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Converging Rational Choice and AI in Evolutionary Management Systems

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Abstract: In the context of rapidly evolving socio-economic systems operating within chaotic and uncertain environments, rational decision-making has become a critical challenge for management. This study examines the convergence of subject-specific rational choice theories—behavioural theory and decision-making theory—with artificial intelligence (AI) to enhance the precision and adaptability of managerial decisions. The research objective is to systematize the constructs of these theories and elucidate their integration into "machine intelligence", enabling robust solutions for complex organizational problems. Methodologically, the work employs principles of differentiation and integration, systemic and organismic approaches, and combines rational choice frameworks with evolutionary algorithms, agent-based modelling, and game theory. Key findings include: (1) a structured presentation of rational choice constructs as combinatorial elements for AI-driven decision-making; (2) an algorithmic framework for sequential convergence of behavioural and decision-making theories within AI systems. The novelty lies in revealing the temporal and substantive synergy between these theories, particularly their capacity to simulate human-like rationality in dynamic contexts. Results demonstrate that embedding integrated knowledge into AI facilitates adaptive responses to turbulence, reducing cognitive biases and information asymmetry. The study concludes that robust management systems, leveraging AI-enabled evolutionary computations, emerge as pivotal tools for proactive adaptation in socio-economic environments. This convergence not only refines decision-making accuracy but also positions AI as a co-pilot in addressing non-repetitive, multifactorial challenges. The implications extend to advancing "management through environment" models, where autonomous heuristic intelligence ensures sustainability amid accelerating global changes.

1 INTRODUCTION

Civilization has entered an era of accelerated dynamics, marked by diverse and rapidly shifting scenarios. In each scenario, socio-economic systems are compelled to make rational decisions to prevent instability and inefficiency. A growing demand for rational choice outcomes has emerged due to the influx of non-repetitive challenges. Decision-making processes underpin all goal-oriented human activities. In management, they serve to develop optimal strategies for strategic, tactical, and operational planning of production systems.

Rational choice theory is shaped by two distinct scientific disciplines—behavioral theory and decision-making theory. In behavioral theory, decision-making authority rests entirely with the decision-maker (DM). However, multifactorial impacts on socio-economic systems, time constraints, information scarcity, and inherent cognitive limitations of DMs often hinder desired outcomes. To transcend bounded rationality, the concept of "rationality as optimization" (Simon, 1993) integrates heuristic methods with formalized techniques such as optimization, mathematical statistics, game theory, and set theory.

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The evolution of decision-making theory parallels advancements in scientific rationality—classical, non-classical, and post-non-classical. Each rationality type offers tools for decisions under certainty, measurable uncertainty (risk), and complete uncertainty. Initially, the "human intellect–calculator" paradigm dominated, with DMs leading the process. Today, computational advancements have ushered in the cognitive era (Malinetsky, 2011), where AI increasingly assumes a leading role in rational decision-making by simulating DM behavior and selecting context-appropriate actions.

Organizational systems, conceptualized as "organisms", prioritize models, methods, and evolutionary algorithms embedded in AI. These systems facilitate the convergence of behavioral theory, decision-making theory, and AI theory (Frank, 1995). While AI intellectualization progresses rapidly, challenges in rational choice for adapting socio-economic systems remain unresolved.

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2 METHODS AND MATERIALS

2.1 Origins and Development of Rational Choice Theory

To trace the origins of rational choice theory in organizational management, we turn to the works of Herbert Simon, a pioneer in decision-making theory. Simon (Simon, 1960) identified three stages of decision-making processes:

- Intelligence Activity: Identifying the causes necessitating decisions through situational analysis.
- Design Activity: Generating, developing, and analysing potential courses of action (solution preparation).
- Choice Activity: Selecting a specific course of action.

