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Rational Expectations Hypothesis: AI's Impact on Rationality Analysis

Rasyonel Beklentiler Hipotezi: Yapay Zekanın Rasyonellik Analizi Üzerindeki Etkisi

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ÖZ

Yapay zeka (AI), büyük veri setlerini işleyerek ve karmaşık karar verme süreçlerini optimize ederek ekonomik rasyonalite analizini önemli ölçüde etkiler. Geleneksel ekonomi teorisi, aracıların tutarlı ve rasyonel kararlar aldığını varsayar, ancak bu, karmaşık problemlerin çözümündeki bilinmeyenler nedeniyle her zaman mümkün değildir. YZ'nin gerçek zamanlı analiz ve tahmin yetenekleri, değişen koşullara ve yeni verilere uyum sağlayarak doğruluğu ve verimliliği artırabilir. Bununla birlikte, YZ modelleri önyargılı olabilir ve insan şüpheciliğinden yoksun olabilir, bu da hatalı analizlere ve açıklanamayan karar verme süreçlerinin "kara kutu sorununa" yol açar. Bu sınırlamalara rağmen, YZ daha objektif bir bakış açısı sunarak faydayı maksimize eden kararları geliştirebilir. Bununla birlikte, YZ'ye güvenmek, insan karar verme sürecine olan güveni azaltarak bir bağımlılık yaratabilir. Bu makale, YZ'nin ekonomik rasyonellikteki rolünü hem bir fırsat hem de bir risk olarak araştırmaktadır.

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A B S T R A C T

Artificial intelligence (AI) significantly impacts the analysis of economic rationality by processing large data sets and optimizing complex decision-making processes. Traditional economic theory assumes agents make consistent, rational decisions, but this is not always feasible due to unknowns in solving complex problems. AI's real-time analysis and predictive capabilities can improve accuracy and efficiency, adapting to changing conditions and new data. However, AI models can be biased and lack human skepticism, leading to erroneous analyses and the "black box problem" of unexplained decision-making processes. Despite these limitations, AI can enhance utility-maximizing decisions by offering a more objective view. Yet, reliance on AI could diminish confidence in human decision-making, creating a dependency. This paper explores AI's role in economic rationality as both an opportunity and a risk.

1. Introduction

"Forgive me, Aristotle, irrational behaviour is not rare, but normal." Stuart Sutherland

Famous British psychologist Norman Stuart Sutherland (1927 –1998) wrote his seminal work titled, "Irrationality: The Enemy Within" in 1992. Sutherland expounds the

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human rationality within the scope of statistical concepts and probability theory. Sutherland concludes that cognitive biases, emotions and social influences impact human rationality and decision-making the foremost.

Rationality within the theory of rational expectations is one of the basic hypotheses of traditional economic theory. Rational expectation theory is a macroeconomic construct that posits the confluence of human rationality, information available and lived experiences for human decision-making. The theory posits past economic outcomes as a precursor to future economic outcomes. The theory also posits that the government’s fiscal policy changes are not the only determining factors within the confines of the state’s economy. The rational agent’s current economic expectations influence future economic expectations.

The discourse on the rational expectations theory led to the efficient market hypothesis (“EMH”) as the dominant assumption model used to explain business cycles. EMH is often used to explain the anticipated inflation rates within the economic cycles based on the doctrine of rational expectations.

The rational expectations theory posits the economic agent maximizing their utility as a consumer and organisational profit as the product. The agent selects the producer to maximize their ability by choosing the most appropriate means of selection under the assumption of rational behaviour. This assumption predicts that utility and profit maximization occurs under the assumption of zero uncertainty and complete information. Rationality requires the agent to make consistent, stable and transitive decisions to achieve their goals. The “rationality” assumption posits that individuals will always make rational decisions, given a set of facts and under prescribed conditions.

