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Reasoning under Uncertainty: A Dual-Process Perspective on Decision-Making in the Digital Age

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Abstract:

In increasingly complex and data-saturated organizational environments, understanding the cognitive mechanisms behind managerial decision-making has become a critical research issue. While classical models portray decision-makers as rational actors following linear, logic-based processes, behavioral research highlights the influence of cognitive biases and heuristics. This conceptual paper draws upon dual-process theory (Kahneman, Stanovich & West), which distinguishes between two cognitive systems: System 1, fast and intuitive, and System 2, slow and analytical. Building on a multidisciplinary literature review spanning cognitive psychology, behavioral decision-making, and management science, the paper explores how information uncertainty influences the activation of these reasoning styles. It further considers the growing presence of digital decision environments, such as Business Intelligence platforms and artificial intelligence systems, which seek to reduce uncertainty but may also shift cognitive dynamics. The article aims to provide a theoretical foundation for understanding how individuals adapt their reasoning under uncertainty, and to inform the future design of cognitively aligned decision support tools. It targets scholars in organizational behavior, cognitive decision theory, and information systems, offering a structured conceptual framework for advancing research and managerial insight. This is a theoretical contribution without original empirical data, but grounded in contemporary challenges facing decision-makers in technologically mediated contexts.

Keywords : decision-making – uncertainty – cognitive styles – System 1 / System 2 – Business Intelligence – artificial intelligence.
Classification JEL : D81 – M15
Paper type : Theoretical Research

Résumé:

Dans un environnement organisationnel marqué par la surcharge informationnelle et l'incertitude, la compréhension des mécanismes de prise de décision devient un enjeu crucial. Si les approches classiques postulent un décideur rationnel suivant une démarche logique et séquentielle, les recherches contemporaines issues de l'économie comportementale soulignent la prégnance des biais cognitifs et des raisonnements approximatifs. Cet article propose un cadre conceptuel mobilisant la théorie du double processus (Kahneman, Stanovich & West), qui distingue deux systèmes cognitifs : l'un rapide, intuitif et automatique (Système 1), et l'autre plus lent, réfléchi et analytique (Système 2). À partir d'une revue approfondie de la littérature en psychologie cognitive, en sciences de gestion et en systèmes d'information, l'article examine comment l'incertitude informationnelle influence l'activation de ces styles de raisonnement. Ce travail s'inscrit dans le contexte des environnements numériques contemporains, tels que les systèmes de Business Intelligence et les dispositifs basés sur l'intelligence artificielle, qui visent à réduire l'incertitude mais introduisent aussi de nouveaux défis cognitifs. L'ambition est double : proposer un éclairage théorique sur les formes de rationalité mobilisées en situation d'incertitude, et ouvrir des pistes pour une meilleure conception des outils d'aide à la décision. L'article s'adresse aux chercheurs en management, psychologie organisationnelle et systèmes d'information, et s'inscrit dans une démarche conceptuelle et théorique visant à structurer un cadre explicatif transférable aux environnements décisionnels complexes.

Mots clés : prise de décision – incertitude – styles cognitifs – Système 1 / Système 2 – Business Intelligence – intelligence artificielle.
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1. Introduction

In an era marked by data proliferation, volatile environments, and digital transformation, organizational decision-making is increasingly confronted with uncertainty. From strategic planning to operational choices, managers are required to process large volumes of information—often incomplete, ambiguous, or conflicting—while maintaining responsiveness and effectiveness. Traditional decision-making models, rooted in economic rationality, have long portrayed individuals as deliberate agents who evaluate all available alternatives in a linear and optimal fashion (von Neumann & Morgenstern, 1944; Simon, 1955). However, this normative vision has been challenged by decades of research in behavioral sciences, emphasizing the role of bounded rationality (Simon, 1957), cognitive heuristics (Tversky & Kahneman, 1974), and intuitive judgments (Gigerenzer & Gaissmaier, 2011; Hogarth, 2001).

Over the past decades, decision sciences have evolved from purely normative models toward integrative frameworks that combine insights from psychology, management science, and information systems. This evolution reflects a recognition that managerial decision-making is not only a matter of computational optimization, but also a socially embedded, cognitively bounded, and technologically mediated process. As such, effective decision-making must be understood through the combined lenses of cognitive psychology (how individuals think), management science (how organizations structure decisions), and information systems (how technology supports or constrains reasoning).

This theoretical shift has led to models that explain dual modes of reasoning. Dual-process theories (Kahneman, 2011; Stanovich & West, 2000; Epstein, 1994) distinguish between two cognitive systems: System 1, which is fast, automatic, and intuitive, and System 2, which is slower, deliberate, and analytical. These systems do not operate in isolation but are dynamically mobilized depending on situational demands. Under conditions of clarity and structure, individuals tend to engage System 2 and adopt rational strategies. Conversely, in uncertain, time-pressured, or information-poor settings, System 1 may dominate, leading to intuitive or heuristic-based decisions (Evans, 2008; Hammond et al., 1987). Moreover, recent research suggests that this interplay is further shaped by contextual factors such as cognitive load (Sweller, 1988), perceived ambiguity (Furnham & Ribchester, 1995), and individual experience (Kahneman & Klein, 2009; Vosgerau & Peer, 2018).

In managerial contexts, these cognitive systems manifest in specific ways. System 1 may drive rapid judgments during crises, negotiations, or market shocks, where speed is prioritized over exhaustive analysis. System 2, in contrast, underpins strategic planning, budgeting, and policy development, where time allows for data-driven reasoning. However, the boundary between the two is porous, and effective decision-making often involves an adaptive oscillation between intuitive and analytical modes depending on task demands and environmental volatility.

