals them from humans. It is useful to remember that Jain, Garg, & Khera (2023) found that this structure leads to the lowest level of perceived trust.

The second hybrid structure considered by Shrestha, Ben-Menahem, & Von Krogh (2019) is comparable to Jain, Garg, & Khera's (2023) Configuration 5, sequential without specialization (HA). In this case it is the human that acts as a filter for possible alternatives, to be then evaluated by the AI. This configuration is appropriate when the human is confident on a relatively small number of alternatives, but a high amount of data needs to be processed to evaluate these alternatives. For these reasons, this structure is fit for contexts with a small size of the alternatives set, as this is evaluated by a human who does not possess the computational capabilities to explore a vast set of alternatives. However, the specificity of the decision search space is high. Interpretability depends on the possible involvement of a human after the AI evaluation, although this would make the process slower and lose in replicability.

The last structure analyzed by Shrestha, Ben-Menahem, & Von Krogh (2019) is the aggregated human-AI decision making, in which specialization is present. The ultimate decision is taken "using an aggregation rule such as majority voting or (weighted) averaging" (Shrestha, Ben-

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Menahem, & Von Krogh, 2019, p. 76). The authors deem this structure useful for investment decisions, providing the example of Deep Knowledge Ventures, a Venture Capital firm, who appointed an algorithm, VITAL (Validating Investment Tool for Advancing Life Sciences), as an effective board member. In this way, the algorithm focused on objective, quantitative data, whereas human decision makers focused on qualitative data, like ethical considerations or reputational factors. This helped the board to objectively analyze investment decisions and identify variables that may be overlooked by humans.

This structure effectively reduces the risk of amplification of human biases in AI decisions. In fact, in a sequential configuration where the AI decision relies on the work of humans, the AI could amplify human biases like discrimination, favoritism, or simply systematic errors.

The authors advise managers “to map these five dimensions [i.e., specificity of the decision search space, interpretability of the decision-making process and outcomes, size of the alternatives set, decision-making speed, replicability of decisions] to the unique strengths and weaknesses of human and AI-based algorithmic decision making in terms of human’s judgement and interpretability and AI’s capability of alternative filtering and predicting with high accuracy” (Shrestha, Ben-Menahem, & Von Krogh, 2019, p. 77).

Consequently, the structure of the decision-making process is influenced by a series of contingencies, including:

- The specificity of the decision search space.
- The interpretability of the decision-making process and outcomes.
- The size of the alternatives set.
- The decision-making speed.
- The replicability of decisions.

### 3.6. Decision-making process n° 4: Yablonsky (2019)

Yablonsky (2019), through a conceptual study, proposes an Artificial Intelligence, Big Data (BD) and Advanced Analytics (AA) innovation value chain in the context of digital business platforms, with a focus on data-driven human-machine relationships. In fact, data is “the raw material for decision making” (Yablonsky, 2019, p. 16) and “AI innovation is powered by BD and AA” (Yablonsky, 2019, p. 17).

The author begins with a proposed AI/BD/AA micro-level value chain, that consists of the following activities (Yablonsky, 2019, p. 24-25):

1. AI Awareness/Big Data Acquisition (BDAc): data is collected from multiple sources and cleaned before being stored in a data warehouse or lake.
2. Adjustment of AI/Big Data Analysis (BDAn): Machine Learning techniques and other types of analyses make the data collected usable for the specific decision-making context.
3. Measurement of AI/Big Data Curation (BDC): data is managed to ensure data quality.
4. AI Reporting and Interpretation/Big Data Storage (BDS): standardization and visualization techniques are used to allow for fast access to the data.
5. AI Decision Making/Big Data Usage (BDU): data is finally used to take a decision.

Then, Yablonsky (2019, p. 26) states that there are five levels of AI maturity, “from a completely ad hoc approach with limited awareness to one in which an AI innovation strategy is integrated into the organization’s culture at every level”. Each maturity level allows to perform different activities of the AI/BD/AA value chain, and therefore it corresponds to different human-machine configurations. *Figure 15* illustrates the AI/BD/AA maturity levels. To appreciate the growing level of AI automation with the growing level of maturity, Yablonsky (2019) analyzes the relationship between humans and the machine, specifying the appropriate task division between them for each level.

## Contingent Views on AI Adoption in Organizational Decision Making

Yablonsky (2019) creates the following correspondences between maturity levels and AI/BD/AA activities:

- The Human Led (or Initial Analytics) level covers partly the first two activities in the value chain, that is AI Awareness/Big Data Acquisition and Adjustment of AI/Big Data Analysis. The other activities (analysis and reporting) are too complex for the capabilities of the enterprise; therefore, the process primarily relies on human analyses.
- The Human Led, Machine Supported (or Advanced Analytics I) level adds to the previous one the third (Measurement of AI/Big Data Curation) and the fourth (AI Reporting and Interpretation/Big Data Storage) activities, still not completely (human agents remain central) but partly.
- The Machine Led, Human Supported (or Advanced Analytics II) level covers completely the first three activities, and partly the last two. Here, machines begin to take the lead, while humans oversight the process and take the final decision.
- The Machine Led, Human Governed (or Advanced Analytics III) level allows to automate the first four activities, but humans still take the final decision.
- The Machine Controlled (or Advanced Analytics IV) level automates every activity in the value chain. Humans are not involved in the process.

However, the author notes that “the specific completeness of the AI/AA/BD implementations are determined by the size of the organization, domain-specific usage and industry” (Yablonsky, 2019, p. 25).

Consequently, the human-machine relationship in business decision-making processes is influenced by the level of Artificial Intelligence, Big Data, and Advanced Analytics maturity.

## Contingent Views on AI Adoption in Organizational Decision Making

Stage of AI/BD/AA maturity	Who produces insights?	Who decides and how?	Who acts based on decision?
1. Human Led	Human analyzes and produces insights using limited technology.	Human decides based on experience and rules.	Human acts or executives.
2. Human Led, Machine Supported	Human analyzes and produces insights using a portfolio of tools.	Human decides based on optimized machine prescriptions.	Human acts or executives.
3. Machine Led, Human Supported	Machine analyzes and produces insights with human review.	Human decides based on optimized machine prescriptions.	Human acts or executives with machine oversight.
4. Machine Led, Human Governed	Machine analyzes and produces insights without human review.	Machine decides within a framework of human governance.	Machine acts or executes with human oversight.
5. Machine (Machine Led & Machine Governed)	Machine analyzes and produces insights.	Machine decides.	Machine acts or executes.