AI technologies have added a new dimension to the traditional understanding of rationality analysis and have led to significant changes due to machine learning automation in economic decision-making processes. AI-based rational expectation tools use big data analysis, machine learning algorithms and predictive capabilities, to help manage economic decision-making processes efficiently. AI technologies can support rational decision-making by reducing the challenges that result from opaque information and market uncertainty. Uncertainty also refers to the rational agents' inability to fully predict future events or outcomes. Rational expectations theory assumes that individuals make decisions to achieve the best outcomes despite these uncertainties.

This paper offers a qualitative conceptual analysis of AI’s impact on Rationality analysis within the scope of Rational Expectation Theory based on contemporary discourse.

Literature Review

Bettis & Hu (2018) explain the relationship between behavioural strategy, computational complexity theory, and artificial intelligence, drawing upon the foundational work of Herbert A. Simon and Alan Newell. It highlights the concept of “bounded rationality” and the importance of heuristics in decision-making processes, which are central to both economics and AI. By leveraging these fields, the study seeks to provide a more robust theoretical framework for understanding bounded rationality and the role of heuristics in organizational decision-making. Additionally, it introduces the concept of “organizational intractability,” which uses insights from computational complexity theory to identify decision technologies that are practically unfeasible in real-world organizations constrained by time and attention.

Harré (2021) review aims to examine the relationships between artificial intelligence, psychology, and economics through the lens of information theory, specifically focusing on decision theory models. It looks at the approach each field has adopted and how information theory has influenced their development. The main theme includes expected utility theory, its connection to information theory, the Bayesian approach to decision-making, and forms of bounded rationality. The approaches reviewed can, in principle, be applied to computational models to compare with human-like decision-making abilities. However, as pointed out by Savage and Binmore, Bayesian decision-making works in "small worlds" but does not apply to "large worlds." This critique is a central point in discussions about artificial intelligence's human-like learning and decision-making capabilities.

Davidson (2024) investigates the role of artificial intelligence (AI) in economic institutions, particularly concerning Herbert Simon's concept of bounded rationality. The paper seeks to explore how AI's capabilities in data processing, pattern recognition, and prediction may alleviate issues related to bounded rationality and impact economic structures. Furthermore, it critically examines whether AI could enable the viability of central planning in economic organizations while arguing that AI cannot resolve the knowledge problem as outlined by Ludwig von Mises and Friedrich Hayek, and thus does not make central planning feasible at the nation-state or firm level.

Frantz's (2003) study aims to explore the interdisciplinary contributions of Herbert Simon to economics, psychology, cognitive science, artificial intelligence (AI), decision theory, and organization theory, with a particular focus on how his work in AI influenced his understanding of intuition. By analyzing Simon’s belief that human thinking, decision-making, and creativity are not mysterious but rather grounded in observable processes like subconscious pattern recognition, this paper seeks to demonstrate how Simon’s integration of analytical thinking and intuition challenged conventional perceptions of intuition as mystical. The study will examine how Simon's work on AI informed his views on the complementary relationship between intuition and rational analysis.

Smith (2016) explains in his study the shared challenges faced by economics and artificial intelligence (AI) in addressing uncertainty, particularly concerning Keynesian uncertainty. The paper argues that, despite the significant achievements of AI, it remains ill-equipped to provide robust solutions to the problems posed by radical uncertainty. It emphasizes the continued importance of human decision-making in such contexts, highlighting its relative resilience compared to deterministic or probabilistic models. Furthermore, the study seeks to identify alternative models of human decision-making under uncertainty and suggests a research agenda for future exploration at the intersection of AI and economics.

Horvath, et al. (2023) address the need for rational, unbiased policy decisions regarding technology applications, which can have significant societal impacts. It proposes a new framework that combines the structured decision-making method called the Mediating Assessments Protocol (MAP) with artificial intelligence (AI) techniques. These AI methods—dynamic programming, reinforcement learning, and natural language processing—are utilized to reduce human bias and manage uncertainty effectively in decision-making processes. As a practical example, the study examines the process of planning a new wind park in a community, emphasizing key aspects that require careful consideration. The framework aims to improve decision-making in a way that serves society's best interests.