Each stage represents a complex process, often requiring iterations between phases to achieve rational choices. Tasks at any stage may spawn subtasks, necessitating further intelligence, design, and choice activities. Managers are deeply engaged in these interconnected processes, which follow a consistent sequence: ″cause → task → choice″. Simon later termed the entire sequence ″decision-making″, anticipating future advancements in decision-making technologies.

The early development of rational choice theory emphasized individual behavioral theory, where decision-making authority rested entirely with the participant. However, as Simon noted, perceived business situations often diverge from reality due to cognitive limitations, time constraints, and insufficient information or computational resources. These factors contribute to bounded rationality, which the concept of “rationality as optimization” (Simon, 1993) seeks to overcome.

The guiding principle of rational choice theory’s evolution lies in integrating formal methods (e.g., mathematical optimization) with empirical approaches. This addresses two polar task types: non-programmed (non-formalizable) and programmed (formalizable). The axiom “decision-making is synonymous with management” (Simon, 1960, p. 7) underscores the theory’s broad applicability across organizational management levels.

Russian academic literature has produced extensive research on managerial decision-making, refining and expanding decision theory. Dominant themes include social aspects of decision-maker behavior and mathematical tools for optimizing solutions. However, the increasing turbulence, uncertainty, and chaos in organizational environments complicate rational choice formulation. This has led to embedding constructs from behavioral and decision-making theories into artificial intelligence (AI), fostering convergence with AI theory. AI systems now incorporate behavioral theory constructs such as evolutionary game theory, agent-based modeling, genetic algorithms, and evolutionary computations.

Despite technological advancements, organizational decision-making remains human-centric, with active participation from decision-makers (DMs). Emerging reflective technologies facilitate collaboration between DMs and AI through dedicated platforms. Yet, the integration of cognitive AI for rational decision-making—particularly in evidence-based adaptive scenarios for socio-economic systems—remains underdeveloped. To achieve effective human-AI collaboration, AI must be trained in rational choice theories, techniques for analyzing internal and external environmental data, and methods for assembling adaptive scenarios that address external disruptions.

The overarching goal of this research is to establish a coherent theoretical and methodological framework for rational choice theory, systematically integrating insights from behavioral theory, decision-making theory, and organizational management theory.

2.2 Rational Choice in the Context of Behavioral Theory

The development of rational choice theory has been fundamentally influenced by behavioural theory, which seeks to explain the intention of actors to make rational decisions in business contexts. Within behavioural theory, several approaches to rational decision-making have emerged since 1927. Each approach is rooted in methodological individualism and unfolds through the following perspectives (Krstić, 2022):

A1: Human behavior is viewed as a choice among alternatives.

A2: Preferences, beliefs, and constraints are primary determinants of behavior.

A3: Preferences must satisfy conditions of completeness and transitivity.

A4: Individuals select optimal alternatives based on their preferences, beliefs, and constraints while accommodating a broader range of preferences.

Critically, these foundational concepts remain relevant, as subsequent developments build upon prior knowledge while adhering to causality.

Critiques highlight that models assuming a perfectly rational, utility-maximizing actor fail to explain key behavioral aspects of rational choice. To address this, logical frameworks interpreting rational choice as instrumental rationality were introduced (Morgenstern & Neumann, 1953).

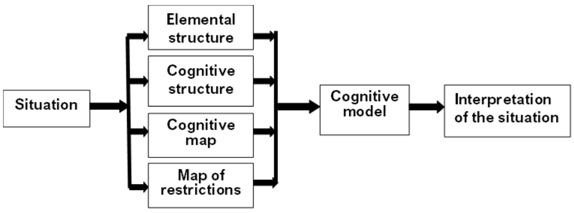

Figure 1: Information Support of the Cognitive Model and Transformation of Data for Situational Interpretation.

Modern decision theory further incorporates cognitive constructs such as cognitive structures, cognitive maps, and constraint matrices to model situational complexity (Fig. 1) (Freydina & Korokh, 2015).