**Figure 15. Stages of AI/BD/AA Maturity. Yablonsky (2019).**

### 3.7. Comparing Traditional and AI-Integrated Decision-Making Processes

Having discussed the possible configurations of decision-making processes integrated with AI, it is useful to draw a direct comparison between them and the traditional decision-making processes discussed in the first chapter (See Section 1.4).

## Contingent Views on AI Adoption in Organizational Decision Making

Both traditional and AI processes present different configurations depending on whether the decision to be taken is strategic or operational, with this distinction representing the primary contingency to be considered in traditional processes. In AI-integrated contexts, however, contingencies extend far beyond this dichotomy: data availability, speed, interpretability, ethical considerations, employees' capability, among others, play a critical role in shaping how the process, and consequently the human-machine relationship, is configured.

Traditional decision-making processes are rooted in the recognition of bounded rationality. As such, they are often characterized by interruptions, iterations, and non-linearity (See Mintzberg, Raisinghani, & Théorêt's (1976) dynamic factors). These reflect the limits of human information processing and the influence of cognitive biases.

AI-integrated processes, on the other hand, tend to be more linear and structured, resembling the logic of a fully rational decision-making process. This seems to support the fact that AI brings human closer to perfect rationality.

The comparison reveals that AI reduces human limitations and cognitive biases and streamlines decision making, but it simultaneously introduces new forms of complexity that organizations need to consider and deal with to fully grasp its potential.

### **3.8. Business Decision Scenarios and Possible Human-AI Configurations**

This section presents a series of business scenarios applying the contingent approach to the AI-supported decision making based on the information collected in the previous sections of this chapter. These scenarios were chosen to explore organizational decision making in a variety of situations, from operational to strategic, and in a variety of functions (product development, marketing, human resources, etc.).

#### **3.8.1. Long-Term M&A Strategy**

A multinational manufacturing company is considering expanding its market share through acquisitions. Its strategy is to focus on one or two large deals annually, favoring long-term

strategic fit rather than the short-term boost in market share. This is the first time the company faces this situation, so the context is highly unfamiliar. The required speed is moderate, but the firm wants to focus on high accuracy. The set of alternatives is relatively small but complex, as only companies with a long-term strategic fit are to be considered. As the decision is highly strategic and there could be reputational and financial stakes at risk, the need for human oversight is very high. However, the team responsible for this decision is low-skilled in terms of AI and data analytics capabilities. The data to be collected is a mix of explicit external data and internal implicit data regarding the organizational culture and the feasibility of the integration.

The optimal human-AI configuration in this case would be Configuration 5, sequential without specialization (HA) (Puranam, 2021; Jain, Garg, & Khera, 2023) for the first part of the process (data collection and evaluation of alternatives). The final decision is taken by a human agent. In the data collection stage, humans collect internal implicit data, and the AI collects explicit external data (Trunk, Birkel, & Hartmann, 2020). Since the potential targets are not many, humans can first filter them based on strategic fit and the internal implicit knowledge (like culture and leadership styles), things that the AI could not reliably detect or interpret. Once the human agent is set on a small number of possible deals, AI processes large volumes of explicit financial and market data to evaluate these targets, simulating potential scenarios and outcomes. Since the context is unfamiliar, humans cannot rely on past experience and are more prone to biases and heuristics, therefore the fact that the AI evaluation comes after the human one guarantees the elimination of these biases (Hao, Demir, & Eysers, 2024).

In this case AI acts as a researcher and as a simulator (D'Amico, et al., 2025). In fact, as the team is low-skilled, augmentation is preferred to automation (Dell'Acqua, Kogut, & Perkowski, 2025).

Therefore, the process is human-led, machine-supported (Yablonsky, 2019), because the need for human oversight is high. This is compatible with the fact that the data analytics skills of the team are low (Yablonsky, 2019).

Since the firm is focused on one or two large deals, “GenAI may also help [...] streamline and accelerate the execution processes” (Ellencweig, et al., 2024).

## Contingent Views on AI Adoption in Organizational Decision Making

The AI models most suited for this case are Machine Learning (supervised) for data collection and assessment of the alternatives, and Generative AI for the creation of simulations and the drafting of documents for the actual deal.

This is a dynamic design decision process (Mintzberg, Raisinghani, & Théorêt, 1976 — See Section 1.4.4.). In fact, the firm is facing this type of situation for the first time, therefore high uncertainty is present, and this creates a need for iterative development and evaluation. This could also be a basic design process, a more linear process going from identification to a newly designed solution, but the complexity of the problem makes interrupts (especially political pressures or unexpected new options), and therefore a dynamic process, more probable.

The solution needs to be custom-made because each large deal requires its own integration strategy. In the development stage, consequently, the predominant routine is design, rather than search.

The process is dynamic, not linear: the organization will move back and forth between development (exploring possible scenarios) and selection (final evaluation of the target).

AI here is active in the identification phase, where it collects and interprets relevant explicit external data, and in the development phase, where it simulates scenarios after acquisition. An execution phase is added to the process theorized by Mintzberg, Raisinghani, & Théorêt (1976), both in this scenario and in the following ones. AI is active in the execution phase as a support tool for due diligence and negotiations.

*Figure 16* illustrates this process.

Therefore, with these contingencies:

- The time horizon is long-term.
- The context is unfamiliar.
- The speed is moderate.
- The preference is for accuracy rather than efficiency.
- The size of the alternatives set is small but complex.
- The decision is highly strategic.
- The need for human oversight is very high.
- The team is low-skilled.

- The data is a mix of explicit external data and internal implicit data.

The optimal human-AI configuration would be sequential without specialization, with the human task coming first.