Parkes & Wellman (2015) study the development of artificial intelligence (AI) as rational agents that perceive the world and act to achieve specific goals, akin to the perfectly rational agent concept in neoclassical economics (*homoeconomicus*). The study reviews progress in building this new type of AI, termed machina economicus, and highlights challenges in designing AI systems capable of effective reasoning in economic contexts. Additionally, it investigates how to design interaction rules in multi-agent systems representing an economy of AIs, suggesting that economic theories of normative design may be more applicable to artificial agents than human ones, due to their higher adherence to rationality assumptions.

Kato & Sbicca (2022) aim to model trust as an investment game where players accept the risk of defection for potential rewards. Traditional game theory doesn't predict trust among selfish players, but experiments show its presence. The study has two goals: to develop an agent-based model demonstrating trust emergence through natural selection, learning, and group formation, and to model bounded rationality using a learning classifier system (LCS). Results indicate natural selection fosters a symbiotic tone while learning and group formation increase trust, with the LCS effectively simulating bounded rationality, aligning with experimental trust levels.

Sent's (1997) study aims to explore the differing interpretations and applications of bounded rationality and artificial intelligence by Thomas Sargent and Herbert Simon. Although both concepts originated from Carnegie-Mellon University, the study highlights the irony in how rational expectations theory, closely associated with Sargent, initially opposed but later seemingly embraced bounded rationality, a concept heavily influenced by Simon. The research investigates whether Sargent's and Simon's views on bounded rationality and artificial intelligence were aligned or if their distinct interests led to different understandings and implementations of these ideas.

Arend (2024) explains how new information technologies, particularly disruptive ones like artificial intelligence (AI) powered by machine learning on big data, contribute to strategic decision-making under uncertainty. By examining AI's impact on business, exemplified by its role in the success of several trillion-dollar platform 'gatekeeper' firms, we analyze its complex relationships with uncertainties discussed in this book. Furthermore, the study investigates the significant and potentially existential implications of these technologies in the context of strategic decision-making.

Marwala, et al. (2017) explain how decision-making changes when artificial intelligence (AI) machines, rather than humans, are responsible for making market decisions. It examines the theory of rational choice, which posits that individuals aim to maximize their utility by using all available information and considering all options to make optimal decisions. The chapter focuses on the advantages AI machines bring to the market, such as more consistent future expectations, reduced bias and variance in prediction errors, and the overall enhancement of rationality in the marketplace.

Hacker (2019)'s study is to explore how different theories of choice—rational and boundedly rational—affect legal and regulatory decisions, particularly under various types of uncertainty. The chapter examines three kinds of uncertainty: Knightian Uncertainty, Technological Uncertainty, and Dynamic Behavioral Uncertainty. The study uses examples like price discrimination, usurious lending, and blockchain to illustrate these uncertainties. Ultimately, the study argues for making normative trade-offs transparent through theories of choice while acknowledging that these theories cannot replace the need for normative judgments in balancing competing interests.

Possible Impacts of AI on Decision-Making Behavior Under Utopia of Complete Rationality: Bounded Rationality and AI

Rationality assumes that economic agents make decisions in order to maximize their utility/profit and make an optimal choice using all available information. But how does the situation change under the assumption that decisions are made by artificially intelligent machines instead of humans? When AI forms expectations about the future, it obtains more consistent results compared to humans, as the bias and error variance in predictions are reduced. This leads to more rational decisions and makes the market more rational (Marwala, et al., 2017).

Decision-making and problem-solving, one of the key aspects of AI, is based on rationality, and a rational agent that chooses the best action based on the available conditions and information can be a person, company, machine or software. Rational agents have clear preferences, model uncertainty and act in a way that maximizes performance. In AI, rationality is the ability of a system to make the best decisions based on the information and goals it has. A rational AI determines the best option among alternatives to achieve the goal, uses logical reasoning, learns from experience and adapts to new situations. Rationality in AI is divided into limited rationality, which makes "good enough" decisions in the real world with limited information and resources, and perfect rationality, which makes the best decisions under ideal conditions (Rationality in Artificial Intelligence (AI), 2024).