Building on this cognitive-behavioral foundation, the present article explores how information uncertainty influences the activation of reasoning styles in managerial contexts. Specifically, it proposes a conceptual framework to better understand the determinants of intuitive versus analytical thinking under varying levels of uncertainty. While the theoretical lens remains anchored in cognitive psychology, the paper also acknowledges the growing role of digital decision environments. Business Intelligence (BI) systems and emerging Artificial Intelligence (AI) technologies aim to reduce uncertainty by enhancing access to data and analytical capabilities (Shollo & Galliers, 2016; Tolpezhnikov et al., 2024).

Yet, the integration of BI and AI into decision-making processes also raises conceptual and practical challenges. From a cognitive perspective, these technologies can both alleviate and exacerbate uncertainty. They can enhance System 2 reasoning by providing structured, relevant, and timely data, but they may also generate cognitive overload, algorithmic opacity, or contradictory outputs that trigger reliance on System 1. This dual effect makes the relationship between technology and cognition complex, requiring a more nuanced understanding of how decision-makers navigate information-rich yet ambiguous digital environments.

Yet paradoxically, these systems may also introduce new layers of complexity or opacity—particularly when algorithmic outputs lack transparency or interpretability (Burton et al., 2020; Doshi-Velez & Kim, 2017). Recent findings indicate that in such contexts, decision-makers may revert to intuitive judgments, not due to ignorance, but as an adaptive response to informational ambiguity (Constantiou, Shollo, & Vendelø, 2019; Attari, Krantz, & Weber, 2021).

By revisiting the foundations of decision-making under uncertainty and aligning them with today's complex technological environments, this article seeks to (1) clarify the cognitive mechanisms at play in ambiguous situations, and (2) offer theoretical grounding for future research and decision-support design. The contribution is conceptual and integrative, targeting scholars in management science, behavioral decision theory, and information systems.

2. Theoretical Foundations on Decision-Making Under Uncertainty

Decision-making has long been a central concern in both managerial theory and cognitive science. To understand how individuals make choices under uncertainty, it is essential to revisit the conceptual models that have historically shaped this field. This section presents a progression from classical rational frameworks to behavioral theories, culminating in dual-process models that distinguish between intuitive and analytical reasoning. This theoretical trajectory allows us to explore how uncertainty—especially informational ambiguity—can influence cognitive processes and reasoning styles in modern decision environments.

2.1. Classical Decision-Making Models: The Ideal of Rationality

Classical decision-making theories have long portrayed individuals as rational agents who process information logically and exhaustively to reach optimal outcomes. This view, deeply rooted in economics and early management science, assumes that decision-makers are fully informed, capable of ranking alternatives, and consistent in their preferences. In such models, uncertainty is often reduced to quantifiable risk, allowing decision-makers to compute expected utilities and make choices accordingly (von Neumann & Morgenstern, 1944).

At the core of this rational paradigm lies the idea of an objective reality that can be fully captured through systematic information gathering and analytical evaluation. Herbert Simon (1955) formalized this perspective through the notion of **"economic man,"** a theoretical construct capable of maximizing utility in a predictable and structured environment. Later models, such as those developed by March and Simon (1958), retained this optimization logic but began to question its psychological plausibility, introducing the idea of information limitations.

In classical models, the decision-making process is typically structured into sequential steps: identifying the problem, defining objectives, generating alternatives, evaluating outcomes, and selecting the best course of action (Bazerman & Moore, 2013). These stages reflect an idealized cognitive process where uncertainty is manageable, and decision-makers act with clarity and coherence.

Despite its normative elegance, this rationalist model has been increasingly criticized for its limited applicability to real-world organizational settings. In practice, decision-makers often lack complete information, face time constraints, and operate under emotional or political pressures that hinder exhaustive analysis (March, 1994). Moreover, the assumption of stable preferences and calculative consistency does not always hold, particularly in environments characterized by complexity and information ambiguity.

As a result, while the classical model remains foundational in decision theory, it offers only a partial lens for understanding how individuals actually make decisions under uncertainty. This realization has paved the way for alternative theoretical perspectives—most notably those from behavioral economics and cognitive psychology—that recognize the bounded nature of human rationality and the pervasive influence of cognitive shortcuts. These developments are explored in the following section.

2.2. Behavioral Approaches: Bounded Rationality, Biases and Uncertainty

The classical model of decision-making, with its emphasis on optimization and comprehensive information processing, has been widely criticized for its unrealistic cognitive assumptions. In response, behavioral scholars have introduced alternative models that account for the cognitive limitations of individuals, particularly under conditions of uncertainty. At the forefront of this paradigm shift is Herbert Simon's (1955, 1957) theory of bounded rationality, which posits that individuals do not seek to optimize but rather to "satisfice"—that is, to select the first option that meets acceptable thresholds. This concept acknowledges that decision-makers operate with limited cognitive resources, incomplete information, and time constraints.

Bounded rationality laid the groundwork for a vast body of research on heuristics and cognitive biases, most notably the work of Tversky and Kahneman (1974). Heuristics—mental shortcuts or rules of thumb—allow individuals to make decisions quickly, but they also introduce systematic biases. For instance, the availability heuristic leads individuals to overestimate the likelihood of events that are easily recalled, while the representativeness heuristic can result in the neglect of base-rate information. These deviations from normative logic are not random errors but patterned responses to environmental and informational constraints.