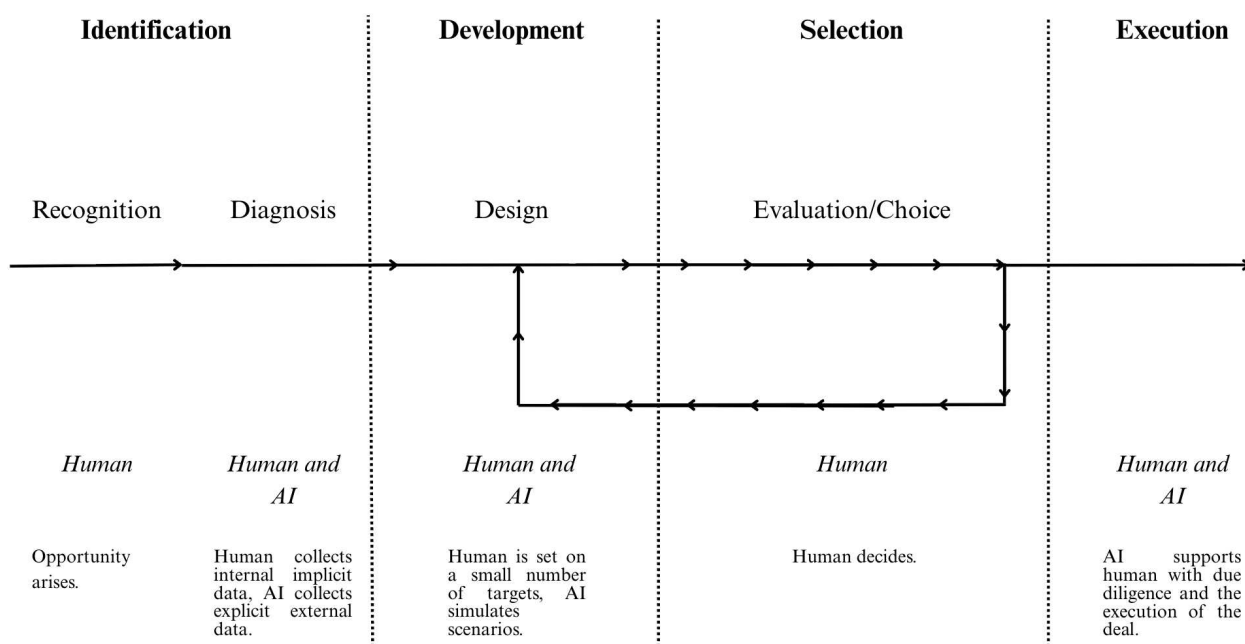


Figure 16. Long-Term M&A Strategy. Author’s elaboration.

### 3.8.2. Short-Term M&A Strategy

A global technology firm aims at acquiring dozens of small AI startups to quickly expand capabilities and talent and boost its market share. In this case speed is critical, as competitors may be pursuing the same targets, and therefore delays could result in losing opportunities. This is why efficiency is preferred to accuracy. Each deal has a low individual financial impact, but the aggregate strategic value is high. The alternatives set is extremely large, as there are hundreds of potential targets in the global AI startup context. The reputational and integration risks are smaller with respect to the previous case, but still there must be coherence between the chosen startups, so the need for human oversight is medium. The data that needs to be collected is mostly explicit external data like funding rounds or patents.

## Contingent Views on AI Adoption in Organizational Decision Making

The optimal human-AI configuration in this case is Configuration 3, sequential without specialization (AH) (Puranam, 2021; Jain, Garg, & Khera, 2023), as the machine first filters the huge alternatives set using explicit external data following guidelines set by human decision makers, and the role of the human agent is to validate the final choices of the machine and ensuring portfolio coherence and alignment with the strategy of the company. Although the process would be faster if the work was parallel, this would not be feasible in this case as the alternatives set is extremely large. If the alternatives set were smaller, humans and AI could evaluate simultaneously the alternatives, and then human decision makers would have the final say.

The role of the AI here is of a researcher, interpreter (as it evaluates the candidates based on strategic criteria) and communicator (as it generates reports about the top targets) (D'Amico, et al., 2025).

This process is machine-led but human-governed (Yablonsky, 2019), as the AI works on every stage of the process, but humans take the final decision.

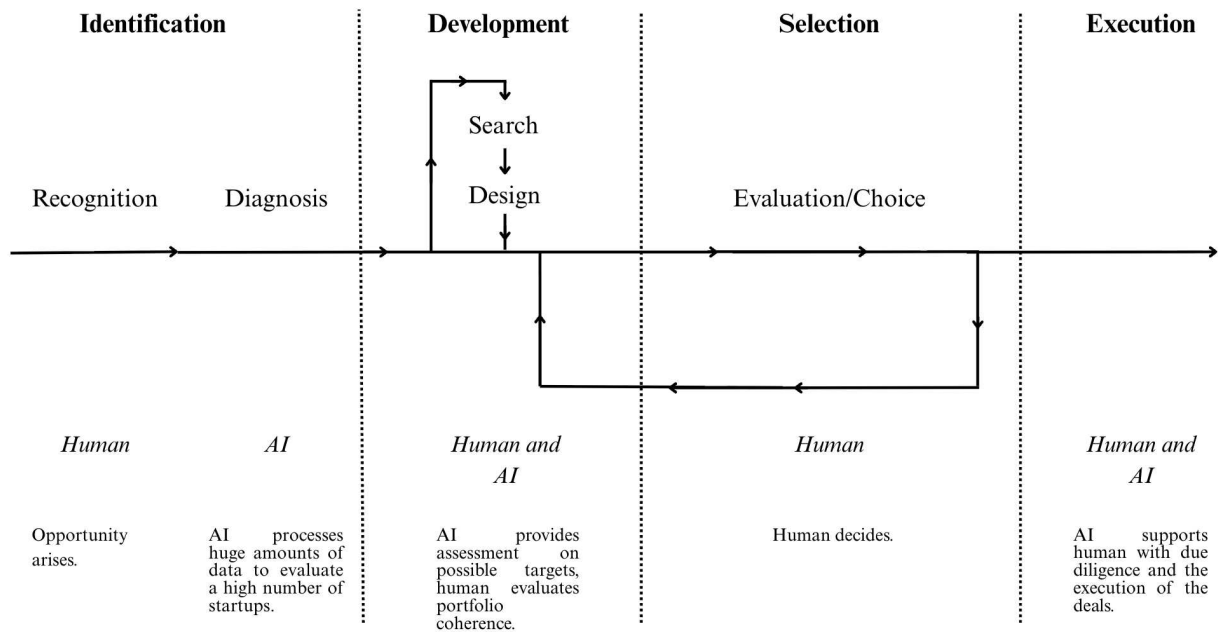
The AI models most suited for this case are Machine Learning (supervised and unsupervised) for data collection and assessment, and Generative AI for communication and reporting between AI and humans.