Rationality in decision-making requires an effective approach to solution generation and implementation. Initially, exploring possible solutions increases the probability of problem solving. Setting success and failure criteria for potential solutions reveals which options are more efficient. Analyzing the possible outcomes of each of the solutions allows us to establish a priority order by identifying their strengths and weaknesses. Selecting and testing the best solution provides validation before implementation and measures its effectiveness by observing early results. If the chosen solution does not solve the problem, other alternatives can be tried.

The application of rationality in AI is based on a variety of techniques and approaches. Decision theory focuses on evaluating the potential consequences of actions to determine the option with the highest expected utility, and this method is frequently used in planning and problem solving (Rationality in Artificial Intelligence (AI), 2024). The discussion of decision theory in the context of rationality has been particularly intense in social sciences such as economics and psychology. In this context, rational decision-making refers to individuals acting in a logical and consistent manner in order to achieve the best outcomes. The concept of rationality is mostly analyzed within the framework of utility theory. According to utility theory, individuals try to choose the option that will provide the highest total utility by evaluating the possible outcomes of each option (Von Neumann & Morgenstern, 1944). Expected utility theory suggests that decision makers make decisions based on a model in which the outcomes of each option are multiplied by their probabilities and then these values are summed. According to this theory, decision makers try to maximize expected utility. Savage (1954) argues that decision makers will make the most rational choice in uncertain situations by knowing the probabilities of the outcomes of the options and evaluating each outcome against a measure of utility. Rational decision-making is also based on assumptions such as full information and rational thinking. This assumption requires decision makers to have all the information available to them from their environment and to process that information in a logical way. This is particularly examined in the framework of rational choice theory. Becker (1976) stated that according to this theory, individuals make decisions with the aim of maximizing their self-interest. However, the theory of rationality is based on the assumption that decisions are made only within an abstract framework of logic, and human behavior can often deviate from this ideal rationality. Kahneman and Tversky (1979) introduced a psychological approach to decision theory, arguing that people are often influenced not by rationality but rather by psychological factors (e.g. risk aversion, tendencies to deal with uncertainty). This forms the basis of behavioral decision theory and shows that people sometimes deviate from rationality. Game theory allows us to model competitive and cooperative scenarios by analyzing strategic interactions between agents (Von Neumann & Morgenstern, 1944). This theory examines situations in which individuals or groups try to achieve the best outcomes by considering each other's strategic decisions. In competitive scenarios, each agent tries to maximize its own interests, while in cooperative scenarios, cooperative strategies can be developed to achieve common goals (Nash, 1950). Machine learning learns from data to identify patterns, make accurate predictions and improve decision processes over time. Logic and reasoning involves the use of logical rules for informed reasoning and decision making. Reinforcement learning learns policies that maximize cumulative rewards through rewards and punishments by interacting with an environment and is particularly effective in sequential decision-making problems. Achieving rationality in AI involves challenges such as uncertainty and incomplete information, computational complexity and ethical-social considerations. Making decisions with uncertain data requires complex algorithms, while optimal decision processes increase computational cost. Furthermore, it is important that decisions are ethical and compatible with human values (Rationality in Artificial Intelligence (AI), 2024).

Full rationality, an ideal state used in classical economic thought, is a concept based on the assumption that economic agents are fully informed, use perfect logic and always make the best decision that maximizes their own utility/profit (Toksoy & Turgut, 2023). Complete rationality is an ideal situation in which individuals have full information, use perfect logic and maximize utility by evaluating all possibilities. This approach assumes that the individual has unlimited processing capacity and a foresight that is not affected by uncertainties. In real life, however, people cannot achieve this ideal due to limited information, processing capacity, time and emotional factors. Considering these limitations, Nobel Prize winner Herbert Simon developed the concept of "bounded rationality" (Simon, 1991). This concept argues that people make "good enough" rather than "best" decisions. Although full rationality is important as a theoretical model, it is limited in explaining the real world (Demirhan & Mirabi, 2024).