In decision contexts characterized by uncertainty, these heuristics become particularly salient. Unlike risk, which is measurable and probabilistic, uncertainty refers to situations where probabilities are unknown or unknowable (Knight, 1921). Under such conditions, individuals are less able to rely on calculated reasoning and more prone to intuitive judgments and simplifications (Kahneman & Tversky, 1982; Gigerenzer & Gaissmaier, 2011). Behavioral decision-making thus emerges not as a flawed version of rationality, but as an adaptive response to complex, ambiguous environments.

Furthermore, the organizational context often amplifies these cognitive dynamics. Time pressure, overload of information, conflicting goals, and emotional factors can all distort rational evaluation and lead to what March and Olsen (1976) describe as "garbage can" decision processes—where solutions, problems, and participants are loosely coupled in unpredictable ways. Such conditions make it increasingly difficult to follow systematic reasoning paths, and highlight the need for theoretical frameworks that better account for the interplay between uncertainty and cognitive functioning.

These insights have laid the theoretical foundation for dual-process models, which aim to capture the interaction between intuitive and analytical reasoning in real-world decision-making. The next section elaborates on these models and their relevance to environments marked by informational ambiguity and technological mediation.

While much of the literature has traditionally contrasted classical and behavioral approaches, recent advances emphasize more integrative perspectives. Rather than viewing rationality and intuition as mutually exclusive, contemporary models conceptualize decision-making as a **dynamic continuum** shaped by context, expertise, and emotional states (Hodgkinson & Sadler-Smith, 2018; Sinclair, 2014). This continuum framework suggests that bounded rationality, emotion, and intuition can coexist and interact in varying proportions, depending on situational demands and cognitive resources. For instance, Hammond et al. (1987) propose a "cognitive continuum theory" in which analytical and intuitive processes are mobilized fluidly rather than in discrete modes, allowing decision-makers to adapt their reasoning style dynamically. Such integrative views are increasingly relevant for managerial contexts, where decisions often blend structured analysis with adaptive judgment in response to evolving uncertainty.

2.3. Dual-Process Theories and Cognitive Reasoning Styles

While behavioral approaches have highlighted the limitations of human rationality, they have also paved the way for a more refined understanding of how individuals process information and make decisions under uncertainty. One of the most influential frameworks in this regard is dual-process theory, which conceptualizes decision-making as the result of two distinct but interacting cognitive systems: System 1 and System 2 (Kahneman, 2011; Stanovich & West, 2000).

System 1 operates automatically, quickly, and with minimal cognitive effort. It relies on intuition, pattern recognition, and affective responses, enabling individuals to respond rapidly to familiar or urgent situations. In contrast, System 2 is slower, effortful, and reflective. It is responsible for analytical reasoning, logical computations, and the inhibition of automatic responses (Evans, 2008). Although often associated with accuracy and rationality, System 2 is resource-intensive and not always engaged, especially under stress or cognitive overload.

Rather than functioning in isolation, these systems interact dynamically. The relative influence of each system should therefore be conceived as a fluid continuum rather than a strict dichotomy, with moment-to-moment shifts shaped by contextual cues such as time pressure, task framing, or perceived information reliability (Evans, 2008; Hammond et al., 1987). System 1 often generates an initial response, which System 2 may then monitor, endorse, or override. However, under conditions of uncertainty, time pressure, or information overload—frequent in real organizational settings—System 1 tends to dominate (Hogarth, 2001; Stanovich, 2009). This shift is not inherently flawed: intuitive processes can be effective, especially when based on expertise or when decisions must be made quickly (Kahneman & Klein, 2009). Yet they also increase vulnerability to biases and errors, particularly when uncertainty distorts information salience or when prior patterns are no longer reliable.

Recent research has emphasized the importance of individual differences in cognitive style. Some decision-makers exhibit a chronic tendency toward intuitive thinking, while others are more deliberative by default (Pacini & Epstein, 1999; Witteman et al., 2009). These stable preferences interact with contextual cues—such as the level of ambiguity or task complexity—to determine which system is activated. These tendencies act as continuous weights on the contribution of each system, so that expertise, tolerance for ambiguity, and cognitive style modulate the proportion of intuitive versus analytical processing in any given decision episode (Kahneman & Klein, 2009; Vosgerau & Peer, 2018). This person-environment interaction is especially relevant in the era of digital decision environments, where decision support systems, dashboards, and AI recommendations are becoming integral to managerial work.

In real-world settings, contextual determinants such as organizational culture, decision stakes, and information presentation can lead to co-activation patterns where intuitive insights seed hypotheses that are subsequently audited by deliberative analysis, and vice versa.

Technological tools, particularly in Business Intelligence (BI) and Artificial Intelligence (AI) domains, aim to support analytical thinking by structuring information and reducing uncertainty. However, paradoxically, they can also introduce new ambiguities—such as opaque algorithms or conflicting indicators—that may activate intuitive shortcuts instead of analytical reasoning (Shollo & Galliers, 2016; Cardinaels & Yin, 2024). This suggests that in BI/AI-supported environments, dual-process activation is better understood as a context-sensitive interplay, where analytical outputs structure evidence for reflection while intuitive expertise highlights anomalies or salient cues for further investigation (Shollo & Galliers, 2016).

This highlights the need to consider not only technological affordances but also cognitive mechanisms when analyzing decision behavior in information-rich contexts.

In summary, dual-process theory provides a powerful lens to examine how uncertainty and informational complexity shape the reasoning styles of organizational decision-makers. It also

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serves as a conceptual bridge between traditional behavioral approaches and the emerging challenges posed by digital and AI-mediated decision environments.