This is a modified search decision process (Mintzberg, Raisinghani, & Théorêt, 1976). In this case acquisitions follow a repeated and partially standardized process, adapted for each target, therefore the solution is modified. The predominant routine in the development phase is still design, although it is more limited than it was in the previous case, and the search routine is necessary to find ready-made solutions suitable to be modified. There are also less cycles.

AI here is active in the identification phase, where it screens the global startup ecosystem, partly in the development phase where it provides objective assessment on possible targets, and finally in the execution phase as a support tool.

*Figure 17* illustrates this process.

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**Figure 17. Short-Term M&A Strategy. Author's elaboration.**

Therefore, with these contingencies:

- The time horizon is short-term.
- The speed is critical.
- The preference is for efficiency rather than accuracy.
- The size of the alternatives set is extremely large.
- The decision is strategic.
- The need for human oversight is medium.
- The data is explicit external.

The optimal human-AI configuration would be sequential without specialization, with the AI task coming first.

### 3.8.3. Product Development Decision

A global consumer electronics company wants to launch a new wearable device. The concept of the product and its features are already partially defined, but the company is unsure about the success of the product in the market. The required speed is moderate to high since

## Contingent Views on AI Adoption in Organizational Decision Making

competitors could beat the firm to launch. The alternatives set of the possible features, price points and segments to target is medium-sized but highly complex, as there could be multiple combinations. The need for human oversight is high because of possible brand reputation damages and compliance for safety standards. The data to be collected is explicit external (market) data. This is a familiar context for the decision-making team, whose data analytics capabilities are advanced.

The optimal human-AI configuration is Configuration 2, parallel with specialization (Puranam, 2021; Jain, Garg, & Khera, 2023), or aggregated human-AI decision making (Shrestha, Ben-Menahem, & Von Krogh, 2019). Data collection is entirely in the hands of the AI, since the data is explicit external data (Trunk, Birkel, & Hartmann, 2020). AI then focuses on quantitative aspects like the analysis of market trends and competitor benchmarking, while humans focus on qualitative, creative, and ethical considerations. In this case, this configuration also helps to make the process faster.

Since this is a familiar context, AI is used as a support tool in parallel with the human work, since the human decision maker relies on experience and not on biases and heuristics (Hao, Demir, & Evers, 2024).

After the final decision, AI could simulate the outcome of the selected product feature, segments, and pricing points, to further validate the option. Therefore, AI acts as a researcher, interpreter, and simulator (D'Amico, et al., 2025).

Since the data analytics capabilities are advanced, the AI can effectively support all the phases of Yablonsky's (2019) micro-level value chain.

The AI models most suited for this case are Machine Learning (unsupervised) for data collection and assessment of the alternatives, and Generative AI for the simulations.

This is a dynamic design decision process (Mintzberg, Raisinghani, & Théorêt, 1976), as it is probable that there are multiple iterations between development and evaluation. The recognition of the need for a decision arises from an opportunity. The solution is a combination of modified and custom-made, since the basic product concept already exists, but the final features and strategy must be tailored.

## Contingent Views on AI Adoption in Organizational Decision Making

It is important to note that Mintzberg, Raisinghani, & Théorêt (1976) argue that this kind of process is the one that takes the longest, and this would be in contrast with the need for moderate speed in this situation. However, with the integration of Artificial Intelligence the time spent in identification and development is significantly reduced.

AI here is active in the identification phase to collect data, in the development phase to analyze quantitative data, in the selection phase to validate the final option with simulations, and in the execution phase as a support tool.

Figure 18 illustrates this process.

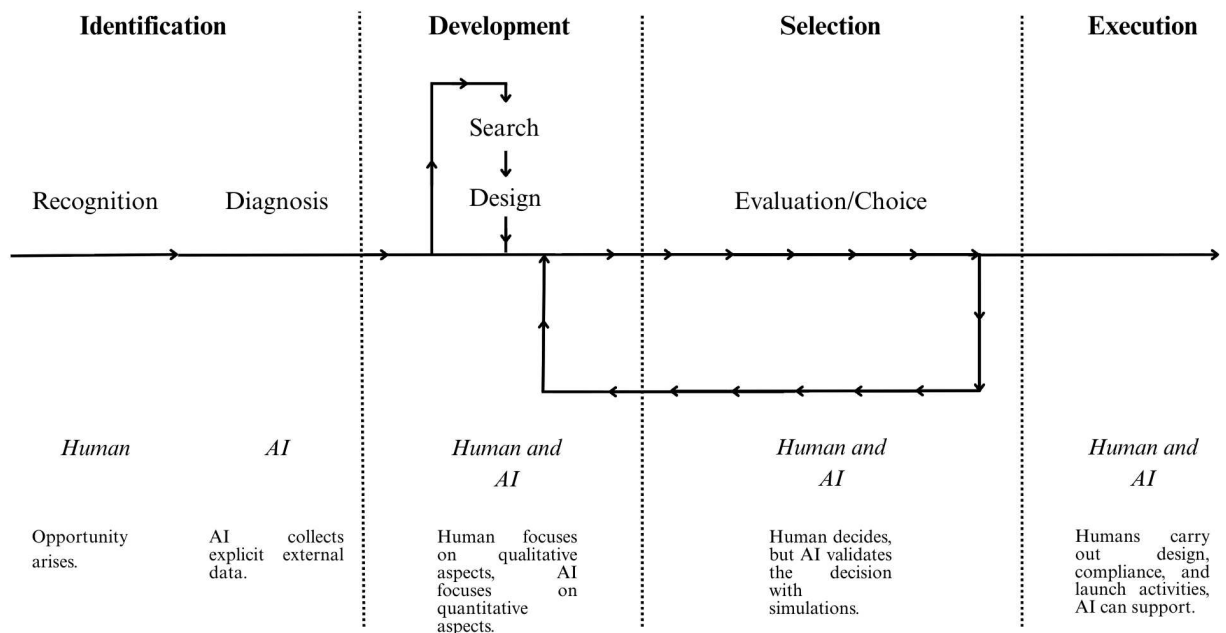


Figure 18. *Product Development Decision*. Author's elaboration.