Rational decision making is an information-based and logic-based approach that individuals follow in the decision-making process to maximize utility. This process involves carefully evaluating available information, analyzing it with sound logic, and making the most efficient use of available resources (Marwala, 2015). However, arguing that it is not always possible to access all the information in the decision-making process and that human logic may not work perfectly in all situations, Simon emphasized with the concept of "bounded rationality" that people have only limited information and limited processing capacity when making decisions, so their decisions may deviate from the ideal.

At this point, the rise of AI questions traditional limitations in decision-making processes. Tshilidzi Marwala, who has done significant work on AI, decision theory and bounded rationality, argues that with the development of AI, the limits of rationality envisioned by Simon's theory have become more flexible. AI, with its superior capabilities in accessing information, analyzing big data and solving complex problems, supports human decision-making processes, allowing these limits to be overcome. This situation requires the concept of bounded rationality to be re-evaluated and considered in a broader perspective with AI.

According to Herbert Simon's theory of bounded rationality, humans do not have perfect knowledge and unlimited processing capacity in decision-making processes. Marwala argues that artificial intelligence (AI) can overcome these limitations. AI is a tool that complements the limits of the human mind with its big data analysis, pattern recognition and predictive capabilities. AI-enabled systems enable better decisions by supplementing incomplete or uncertain information. Marwala emphasizes the importance of AI working with the human factor; the optimal solutions of AI must be balanced with the creative and ethical aspects of humans. The adaptability of learning systems to environmental changes creates a more dynamic model of rationality. Marwala states that AI can optimize decisions even with incomplete data in areas such as health, economics and engineering. However, AI's ethical considerations are necessary for fair and sustainable decisions. As a result, according to Marwala, AI reshapes the concept of bounded rationality, enabling more effective and accurate decisions, but it should be integrated in a balanced way with human intelligence (Efe, A. 2024; Marwala, 2013).

Rational expectations posit that rational agents effectively use all available information to predict the future and that these predictions are systematically accurate. This understanding assumes that economic decisions are shaped within a certain framework of logic and accuracy. Rational choice theory assumes that the information used in decision-making processes is complete and accurate. However, this assumption is not physically and practically applicable in the real world. Because the available information is often limited, full of uncertainties, and agents must deal with these limitations (Marwala, et al., 2017).

AI can enable more accurate and rational decisions thanks to its ability to process large amounts of data quickly. AI can analyze complex data and identify patterns or trends that humans may miss, leading to more informed decision-making. Furthermore, with AI support, decision makers can simulate potential outcomes by considering many variables that humans alone cannot easily calculate (Brynjolfsson & McAfee, 2014; Davenport & Ronanki, 2018). Moreover, AI can help correct people's cognitive biases by providing data-driven insights and reducing the influence of subjective factors in decision-making (Hao, 2021). However, even with accurate data and optimal solutions offered by AI, people may still be influenced by emotional, psychological and contextual biases. Kahneman (2011) highlights how cognitive biases, such as loss aversion or overconfidence, can distort human judgment, even when AI offers optimal solutions. Moreover, AI may not fully explain every situation, especially when it comes to non-quantifiable factors, which can lead to irrational decision-making (Susskind & Susskind, 2015). While AI can efficiently process large data sets, humans may still struggle with "decision fatigue" or the overwhelming complexity of options. Iyengar and DeVoe (2003) argue that the sheer number of options available can create cognitive overload and make decisions difficult to implement, even when supported by rational tools. If AI systems are based on machine learning or imperfect algorithms, they may produce suboptimal or biased results even with large data sets. The mismatch between theoretical rationality and real-world applications can lead to unexpected problems. As AI makes more decisions or provides more influence, unexpected results may occur, especially in complex systems where variables are interdependent, which is difficult to model.

