

**ARTIFICIAL INTELLIGENCE-DRIVEN MANAGEMENT
DECISION-MAKING: THEORETICAL CORE, SUPPORT
AND EVOLUTION**

Yangfan Xu, master's degree student

*Scientific supervisor – Associate professor Zaitseva N. V.
Belarusian National Technical University
Minsk, Belarus*

Abstract. Artificial intelligence technology is driving a paradigm shift in management decision-making, moving from “experience-driven” to “intelligence-driven”. This paper focuses on the fundamental theoretical framework of AI-driven management decision-making.

Keywords: artificial intelligence, management decision-making, human-machine collaboration, data-driven, theoretical framework, multidisciplinary support, etc.

Traditional management decision-making, rooted in the rational actor assumption, follows a linear logic of goal setting-plan formulation-evaluation and selection-execution and feedback.

However, it faces three core limitations in complex environments.

First, limited information processing capacity makes it difficult for managers to handle real-time analysis of massive heterogeneous data.

Second, cognitive biases such as anchoring effects and overconfidence inevitably lead to decision-making errors.

Third, insufficient dynamic adaptability hinders rapid response to non-linear changes in external environments like market fluctuations and technological advancements.

These limitations have rendered traditional decision-making increasingly ineffective in managing complex systems during the digital economy era. Meanwhile, Simon's “theory of bounded rationality” has long revealed the inherent limitations of human decision-making [1].

Behavioral economics research further confirms that cognitive biases such as anchoring effects and overconfidence exacerbate decision-making errors, leading to resource misallocation and efficiency losses in organizations [2].

Against this backdrop, artificial intelligence technology – driven by its core strengths in massive data processing, complex problem modeling,

and dynamic iterative optimization – has emerged as a critical enabler to overcome the limitations of traditional decision-making frameworks.

Artificial intelligence-driven management decisions break through the traditional paradigm and build a closed-loop intelligent logic of “data – model – decision – feedback”.

Its core kernel is embodied in three points:

1. Human-AI collaboration in decision-making: The decision-making entity evolves from a single manager to a collaborative system of “human decision-makers + AI systems”. AI handles technical tasks like data processing, model computation, and scenario simulation, while humans focus on value judgment, ethical considerations, and strategic calibration – creating a “technology-enabled + human-led” division of labor mode [2].

2. Data-driven decision-making: The foundation of decision-making has shifted from empirical intuition + limited data to full data + deep insights. Through data collection, cleaning, and modeling, hidden causal relationships and underlying patterns are uncovered, enabling decisions to evolve from 'qualitative judgment to a precise model combining quantitative analysis + qualitative calibration [3].

3. Dynamic Iteration of Decision-Making Process: Leveraging machine learning's iterative optimization capabilities, the decision-making system continuously adjusts model parameters and optimizes decision-making strategies based on real-time feedback data, creating a dynamic cycle of 'decision-making-execution-feedback-optimization' to adapt to the evolutionary characteristics of complex systems [4].

The theoretical system of artificial intelligence-driven management decision is based on the interdisciplinary basis of management science, computer science, economics, psychology, etc.

The basic theory of AI-driven management decisions is highly applicable in the following scenarios:

1. Structured and semi-structured decision-making scenarios, such as production scheduling, inventory optimization, risk assessment, and customer segmentation, feature readily available data and relatively clear decision rules, enabling AI models to operate efficiently.

2. In complex system collaborative decision-making scenarios – such as supply chain coordination, cross-departmental resource allocation, and regional public service scheduling – integrating multi-source data and balancing stakeholder interests is essential. AI's comprehensive modeling and

collaborative optimization capabilities can significantly enhance decision-making effectiveness.

3. Dynamic iterative decision-making scenarios, such as dynamic pricing, precision marketing, and emergency management, require rapid adjustments based on real-time feedback. AI's iterative learning capability perfectly meets these scenario requirements.

The theoretical evolution of AI-driven management decision-making is not a simple superposition of technology, but a three-stage evolution of “tool empowerment-process optimization-paradigm change”.

The first stage: the tool empowerment stage (1990–2010). The core feature is AI as an auxiliary tool to compensate for the efficiency shortcomings of traditional decision-making. The theoretical focus is on technological application – how to use expert systems and simple machine learning algorithms (such as decision trees and logistic regression) to solve structured decision problems (like inventory calculation and financial budgeting). At this stage, the theoretical foundation is the 'technological tool theory, where AI is viewed as a tool to enhance human decision-making efficiency without altering the core logic of traditional decision-making [8].

The second stage: Process optimization stage (2011–2020).

With the advancement of big data technology and deep learning, AI has begun to permeate the entire decision-making process. The theoretical focus has shifted to “process reengineering”, which involves integrating data across decision-making stages (such as demand forecasting, production scheduling, and logistics coordination) to establish cross-departmental and cross-organizational decision-making processes. The core theory is “data-driven decision-making theory”, which emphasizes replacing experience with data to optimize decision accuracy and coordination. However, the ultimate control over decision-making remains in human hands [9].

The third stage: the paradigm change stage (2021 to now).

Breakthroughs in generative AI, digital twin, and reinforcement learning technologies have propelled decision theory into a paradigm shift era. The theoretical focus now centers on “human-machine symbiosis”, with core concepts including “hybrid augmented intelligence theory” (complementary advantages between human and AI intelligence) and “complex system decision theory” (decision-making logic addressing uncertainty, nonlinearity, and emergence [10].

This marks a transformation from the traditional “human-led, AI-assisted” model to a collaborative, mutually reinforcing symbiotic paradigm, establishing a new decision-making framework [11].

The basic theory of artificial intelligence-driven management decision-making is still in a rapid development stage. In the future, we need to focus on three research directions:

1. The coupling mechanism of human-machine collaborative decision-making: This research explores the division of decision-making authority between humans and AI, information exchange patterns, and trust-building pathways, establishing a collaborative theory of “complementary strengths and shared risks” [12].

2. Decision theory in complex uncertain environments: To address extreme uncertainty scenarios such as black swan events and technological mutations, we develop AI decision models with both robustness and adaptability, thereby improving decision theory for complex systems [13].

3. Ethically embedded decision theory: This approach integrates ethical objectives such as fairness, transparency, and sustainability into the design and optimization of AI decision-making models, establishing a dual-objective theoretical framework that combines technical efficiency with ethical compliance [13].

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