Therefore, with these contingencies:

- The time horizon is short-term.
- The speed is moderate to high.
- The decision is strategic.
- The size of the alternatives set is medium but highly complex.
- The need for human oversight is high.
- The data is explicit external.

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- The context is familiar.
- The data analytics capabilities are advanced.

The optimal human-AI configuration would be aggregated human-AI decision making with specialization.

### 3.8.4. Dynamic Pricing in E-Commerce

A large online retailer wants to optimize pricing for thousands of products daily. The required speed is extremely high since the optimization needs to happen in real time. The alternatives set is massive and continuously changing. In this case, the need for human oversight is low. The data to be collected is external explicit. The decision is operational, and the firm prioritizes efficiency rather than a good complementarity between humans and AI.

The optimal human-AI configuration in this case is the full human-to-AI delegation. This is because the alternatives set is huge, speed is critical, and interpretability is less important than accuracy and replicability of the process (Shrestha, Ben-Menahem, & Von Krogh, 2019). Also, the decision is operational, and the firm is not interested in the complementarity between human and machine. Since efficiency is key, automation is preferred to augmentation (Maragno, et al., 2023).

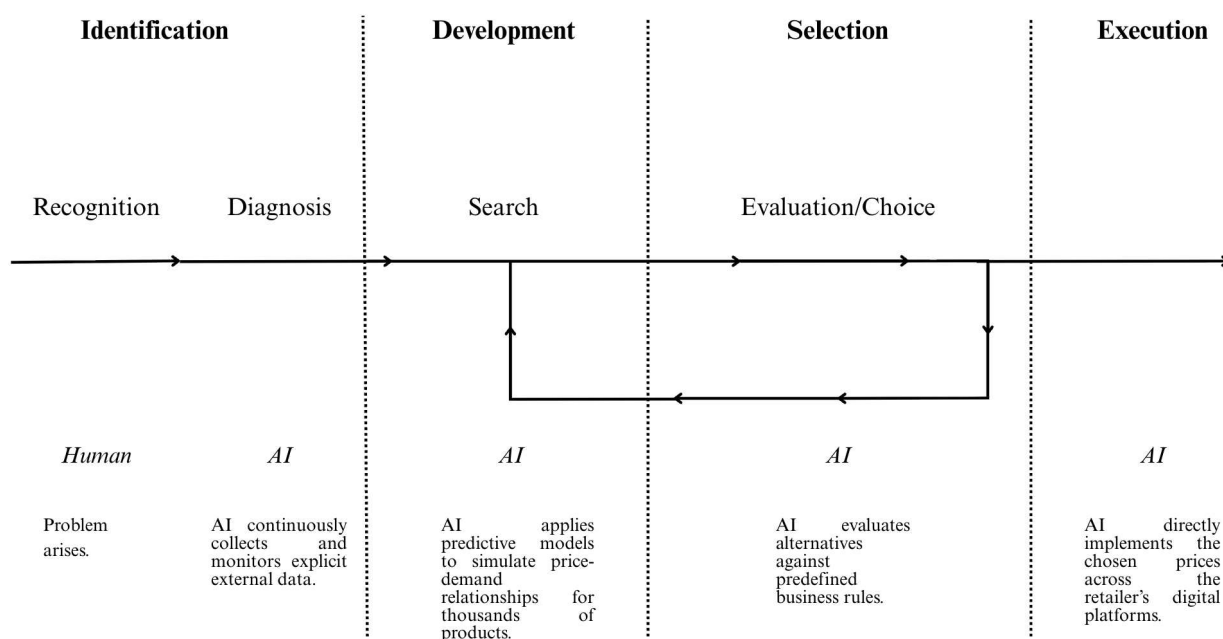
The AI models most suited for this case are Machine Learning (reinforcement and supervised) to continuously learn optimal pricing strategies, and Agentic AI to implement the real-time adjustments directly into the e-commerce.

This is a basic search decision process (Mintzberg, Raisinghani, & Théorêt, 1976). It is a straightforward process, in which automation algorithms are applied to well-defined tasks to find ready-made solutions. There is no design involved since efficiency and replicability dominate. The recognition of the need for a decision arises with the problem of the optimization of the prices of thousands of products daily.

AI here is active in every phase of the process, from identification to scan prices and demand data, to execution in the retailer's platform.

*Figure 19* illustrates this process.

## Contingent Views on AI Adoption in Organizational Decision Making



**Figure 19. Dynamic Pricing in E-Commerce. Author's elaboration.**

Therefore, with these contingencies:

- The speed is extremely high.
- The size of the alternatives set is massive.
- The need for human oversight is low.
- The decision is operational.
- The data is external explicit.
- The firm prioritizes efficiency rather than complementarity.

The optimal human-AI configuration would be the full delegation to AI.

### 3.8.5. Supply Chain Decision

A global logistics firm needs to program shipments daily, balancing cost, time, and environmental impact. The required speed is high, as the decision is taken daily. The alternatives set is large but well-defined, and the need for human oversight is low to medium. The data that needs to be collected is internal explicit.

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The optimal human-AI configuration in this case could be, again, the full delegation to AI, as the machine can evaluate a high number of possible route combinations and propose optimal sets. In fact, this is a highly operational decision, in which AI surpasses humans (Trunk, Birkel, & Hartmann, 2020). However, the process could also be sequential without specialization (AH) (Puranam, 2021; Jain, Garg, & Khera, 2023) if there is the need for human validation in case of external unforeseen factors (like union strikes or weather anomalies).

The AI models most suited for this case are dynamic Constraint Satisfaction Problems (CSPs) to adapt the optimal routes dynamically in response to changing conditions, and Agentic AI to create daily shipments schedules automatically.

This is a basic or modified search decision process (Mintzberg, Raisinghani, & Théorêt, 1976). The solution is ready-made, since optimized routes already exist, but sometimes they need to be adjusted when unforeseen events require human intervention, and in this case the solution would be modified, and the design routine would be present.