3 RESULTS

Over time, behavioral theory has integrated key insights into rational choice, including axioms, models, and choice functions. Below are core axioms of rational choice:

- Disjunction.

For any alternatives x and y, either x is preferred to y (xPy), y is preferred to x (yPx), or indifference holds (xIy). Formally:

$$\forall x,y\ [(xPy) \vee (yPx) \vee (xIy)] \tag{1}$$

- Transitivity.

For any three actions x, y, and z, if x is preferred to y and y to z, then x is preferred to z:

$$\forall x,y,z\ [(xPy \wedge yPz) \rightarrow xPz] \tag{2}$$

There are two main types of cognitive ability:

1. Bounded Cognitive Capacity. The choice function is represented as a clearly binary relation.

2. Unbounded Cognitive Capacity. A rational individual possesses unlimited reasoning and information-processing abilities. "Infinity" here implies that if a valid reasoning method exists, it is employed effortlessly (Akerlof, 2007).

Managerial Rational Choice hinges on two enduring principles:

- maximization of expected utility for selected alternatives;
- consequentialism: Evaluating alternatives based on anticipated outcomes and consequences.

In the process of rational choice, various approaches and models of individual behavior proposed by a number of scientists are used.

1. Rational-Heuristic Models (Kiss, 2006) propose logical rules guiding rational choice, enabling the discovery of "successful actions". Rational choice in accordance with the rules laid down in the model is based on the use of analytical tools.

2. Problem Identification (Lakatos, 1976). Selecting a problem as a starting point and adjusting based on experimental results.

3. Alternative Generation (Bandura, 1986). In this approach, heuristics can take two forms:

- Empirical – leveraging existing data to formulate new options;
- Theoretical – simulating scenarios where prior knowledge is insufficient.

4. Elster's Rational Choice Model (Elster, 2009) posits desires as the sole independent variable, influencing actions, beliefs, and evidence.

5. Social Identity and Decision-Making (Sato, 2013) introduces identity constructs that shape decision-making competence:

- Conscious Incompetence – awareness of skill gaps;
- Conscious Competence – confidence in one's abilities;
- Unconscious Incompetence – unawareness of deficiencies;
- Unconscious Competence – unrecognized proficiency.

Behavioral theory delegates rational choice to the decision-maker (DM), relying on their competence to select alternatives that optimize outcomes under perceived constraints. Preferences are quantified as measurable utilities or penalties for suboptimal choices. However, DMs often face bounded rationality—limited by cognitive biases and incomplete information. Simon's "rationality as optimization" (Simon, 1993) addresses this by merging heuristic methods with formal optimization techniques, integrating operations research into managerial practice. This marks the convergence of behavioral and decision-making theories, enhancing rational choice frameworks.

Decision-making theory employs optimization, game theory, and operations research to address strategic, tactical, and operational challenges. Four decision levels are identified: routine, selective, adaptive, and optimization (Woodcock & Francis, 1991). Modern complexity necessitates collaboration between human intellect and AI, with the latter increasingly handling combinatorial and computational tasks.

Choice and decision-making processes form the foundation of all goal-oriented human activities. In organizational management, they serve to develop optimal solutions for strategic, tactical, and operational planning of production systems and facilities. Optimal (effective) decisions enable achieving the desired minimum/maximum of the goal criterion. As management systems grow in complexity, computational technologies and tools continuously evolve to enhance the validity and efficiency of decision-making outcomes. Complexity arises not only from system design and reliability but also from properties such as equilibrium instability, parameter fluctuations (key variables), nonlinear relationships, and preference asymmetry. The philosophy of science concludes: "Complexity is an inherent property of any phenomenon, system, or object under study" (Knyazeva, 2013).

Historically, decision-making has been categorized into four levels (Woodcock & Francis, 1991):

1. Routine – standard, repetitive decisions;
2. Selective – choosing alternatives aligned with real-world challenges;
3. Adaptive – deliberate intention to execute adaptation processes from a set of alternatives;
4. Optimization – selecting the best solution to address challenges.