Although dual-process theories provide a valuable distinction between intuitive (System 1) and analytical (System 2) reasoning, their activation is far from uniform across individuals or contexts.

Empirical studies show that factors such as domain expertise, cognitive load, emotional state, and organizational culture can significantly influence which system is mobilized (Kahneman & Klein, 2009; Evans & Stanovich, 2013; Sadler-Smith, 2016). For example, experts may rely on intuition in familiar domains without sacrificing accuracy, whereas novices tend to engage more analytical processing to compensate for limited experiential knowledge. Similarly, time pressure or high-stress situations can shift even experienced decision-makers toward heuristic shortcuts. This variability highlights the need to view the two systems not as rigid categories, but as flexible resources that interact dynamically within real-world decision contexts.

Furthermore, while traditional uncertainty frameworks often address measurable risks, incomplete data, or ambiguous information, contemporary decision environments—particularly in digital and algorithmic contexts—are increasingly characterized by *unknown unknowns* (Knight, 1921; Walker et al., 2013). These refer to uncertainties that cannot be anticipated or quantified ex ante, such as emerging market disruptions, unforeseen algorithmic biases, or sudden shifts in stakeholder behavior. Unlike classical ambiguity, such radical uncertainties challenge both analytical prediction models and intuitive pattern recognition, requiring adaptive strategies that combine scenario planning, resilience-building, and continuous information scanning (Taleb, 2007; Kay & King, 2020). Recognizing this category of uncertainty expands the theoretical model to better reflect the volatile, uncertain, complex, and ambiguous (VUCA) conditions prevalent in contemporary managerial environments.

3. Conceptual Framework and Propositions

Understanding how individuals process information and make decisions under uncertainty requires not only revisiting foundational theories but also integrating these insights into a coherent conceptual framework. Building on the dual-process model, this section proposes a theoretical articulation of how information uncertainty may affect the activation of intuitive (System 1) or analytical (System 2) reasoning in organizational decision-making contexts.

3.1. Information Uncertainty as a Cognitive Trigger

Uncertainty has always posed a fundamental challenge to human decision-making, but its **epistemological nature** and **cognitive consequences** are often misunderstood. Drawing on the seminal work of Knight (1921), uncertainty is distinguished from risk in that it refers not to probabilistically known outcomes, but to situations in which **the probabilities themselves are unknown or unknowable**. This form of **epistemic ambiguity** becomes particularly salient in modern organizational environments where decision-makers rely on large volumes of data, dashboards, and predictive algorithms—often embedded in Business Intelligence (BI) and Artificial Intelligence (AI) systems.

Information uncertainty can manifest in multiple ways: **incomplete data**, conflicting indicators, ambiguous causality, or rapidly changing contexts that render historical data obsolete (Shollo & Galliers, 2016; Lipshitz & Strauss, 1997). Beyond these forms, contemporary digital contexts increasingly expose decision-makers to “fundamental uncertainties” (Kay & King, 2020) or “unknown unknowns” (Knight, 1921). These refer to situations where not only the outcomes but even the relevant variables are unforeseeable ex ante. In fast-evolving algorithmic environments, such radical uncertainty may stem from emerging technologies, sudden regulatory changes, or unforeseen interactions between autonomous systems. Unlike classical ambiguity, these conditions undermine both probabilistic modelling and heuristic pattern recognition, requiring adaptive strategies that emphasize resilience, exploratory analysis, and continuous environmental scanning. Unlike random noise, such uncertainty often reflects deeper structural ambiguity, leading to what Weick (1995) describes as a collapse in sensemaking. In such conditions, the process of interpreting and selecting information becomes cognitively demanding and emotionally taxing.

From a cognitive standpoint, uncertainty functions as a **trigger for system activation** within the dual-process framework. The analytical system (System 2), responsible for reflective and effortful reasoning, requires **cognitive stability**: consistent information, known parameters, and clearly framed problems. Uncertainty disrupts this stability by increasing **cognitive load**—that is, the mental effort required to process and integrate information coherently (Sweller, 1988; Evans, 2008). As this load exceeds available attentional and working memory resources, the brain shifts toward **System 1**, the intuitive and automatic mode of reasoning, as a compensatory strategy.

This shift is not merely a cognitive shortcut, but a **structural adaptation**: System 1 enables individuals to respond swiftly to ambiguous situations by drawing on heuristics, pattern recognition, or affective cues (Kahneman, 2011). While efficient, such mechanisms are prone to error—particularly when uncertainty alters the **salience** of information, making irrelevant details appear more influential or masking critical cues. This is often observed in volatile business contexts where decision-makers overreact to recent trends or exhibit confirmation bias in the face of ambiguous evidence (Tversky & Kahneman, 1974).

In digital decision environments, this phenomenon is exacerbated. Tools designed to reduce uncertainty—such as dashboards, machine learning algorithms, or data visualizations—can paradoxically **generate new layers of ambiguity**: lack of algorithmic transparency, inconsistent metrics, or overload of conflicting signals (Cardinaels & Yin, 2024; Tolpezhnikov et al., 2024). As a result, decision-makers may simultaneously experience a **surfeit of data and a deficit of clarity**, further reinforcing reliance on intuitive judgment.

In sum, information uncertainty acts not only as a contextual variable but as a **cognitive determinant** of reasoning mode activation. Its role as a **trigger** in the dual-process architecture underscores the need for conceptual models that go beyond informational input and consider the interpretive and neurocognitive conditions under which decisions are made.