AI here is active in each phase of the process.

Figure 20 illustrates the process.

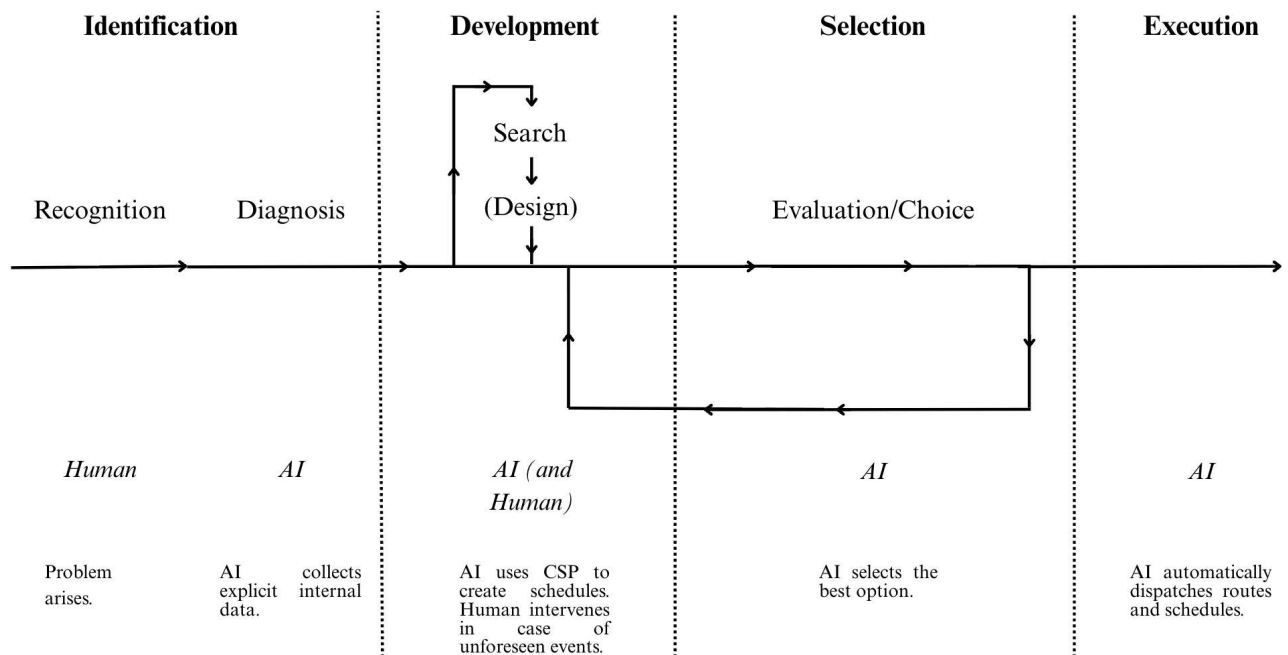


Figure 20. Supply Chain Decision. Author's elaboration.

Therefore, with these contingencies:

- The speed is high.
- The size of the alternatives set is large.
- The decision is operational.
- Efficiency is preferred to accuracy.
- The need for human oversight is low to medium.
- The data is internal explicit.

The optimal human-AI configurations can be full delegation or sequential without specialization, with the AI task coming first.

### **3.8.6. HR Recruitment for Specialized Roles**

A tech company wants to hire a niche AI ethics specialist. The required speed is low to moderate. The alternatives set is small, but the need for human oversight is very high because of the assessment of the values and ethics alignment of the candidate. The data to be collected is partly external explicit, but mainly implicit from interviews. The context is highly unfamiliar, since it is the first time the company hires such a role.

The optimal human-AI configuration in this case is Configuration 4, sequential with specialization (AH) (Puranam, 2021; Jain, Garg, & Khera, 2023). This is because the AI filters possible candidates from a large database, but humans perform interviews and assess the actual fit of the candidate, collecting implicit information that the AI would not be capable to detect or interpret. In unfamiliar settings, according to Hao, Demir, & Evers (2024), human decision makers are more prone to rely on heuristics and biases, so the filtering of the candidates done by the AI on the basis of explicit criteria reduces the risk of a biased selection. The required speed supports the idea of a sequential process rather than a parallel one.

The AI models most suited for this case are Large Language Models (LLMs) to filter candidates based on their CVs and possible papers.

This is a political design decision process (Mintzberg, Raisinghani, & Théorêt, 1976). The solution is custom-made since the role is highly specific, therefore there is no ready-made

## Contingent Views on AI Adoption in Organizational Decision Making

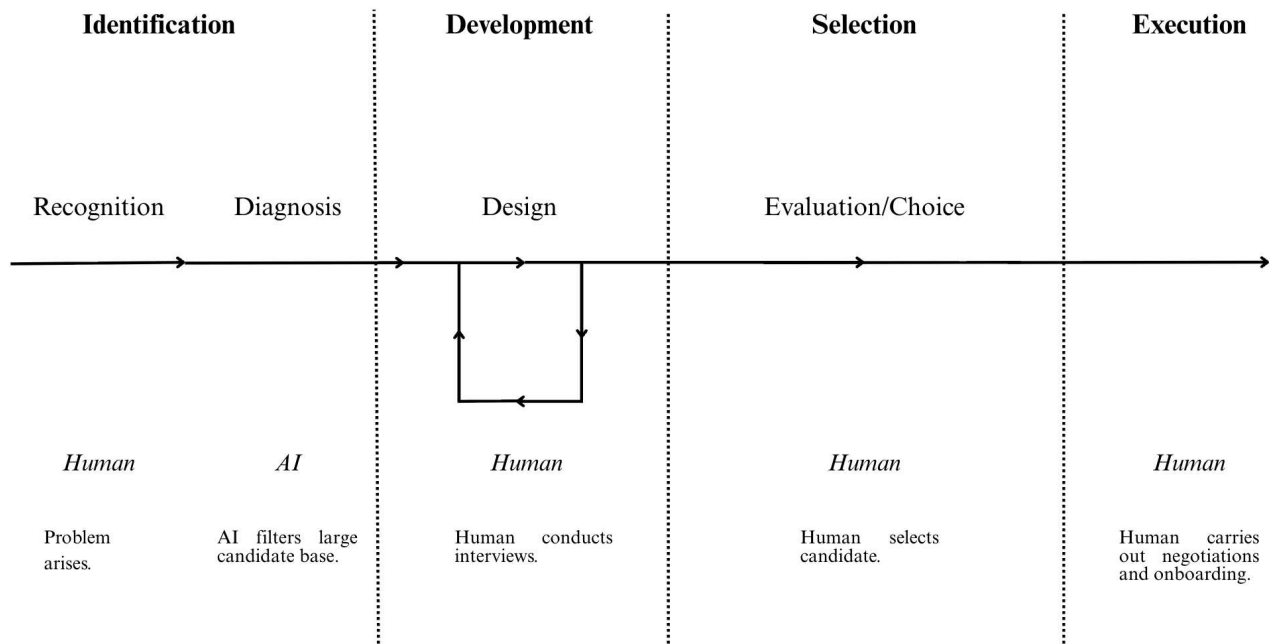
solution. In this case, political design, a development activity, is substantial because of the need for a high values and ethics alignment, a cultural fit, and the consideration of political aspects, such as the stakeholders' view on the candidate. In fact, multiple interests shape the outcome. AI here is active in the identification phase to filter candidates from databases using LLMs. *Figure 21* illustrates the process.