At all levels, the rationality of choice depends on the "work of the mind", which possesses systematic knowledge and applies it to solve non-recurring problems.

In the modern era, the conditions for formulating rational solutions to situational changes have grown more complex. This is driven by:

- the multifactorial influence of the external environment on system states;
- expanding information fields with diverse data types in dynamic contexts.

This necessitates offloading human cognitive tasks to artificial intelligence (AI). Initially, decisions are generated through collaboration between "human intellect" and "artificial intelligence".

As computational technologies advance, AI assumes a dominant role, handling complex computations and combinatorial tasks. AI development integrates logical-mathematical frameworks derived from the convergence of behavioral theory and decision-making theory. Collaboration between decision-makers (DMs) and "machine intelligence" enhances managerial capabilities (Shelley, 2019). Neurosurgeon Henry Marsh metaphorically captures this dynamic: "If you hold a hammer, every problem looks like a nail."

3.1 AI and Scientific Rationality

AI theory evolves alongside scientific rationality—classical, non-classical, and post-non-classical. Each rationality type provides tools for decision-making under certainty, statistical uncertainty (risk theory), and complete uncertainty.

The typology of scientific rationality stems from bounded rationality (Simon, 1993), rooted in the limitations of human cognitive tools. As North (North, 2010, p. 31) defines: "Rationality refers to explanations that are logically consistent and empirically testable".

A key feature of scientific rationality evolution is the invariant core within each type, ensuring continuity. New rationality types do not negate prior ones but redefine their scope. Classical rationality, for instance, laid the groundwork for fundamental research but no longer dominates (Stepin, 2013, p. 91). Each rationality type establishes rules, formal patterns, or "templates" for cognitive activity.

3.2 Algorithmic Implementation and Human-AI Interaction

The algorithmic depth of problem-solving depends on the type of scientific rationality embedded in AI. For example, AI trained in classical rationality employs mathematical programming to identify optimal solutions. The interaction between human intellect and AI follows procedures such as:

1. Problem formulation and task definition.
2. Goal setting and optimality criterion selection.
3. Information infrastructure development.
4. Mathematical/simulation model construction with future exogenous parameter ranges.
5. Generating an initial set of alternatives (ISA) to select the best option.
6. Organizing interactive collaboration between DMs and AI.

Collaboration between the two "subjects" involves iterative and interactive processes:

- Interactive processes – reflexive exchanges on a shared platform, where information is transferred until consensus is reached.
- Iterative processes – cyclic refinement to improve decision accuracy.

Probabilistic models in rational choice theory are emerging to explain deviations from optimal solutions (Kruis et al., 2020). These advancements mark a near-future leap in rational choice theory, bridging gaps between human intuition and machine precision.

4 DISCUSSION

The ability of artificial intelligence (AI) to infer managerial actions depends on the constructs of subject-specific theories and intellectual systems that form its "brain". From the perspective of achieving truthful rational choice, we briefly examine intellectual systems that integrate constructs from behavioural theory and decision-making theory through evolutionary game theory, agent-based modelling, genetic algorithms, and evolutionary computations.

Several constructs from behavioural theory are implemented in evolutionary game theory systems, which solve problems by determining individual utility functions for each participant and modelling their economic behaviour. The search for solutions aligns with specific concepts. For example, adhering to the Nash equilibrium principle: rational players adopt strategies that create equilibrium relative to competitive positions. The potential behaviour of a decision-maker is characterized by a set of strategies and adaptation processes. A strategy set is derived where no individual player can increase their payoff by changing their strategy while others' strategies remain fixed. Another key concept is dominance elimination: a player's strategy is considered dominated if an alternative strategy yields a higher payoff regardless of other players' actions.