3.2. From Uncertainty to Reasoning Style: A Dual-Process View

Dual-process theory posits that human cognition operates through two qualitatively distinct systems: System 1, which is fast, automatic, and intuitive, and System 2, which is slow, effortful, and analytical (Kahneman, 2011; Stanovich & West, 2000). In controlled environments where information is complete, reliable, and easy to interpret, System 2 tends to dominate, allowing individuals to engage in deliberate evaluation. However, under conditions of uncertainty, the balance between these systems shifts—often dramatically.

Uncertainty disrupts the cognitive preconditions for analytical reasoning. Without clear reference points, consistent indicators, or structured causality, System 2 struggles to construct logical paths, while System 1 is readily activated to provide immediate, albeit approximate, interpretations. This cognitive reallocation is not solely a matter of mental efficiency—it reflects a neuropsychological response to perceived ambiguity and complexity (Evans & Stanovich, 2013). Indeed, the brain favors minimal effort and defaults to System 1 unless System 2 is strongly cued or necessary (Stanovich, 2009).

Crucially, contemporary research suggests that this balance is rarely binary or static. Instead, System 1 and System 2 often operate in overlapping and fluid sequences, with moment-to-moment shifts shaped by both individual and situational factors. These include domain expertise, emotional state, stress level, organizational culture, and even task framing

(Kahneman & Klein, 2009; Sadler-Smith, 2016). For example, an expert under moderate time pressure may integrate rapid pattern recognition with targeted analytical checks, while a novice in the same situation may revert more fully to intuitive heuristics. Similarly, cultural norms around decision speed, hierarchy, or consensus can subtly bias the activation balance between the two systems.

In this sense, uncertainty functions as a situational determinant of cognitive style. In low-uncertainty conditions, information can be more easily processed through systematic analysis, encouraging the engagement of System 2. Conversely, high-uncertainty scenarios inhibit deliberation and increase reliance on intuitive mechanisms such as heuristics or affective judgments (Hogarth, 2001; Tversky & Kahneman, 1974). This is consistent with findings in managerial psychology showing that under ambiguity, executives favor speed over accuracy and lean on intuition rather than data-based models (Sadler-Smith & Shefy, 2004).

It is important to note that this shift is not binary. Both systems may be active, but their relative influence varies depending on the context and cognitive load (Epstein et al., 1996; Kahneman & Klein, 2009). For example, a manager may initially interpret a situation intuitively but still validate or adjust that judgment through deliberative reflection—provided that time and cognitive resources are available. This perspective has led scholars to advocate for interactionist models, which emphasize not only the systems themselves, but also the conditions under which one overrides or complements the other (Evans, 2008; Alter et al., 2007).

Importantly, the nature of information uncertainty in digital environments—including AI systems, predictive analytics, and BI dashboards—can complicate this balance. Decision support systems often appear structured and data-rich but may conceal latent uncertainty due to opaque algorithms, incomplete inputs, or ambiguous output formats (Shollo & Galliers, 2016; Cardinaels & Yin, 2024). This creates a cognitive paradox: even in technologically enhanced environments, decision-makers may still resort to intuitive reasoning when clarity is lacking or overload prevails.

Beyond this paradox, BI and AI technologies actively reshape the interplay between intuitive and analytical reasoning. Well-structured dashboards and transparent algorithms can lower extraneous cognitive load and sustain System 2 engagement, while overly complex interfaces, inconsistent metrics, or opaque models tend to accelerate a shift toward System 1 heuristics. Moreover, algorithmic decision aids may introduce domain-specific cognitive biases—such as automation bias, data bias, or confirmation bias reinforced by recommendation systems—that influence both intuitive and analytical judgments. These factors create an additional layer of "emergent uncertainty" unique to digital contexts, where the opacity and rapid evolution of algorithms challenge user trust and the stability of reasoning modes.

Thus, rather than assuming that technology eliminates intuition, the dual-process perspective implies that information design, clarity, and interpretability are critical if analytical reasoning is to be sustained. Under uncertainty, the mind protects itself through intuitive shortcuts—but at the cost of exposing decision-makers to cognitive biases and overconfidence.

3.3. Individual and Contextual Moderators

While information uncertainty plays a central role in triggering shifts in cognitive reasoning, its effect on decision-making styles is not uniform across individuals or contexts. A growing body of research suggests that the impact of uncertainty on intuitive versus analytical processing is moderated by both individual-level characteristics—such as expertise, cognitive style, and emotional disposition—and contextual variables, including time constraints, organizational pressure, and the design of decision support systems.

3.3.1. Individual moderators: experience, expertise, and cognitive disposition

One of the most robust moderators identified in dual-process literature is experience.

Experienced professionals often develop domain-specific schemas that allow for more effective intuitive reasoning, even under high uncertainty (Kahneman & Klein, 2009). Such individuals have accumulated enough feedback to refine their heuristics, leading to what is known as "skilled intuition" (Hogarth, 2001). In contrast, novice decision-makers, when faced with uncertainty, may either hesitate excessively or fall prey to biased heuristics due to insufficient knowledge structures (Witteman et al., 2009).

Another moderator lies in individual cognitive style—that is, the stable tendency to rely on either intuitive or analytical reasoning across tasks. Epstein et al. (1996) identify two dimensions: the experiential-intuitive and the rational-analytical. People with a high preference for rational thinking are more likely to engage System 2 processing even when uncertainty increases, whereas individuals who favor experiential styles might default more easily to System 1. Moreover, tolerance for ambiguity has been shown to influence cognitive orientation: those more comfortable with ambiguity are better able to remain analytical under uncertain conditions (Furnham & Ribchester, 1995; Vosgerau & Peer, 2018).