*Figure 21* illustrates the process.

Therefore, with these contingencies:

- The speed is low to moderate.
- The size of the alternatives set is small.
- The need for human oversight is very high.
- The context is unfamiliar.
- The data is partly external explicit, but mainly implicit.

The optimal human-AI configuration would be sequential with specialization, with the AI task coming first.



**Figure 21. HR Recruitment for Specialized Roles. Author's elaboration.**

### 3.8.7. Email Marketing Campaign Optimization

A fast fashion brand wants to personalize email marketing for millions of customers. The required speed is high, as the emails need to be optimized almost in real-time, and the alternatives set is huge and dynamic, because of different messages, offers, and timing, for different segments or even individuals. The need for human oversight is medium-low. The data to be collected is external (for prospects) and internal (for leads and customers) explicit. The data analytics capabilities of the team are advanced.

The optimal human-AI configuration in this case is full delegation to AI. This is because the data is explicit, the alternatives set is huge, and the required speed is high, while interpretability needs are low (Shrestha, Ben-Menahem, & Von Krogh, 2019). The decision is also operational and highly frequent, so according to Dell'Acqua, Kogut, & Perkowski (2025) is ideal for full delegation. This is also supported because of the advanced data analytics capabilities, which guarantee that the AI can handle the entire process (Yablonsky, 2019).

The AI models most suited for this case are Machine Learning (unsupervised) for segmentation, and Generative AI for content generation. In this case, Agentic AI is not used since the system does not autonomously define objectives beyond campaign personalization. However, the process could benefit from Agentic AI if the system dynamically reallocates resources, explores new segments, and operates across different channels with minimal human intervention.

This is a modified search decision process (Mintzberg, Raisinghani, & Théorêt, 1976). The solution is somewhat ready-made since personalized campaigns most of the times follow a structured, repeatable pattern, but it is customized for each customer. Therefore, the solution is modified: the algorithm adapts existing personalization rules dynamically.

It is important to note that Mintzberg, Raisinghani, & Théorêt (1976) recognized every marketing decision they analyzed as a basic search decision process. This seems like a contradiction; however, in 1976 personalization was not feasible because of the technological and organizational capabilities of the era. Additionally, it was not even a requirement of customers, as it is today. Therefore, every solution was ready-made: choose a channel, set a budget, pick a message. Today, on the other hand, Artificial Intelligence makes personalization

## Contingent Views on AI Adoption in Organizational Decision Making

possible, and this means that marketing decisions no longer simply select from ready-made solutions. This does not contradict the authors, but rather shows how AI changes the typology of the process in practice.

AI here is active in every phase of the process.

Figure 22 illustrates the process.

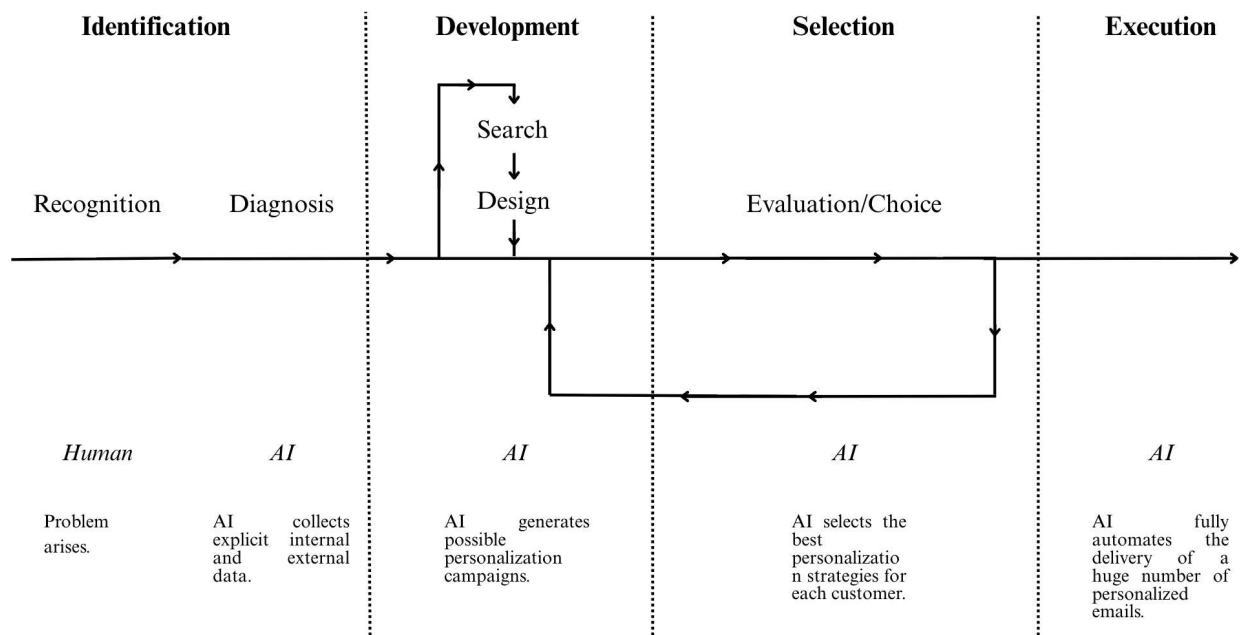


Figure 22. *Email Marketing Campaign Optimization. Author's elaboration.*

Therefore, with these contingencies:

- The speed is high.
- The size of the alternatives set is huge.
- The decision is operational and highly frequent.
- The need for human oversight is medium-low.
- The data is external and internal explicit.
- The data analytics capabilities of the team are advanced.