Agent-based modelling focuses on individual participants (agents) within a system and defines their actions in specific situations. Connections between agents are established, environmental models and agent-oriented models (AOM) are created, and simulations are launched. The goal of AOM development is to track the impact of the system on the meso- and macro-environment. The individual actions of each agent collectively shape the global behaviour of the simulated system in each scenario.

Evolutionary computation theory drives the development of cognitive interaction between the "artificial intelligence–human intellect" pair. The conceptualization of organizational systems as "organisms" emphasizes the importance of models, methods, and evolutionary/genetic algorithms. Evolutionary algorithms are a collective term for methods that simulate the principles of biological evolution—selection, mutation, and reproduction. These algorithms rely on a collective learning process within a population of individuals, each representing a search point in the space of feasible solutions. According to this theory, the behaviour of individuals (termed a population) is determined by the environment, selection rules (evolutionary search), and the completeness of the objective function. Despite the apparent randomness of the population, the evolutionary search process is highly stable (Kureychik et al., 2012).

Algorithms with adaptive search mechanisms include genetic algorithms, genetic programming, evolutionary strategies, and evolutionary programming. The cognitive capabilities of evolutionary operators are closely tied to concepts such as self-adaptation and self-organization of evolving systems.

A critical emphasis in management is the principle that evaluation and decision-making in evolutionary computations occur at every step of change. The system of evolutionary algorithms acquires its own "information-processing machine", operating continuously to assimilate and restructure data.

In the created intellectual systems, convergence occurs between subject theories (behavioural theory and decision-making theory) and methods for reproducing behavioural patterns and generating real-time solutions via software and computational tools. Management enters an artificial intellectual world where human rational actions in dynamic environments directly depend on AI-driven decisions.

As Albert Einstein aptly noted, "We cannot solve our problems with the same thinking we used when we created them" (Einstein, 1965). From this perspective, it is crucial to advance toward innovative models of robust management by incorporating analogies from biological systems' viability. Robust management models belong to the "management through the environment" class, immersing systems into a multidimensional, heterogeneous informational space of external factors. Robust management of socio-economic systems should be viewed as an evolving consumer of AI, equipped with cognitive rational choice theory and evolutionary computation systems. The robust management mechanism integrates autonomous adaptive-heuristic intelligence (Glinskiy et al., 2023).

The urgent and highly complex task addressed by robust management models is the assembly of evidence-based proactive adaptation scenarios and the selection of the optimal one based on criteria such as minimal time expenditure for systemic intervention response and the compensatory effect magnitude, which partially or fully offsets adaptation costs. This task is delegated to evolutionary computation systems. The developed robust management model ensures that operational socio-economic systems can withstand escalating changes, necessitating daily adaptive efforts to maintain sustainable functionality and development (Glinskiy et al., 2023).

The convergence of subject theories with AI theory marks a paradigm shift in decision science. By embedding behavioural and decision-making constructs into AI, we create systems capable of adaptive, human-like rationality. Future advancements in neuro-symbolic AI and quantum computing promise to further bridge the gap between mechanistic precision and cognitive depth.

5 CONCLUSIONS

In the current century, science is witnessing a sequential convergence of subject-specific rational choice theories through the establishment of their logical and functional connectivity with artificial intelligence (AI) theory. The first iteration involves integrating behavioural theory into decision-making theory, creating a logico-mathematical framework to approximate true rationality in managerial decision-making. The second iteration embeds this logico-mathematical framework, developed from subject theories, into AI theory. This is driven by two factors: (1) the growing multifactorial influence of external and internal environmental variables on the state of operational systems, and (2) the advancement of intelligent evolutionary computation systems that mimic natural decision-maker behaviour and enhance the accuracy of rational choice in decision-making.

Among the emerging potential consumers of evolutionary computation systems is robust management of socio-economic systems, which adopts a "management through the environment" approach. This mechanism is equipped with autonomous adaptive-heuristic intelligence, whose primary task is to assemble evidence-based proactive adaptation scenarios and select the optimal one for specific situations.

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