Emotions also act as subtle but powerful moderators. Feelings of anxiety, often induced by uncertainty, can amplify intuitive responses or lead to decision avoidance (George & Dane, 2016). Conversely, individuals with greater emotional regulation may resist affect-driven shortcuts and sustain analytical engagement longer.

3.3.2. Contextual moderators: time, pressure, and digital mediation

Environmental constraints further shape how uncertainty affects cognition. Time pressure has consistently been shown to impair analytical processing and increase reliance on heuristics (Payne et al., 1993; Diederich, 2003). Similarly, organizational norms and performance pressures may reward fast decisions, implicitly encouraging intuitive over analytical processing, particularly in high-stakes environments.

In digital environments—especially those mediated by BI systems and AI tools—the way information is presented can also moderate the effect of uncertainty. For example, dashboard complexity, metric opacity, or lack of interpretability in AI outputs can heighten cognitive load and discourage System 2 engagement (Shollo & Galliers, 2016; Cardinaels & Yin, 2024). Conversely, systems that provide explanatory feedback, clear visualizations, or actionable insights may buffer the disruptive effects of uncertainty and facilitate reflective reasoning (Tolpezhnikov et al., 2024; Wright, 2013).

The interplay between individual and contextual moderators suggests that the cognitive impact of uncertainty is neither deterministic nor unidimensional. Instead, it reflects a dynamic interaction between the decision-maker's capacities and the constraints of the environment. Any robust model of decision-making under uncertainty must therefore account for this situated cognition, wherein both personal traits and technological or organizational contexts jointly influence the dominant reasoning style.

3.4. Schematic Proposition and Conceptual Summary

The preceding sections have established a conceptual framework linking information uncertainty to cognitive processing styles, through the lens of dual-process theory. This relationship is not isolated but embedded within a broader interaction of individual and contextual moderators, including experience, cognitive style, emotional regulation, time constraints, and technological mediation.

To consolidate these insights, we propose a schematic model that synthesizes the key constructs and their relationships. At its core, the model posits that perceived information uncertainty acts as a primary trigger influencing the activation of System 1 (intuitive) or System 2 (analytical) reasoning pathways. This relationship is moderated by two main categories of factors:

- Individual moderators, such as domain-specific experience, preference for rational or intuitive cognitive styles, tolerance for ambiguity, and emotional disposition.

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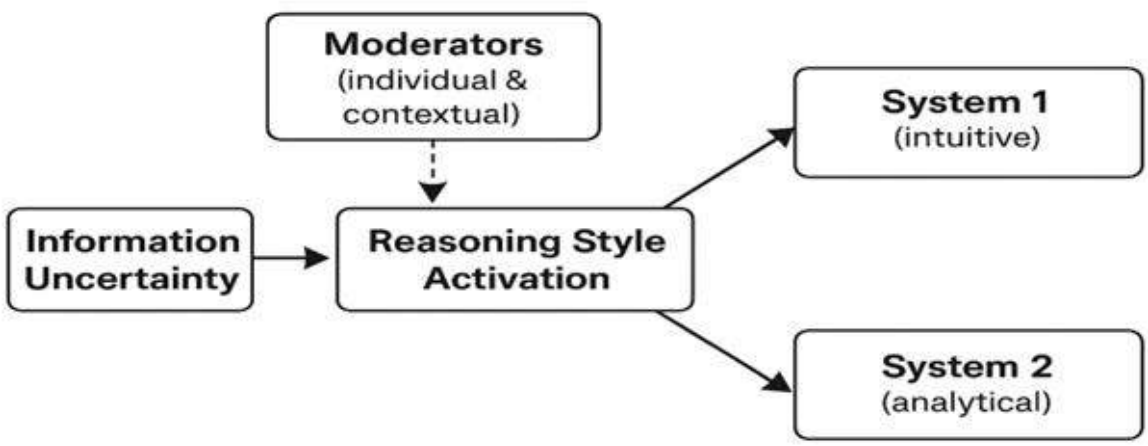
- Contextual moderators, including time pressure, organizational expectations, and the degree of clarity or interpretability provided by decision support technologies (e.g., dashboards, AI outputs).

The model does not assume a strict dichotomy but allows for dynamic interaction between both systems, depending on the magnitude of uncertainty and the availability of cognitive resources. This conceptualization aligns with interactionist views of decision-making, recognizing that reasoning styles emerge from both internal dispositions and external affordances.

The proposed framework contributes to the literature by bridging insights from behavioral decision theory, cognitive psychology, and information systems. It also offers a basis for empirical testing in future research, particularly in digital environments where uncertainty is increasingly prevalent, and decisions are mediated by technology-rich interfaces.

A graphical representation of this model can be developed to visually express the structure:

Figure 1: Conceptual model linking information uncertainty to reasoning style activation



Source: Author's elaboration based on dual-process theory (Kahneman, 2011; Evans, 2008) and information uncertainty literature

This conceptual structure aims to provide clarity on how uncertainty operates cognitively and contextually in decision-making, and why understanding its effects is crucial in modern organizational and technological settings.

4. Discussion and Implications

4.1. Theoretical Implications

The conceptual framework developed in this paper offers several theoretical contributions to the study of decision-making under uncertainty. First, it refines the application of dual-process theories (Kahneman, 2011; Stanovich & West, 2000) by explicitly linking the perceived level of information uncertainty to the activation of intuitive (System 1) or analytical (System 2) reasoning styles. While prior research has emphasized individual predispositions in the use of cognitive systems (Evans, 2008; Hodgkinson & Sadler-Smith, 2003), our model posits that environmental cue—specifically uncertainty—play a central role in shaping the cognitive pathway that individuals adopt during decision-making.