The optimal human-AI configuration would be the full delegation to AI.

### **3.9. Managerial Implications**

The implications for managers are significant: to successfully integrate AI into decision making, firms must design context-specific processes that account for the type of information, the criticality of the task, ethical considerations, skills, and AI literacy, among other factors.

When facing a decision, managers should follow a strict thought process to choose the right configuration of human-AI collaboration. First, they should clarify the nature of the decision: is it strategic or operational, familiar or unfamiliar, short-term or long-term? After this, the type of information involved should be assessed: is it explicit or implicit, internal or external? Then, managers should evaluate organizational capabilities, like the level of AI literacy and the data analytics skills. The level of oversight needed is also an important variable to be evaluated.

On the basis of these considerations, after carefully analyzing all the contingencies at play, managers can select the most appropriate collaboration configuration. In this way, the adoption of AI in decision making becomes not a binary choice of whether to rely on humans or machines, but a design challenge of aligning decision processes, technologies, and organizational structures with specific contingencies.

Leadership styles must also adapt, as in the first stages of implementation there should be more of a transformational leadership to build trust and participation, whereas in later stages, the leadership should be more transactional and efficiency-oriented (Shao, Feng, & Hu, 2015).

Managers must understand that competitive advantage does not derive from the adoption of AI per se, but from a firm's ability to design fit-for-purpose decision-making processes. Managers should move away from benchmarking best practices and instead analyze the contingencies which define their context and how, depending on them, they should configure AI and human roles. Those able to critically consider the role of contingencies will be able to integrate AI more effectively and achieve differentiation in a marketplace where the technology itself is widely available.

### 3.10. Conclusions

The analysis developed in this chapter highlights the need for a contingent approach when integrating AI into organizational decision-making processes. The literature around this topic is limited, but the first section collects references that support the idea that there is no universal, optimal model for human-AI collaboration. Instead, the integration depends on contingencies like the decision characteristics, organizational contexts, and technological capabilities. This is particularly important because, as Deloitte (2023) sustains, competitive advantage emerges not simply from adopting AI tools, but from integrating them in unique ways that reflect firm-specific strategies, values, and contexts.

This chapter also provides four existing frameworks for decision-making processes supported by Artificial Intelligence.

Trunk, Birkel, & Hartmann (2020) emphasize how the type of information available influences the process. In fact, implicit information, such as emotions or tacit knowledge, cannot be accurately collected and interpreted by AI, so the task of collecting it remains in the hands of humans. By contrast, explicit information can be processed most times more efficiently by AI, particularly in contexts where speed is critical. The authors also state that operational decisions are more suited for AI intervention than strategic ones. The process is also influenced by organizational structures, AI literacy, data transparency, and ethical perspectives.

Jain, Garg, & Khera (2023) continue the work of Puranam (2021) and his six human-AI collaboration configurations demonstrating how sequential configurations without specialization tend to generate low levels of trust, whereas parallel configurations with specialization or sequential configurations with specialization improve both trust and role clarity.

Shrestha, Ben-Menahem, & Von Krogh (2019) show that the appropriateness of the configurations depends on factors such as the search space specificity, interpretability, the alternatives set size, speed, and replicability. The authors evaluate three different configurations against these criteria: full human to AI delegation, hybrid (AI-to-human and human-to-AI) sequential decision making, and aggregated human-AI decision making. If the decision search space is small, accuracy is preferred to interpretability, the alternatives set is large, speed is

critical, and replicability is needed, then full delegation is the right choice. The first hybrid structure (AH) is used in contexts where the alternatives set is so large that humans alone could not handle it, although the process becomes slower. The second hybrid structure (HA), on the other hand, is appropriate where the alternatives set is small, but a high amount of data needs to be processed to evaluate these alternatives. The aggregated structure, finally, is useful where the AI focuses on quantitative data, while the human focuses on qualitative data.

Yablonsky (2019) emphasizes that the level of organizational data analytics capabilities is a decisive factor, since firms with advanced capabilities can extract more value from automation, whereas others may need to focus on augmentation. The author proposes five types of processes, each linked with an increasing corresponding level of AI, Big Data, and Advanced Analytics capabilities: human led; human led, machine supported; machine led, human supported; machine led, human governed; machine controlled.

The final section of this chapter proposes a series of business scenarios that put these theoretical insights into practice. Seven cases are presented: a long-term M&A strategy, a short-term M&A strategy, a product development decision, a dynamic pricing case, a supply chain decision, an HR recruitment case for specialized roles, and an email marketing campaign optimization.

What emerges is that the effectiveness of the process depends on contingencies like the time horizon, the speed, the oversight requirements, and organizational capabilities, among others. Moreover, strategic decisions should be governed by humans, with AI acting as a support tool, whereas operational ones, requiring speed and efficiency, and the processing of massive datasets, are prone to full delegation to AI, particularly in cases where the human oversight requirement is low.

The analysis of the seven scenarios leads to these conclusions:

- For strategic, unfamiliar, and high-oversight decisions, the process is a dynamic or political design in which AI supports but humans still dominate.
- For repetitive, operational, and efficiency-driven decisions, the process is a basic or modified search in which AI dominates.

## Contingent Views on AI Adoption in Organizational Decision Making

- For complex and strategic decisions, where huge amounts of data need to be analyzed, and the decision search space is large, the process is a dynamic design in which AI and humans collaborate.

This chapter demonstrates that AI adoption in decision making is not anymore a question of whether to integrate Artificial Intelligence, but how to integrate it. The managerial implications section highlights that there is no one-size-fits-all solution; competitive advantage comes from the ability to align AI models, processes, and organizational structures to the specific context.

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