Second, this work contributes to a dynamic understanding of rationality. Rather than assuming stable cognitive preferences, the model acknowledges that reasoning styles are contextually contingent and adapt to the informational characteristics of the environment (Tversky & Kahneman, 1973; Gigerenzer & Gaissmaier, 2011). In this respect, the framework aligns with recent calls to view intuition and deliberation not as opposites but as complementary mechanisms that are selectively activated based on contextual affordances (Spiliopoulos & Hertwig, 2024).

Third, the introduction of individual and contextual moderators—such as experience, time pressure, or digital mediation—extends classical dual-process approaches by integrating interactionist perspectives. It suggests that reasoning styles are the outcome of a situated interaction between cognitive tendencies and environmental constraints (Cardinaels & Yin, 2024; Tolpezhnikov et al., 2024). This view resonates with current theoretical movements advocating for a situated and bounded view of rationality in complex organizational settings (Shaner et al., 2024).

Finally, the proposed model opens avenues for interdisciplinary dialogue. By bridging theories from cognitive psychology and information systems, the framework fosters a richer conceptualization of how decision-makers navigate uncertainty in data-driven contexts. It provides a foundation for future empirical research investigating the role of emerging technologies (e.g., decision support systems, artificial intelligence) in shaping cognitive activation under uncertainty.

4.2. Managerial Implications

From a managerial perspective, this conceptual framework provides several actionable insights for decision-makers operating in uncertain environments. First, it highlights the critical importance of recognizing the cognitive impact of information uncertainty. When managers face incomplete, ambiguous, or volatile data, their tendency to rely on intuitive judgments increases. This underscores the need to foster awareness of such shifts in reasoning modes, particularly in high-stakes or time-sensitive decisions.

Second, organizations should acknowledge the contextual and individual factors that influence how uncertainty is processed. For instance, more experienced managers may feel comfortable making intuitive calls under uncertainty, while less experienced counterparts may require structured analytical tools or support. Tailoring decision support systems and managerial training to reflect such differences can improve alignment between cognitive preferences and available tools (Vosgerau & Peer, 2018; Attari et al., 2021). In practical terms, this means integrating the framework into BI/AI system design processes through user profiling, iterative testing, and scenario-based training. For example, dashboards can be configured with adaptive layers—providing more aggregated, pattern-focused views for intuitive users and more detailed, drill-down options for analytical users. Similarly, executive education programs can incorporate simulations that expose managers to varying uncertainty levels, training them to recognize and regulate their reasoning mode depending on context.

Third, management should not perceive intuitive reasoning as inherently inferior or irrational. On the contrary, intuition can be highly effective, especially when rooted in deep domain experience and deployed in familiar contexts (Dane & Pratt, 2007). The key lies in developing an organizational culture that encourages metacognitive reflection—i.e., the ability to step back and evaluate whether intuitive or analytical processing is more appropriate for a given situation.

Beyond the individual level, decision-making under uncertainty often unfolds in team settings, where collective cognition, group dynamics, and organizational politics can significantly influence the balance between intuitive and analytical reasoning. In collaborative contexts, shared mental models and transactive memory systems may enhance analytical processing by distributing cognitive load across members, while strong hierarchical pressures or dominant personalities can steer groups toward premature intuitive consensus. Additionally, power dynamics, conflict resolution styles, and cultural norms affect whether intuitive signals are openly discussed or suppressed in favor of data-driven arguments. Embedding the dual-process framework into team decision protocols—such as structured debates, role rotations, or "devil's advocate" assignments—can help maintain a healthy interplay between Systems 1 and 2 at the collective level.

Furthermore, managers can leverage digital decision environments—such as BI dashboards, predictive analytics, or even explainable AI—to mitigate the ambiguity that triggers premature intuitive reasoning. The design of such tools should aim not only to present data, but to enhance information clarity, traceability, and interpretability, thereby supporting deliberate reasoning when needed (Cardinaels & Yin, 2024; Tolpezhnikov et al., 2024).

Finally, leadership teams should invest in training programs that integrate decision-making psychology, equipping managers with cognitive literacy to recognize the influence of uncertainty and to regulate their own decision styles accordingly. This is especially crucial in volatile and data-intensive sectors such as finance, healthcare, and logistics, where both overreliance on instinct and analysis paralysis can lead to suboptimal outcomes.

4.3. Technological Reflections: Business Intelligence, AI, and Cognitive Fit

In the digital age, managerial decision-making increasingly unfolds within technologically mediated environments. Business Intelligence (BI) platforms, data visualization tools, and AI-assisted analytics have transformed the way information is accessed, interpreted, and acted upon. While these technologies promise to reduce uncertainty by enhancing information availability and processing speed, they also create new cognitive dynamics that merit attention.

BI systems are typically designed to support analytical reasoning by providing structured data, performance dashboards, and predictive models. However, under conditions of time pressure or information overload, users may still revert to intuitive heuristics, especially when data interpretations are ambiguous or conflicting (Arnott, 2006; Wixom & Watson, 2010). This underscores the need for decision support systems to align with the cognitive demands of users, a principle known as cognitive fit (Vessey, 1991). Systems that fail to match the user's reasoning mode—e.g., presenting highly analytical tools in intuitive decision contexts—may lead to confusion or misuse.

Moreover, the rise of AI-based decision aids introduces both opportunities and challenges. On one hand, machine learning algorithms can process vast and unstructured data sources, offering probabilistic insights that reduce the cognitive burden on humans. On the other hand, the opacity of AI models (so-called "black box" systems) may increase perceived uncertainty, particularly when users cannot trace the logic behind recommendations (Burton et al., 2020). This paradox may trigger a fallback to intuitive judgment, especially in contexts where decision accountability is high.

To address this, recent advances in explainable AI (XAI) propose techniques for making AI-driven decisions more interpretable and trustworthy (Doshi-Velez & Kim, 2017). Integrating such features into BI environments may enhance users' confidence, promote analytical engagement, and reduce inappropriate reliance on intuition. However, the integration of BI and AI into decision-making processes also raises significant technical and human constraints that can limit their effectiveness. On the technical side, issues such as incomplete integration between systems, inconsistent data pipelines, and limited scalability of analytics platforms can undermine the reliability of outputs. The lack of explainability in many AI models—particularly in deep learning—reduces transparency and makes it difficult for decision-makers to trace causal links between input data and recommendations. From a human factors perspective, resistance to adopting AI-driven tools is often rooted in concerns about job displacement, loss of autonomy, or perceived over-complexity of the systems. Mistrust may also arise when algorithmic recommendations contradict managerial intuition or established practices. Addressing these challenges requires not only improving the technical robustness and interpretability of systems, but also investing in change management strategies, user training, and participatory design approaches that actively involve end-users in system development and refinement. Ultimately, the goal is not to eliminate intuition or promote automation uncritically, but to achieve an adaptive equilibrium between human cognition and technological mediation. Operationalizing this equilibrium requires embedding the framework into technology governance processes. This involves: (1) mapping decision types to optimal reasoning modes; (2) calibrating system features (visualization density, explanation depth) to support that mode; and (3) providing real-time cognitive feedback to users—such as indicators of uncertainty level or algorithmic confidence—so they can adjust their decision strategy accordingly. In BI/AI project roadmaps, these steps can be formalized as design checkpoints, ensuring that cognitive considerations are systematically integrated into deployment and training.

This raises important managerial and technological questions about how to design information systems that accommodate both reasoning systems, and how to train users to calibrate their trust and reliance appropriately. As uncertainty remains a core characteristic of digital decision environments, the interplay between BI, AI, and cognitive psychology will likely become a central field of inquiry for both researchers and practitioners.

Beyond technical and human adoption challenges, the increasing reliance on AI and algorithmic decision support raises critical ethical and social considerations. These include questions of transparency—ensuring that decision processes and data sources are accessible and interpretable to stakeholders—and accountability, clarifying who is responsible for decisions made with algorithmic assistance. Embedded biases in training data or model design can perpetuate and even amplify existing inequalities, potentially leading to unfair or discriminatory outcomes. Privacy concerns also arise when systems rely on sensitive personal or organizational data, especially in jurisdictions with evolving regulatory frameworks such as the GDPR. Addressing these issues requires implementing bias detection and mitigation strategies, adopting fairness-aware machine learning approaches, and establishing governance structures that enforce ethical guidelines and regulatory compliance. Ultimately, ethical integration of AI in managerial decision-making demands a socio-technical approach that balances innovation with societal responsibility.

5. Conclusion

This article has explored the cognitive mechanisms underlying decision-making in contexts characterized by information uncertainty. By mobilizing dual-process theories (Kahneman, 2011; Stanovich & West, 2000), we have shown how uncertainty acts as a powerful situational factor that triggers a shift from analytical (System 2) to intuitive (System 1) reasoning. Contrary to traditional approaches that portray intuition as a cognitive shortcut to be avoided, our framework highlights the adaptive nature of intuitive judgments in environments where information is ambiguous, incomplete, or time-sensitive.

Building upon a robust theoretical foundation, this paper contributes to the literature by offering a situated and dynamic conceptual model, which accounts for both environmental and individual moderators of reasoning styles. Rather than considering cognitive styles as fixed traits, we emphasize their flexible activation in response to varying levels of uncertainty. Experience, time pressure, and perceived data quality emerge as key elements influencing this cognitive transition, thus offering a richer understanding of decision-making processes in real-world settings.

Importantly, the proposed framework is contextualized within digital decision environments, such as those enabled by Business Intelligence (BI) and Artificial Intelligence (AI) technologies. While these systems aim to support analytical processing by delivering structured and traceable information, their design often fails to accommodate the cognitive realities of decision-makers. We have argued that the effectiveness of such tools depends not only on their technical performance but also on their ability to achieve cognitive fit—that is, the alignment between the nature of the task, the characteristics of the user, and the format of the information provided.

From a managerial standpoint, our work provides actionable recommendations for improving decision quality in uncertain conditions. Organizations are encouraged to foster cognitive literacy, develop training programs on adaptive reasoning, and invest in decision-support systems that integrate transparency, interpretability, and user-centered design. Intuition should not be seen as a failure of rationality, but as a complementary process that can yield effective outcomes when properly understood and supported.

Future research directions include the empirical validation of the proposed model through scenario-based experiments and real-world case studies across various industries. It would also be valuable to examine the role of emerging technologies, such as explainable AI (XAI), in helping decision-makers navigate uncertainty more effectively. Additionally, further investigation into the influence of organizational culture, emotional responses, and team dynamics on reasoning modes could enhance the explanatory power of this framework.

In conclusion, this article invites scholars and practitioners to move beyond binary views of intuition versus rationality and adopt a more integrative and context-sensitive perspective. Understanding how decision styles are shaped by uncertainty—and how technology can support this adaptation—represents a promising avenue for advancing both theory and practice in management and information systems.

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