When AI is used as a decision support tool, individuals can increasingly rely on AI to make personal and organizational choices, potentially changing the way people approach decision-making. This reliance may encourage individuals to passively delegate their decisions to AI, thereby reducing personal responsibility and raising important ethical concerns about accountability for AI-induced outcomes. Delegating decision-making authority to AI systems may obscure the accountability of human decision-makers and lead to difficulties in assigning moral responsibility for actions performed by AI. In addition, the use of AI in rational decision-making may have implications for how decisions are framed. Unless AI systems are carefully designed with ethical principles in mind, they may produce rational decisions that prioritize efficiency, cost, or other quantifiable factors, but neglect broader human values or social consequences (Binns, 2018). AI systems may prioritize outcomes optimized by "hard" metrics such as efficiency, resulting in decisions that ignore emotional, ethical or social nuances. This detachment from human values can trigger moral conflicts, especially when AI-driven decisions affect human welfare, such as in the areas of health, justice and social policy (Cowls et al., 2021). Consequently, this raises important questions about the role of AI in promoting values such as justice, empathy and social good in decision-making. However, in the future, a balance may be struck through the collaboration of human reasoning and AI, and questions may be answered in this context. In this case, AI can compensate for cognitive limitations, while humans can remain involved to provide oversight and add values.

Rationality Analysis & AI

AI systems have their limitations. Depending on the machine learning framework and quality of data being used to train the AI, the emerging analytical AI tools may not always be sufficient to fully comprehend the pragmatic modelled human behaviour for rational expectations. The determinants of human complex nature, such as subjectivity, ethical values, social inclusion, collective benevolence and emotional intelligence, form part of the rational agent assumed qualities within the framework of the classical rational expectations theory. It is a monumental challenge to propose an AI-based rational expectation model that would be able to mirror the complexity and divergent subsets within the human condition. It is also a challenge to propose AI AI-based rationality analysis tools that can satisfy the heterogeneous economic environments with peculiar regulatory and fiscal differentiations to produce optimal results.

AI can help in modelling economic rational expectation matrices for optimal decision-making processes to reduce costs. Overt reliance on AI-based rational expectation analysis can increase the dependence on these systems and decrease the rational decision-making abilities of human agents working within the system. This dependence may also lead to dehumanisation within economic decision-making and potentially lead to systemic biases towards the socio-economic ideals of a particular data subset used for training the AI. The dimension of AI manipulation through sociological and ideological settings of a particular dataset used to train the AI is also problematic. The lack of any oversight or advisory framework to check data bias within the AI industry is a source of skepticism overweighing the benefits of AI-based rational expectation analysis systems.

The emergence of AI-based rational expectation analysis tools is a natural progression, given the pervasive use of technology in every sphere of contemporary human life. It would be naive to assume that classical economic modelling relying on a human rational agent would be the choice for present and future economic decision-making at micro as well as macro levels.

The normative agent expectations are observation sets with subsets of current and past economic data, corporate performance reports, government fiscal policies and publically accessible literature. The human rational agent processes the subsets of information with identifiable variables such as consumer asset pricing, inflation, interest rates, income and salary indicators. It is the juxtaposition of the information subsets with the identifiable variables that provide rational expectations and also comparable expectations with a margin of error. The learning pattern of the human agent results in dynamic market expectations, with the caveat of various rules that govern the information collection process and defined information subsets for knowledge inclusion.

Fisher's (1930) 'Adaptive Expectation' approach considers that the difference between the actual realization of the variables and their expected value results in revising the agent's expectations, notwithstanding the acceptable margin of error. The simple processing of information by the agent was termed the 'Naive' expectation model using the adaptive approach.

John Muth (1961) proposed the Rational Expectations Hypothesis (REH) that rejected the Naive Expectation Adaptive Approach and proposed a comprehensive informative description of the economic world as a stochastic aggregate of agents understanding. REH agents are assumed to comprehend the true econometric factors of a prescribed economy with present and future values relevant to the economic variables driving the expectations. The expectations of REH agents are predictable. REH agents rely on economic modelling over a predetermined singular model to form their forecasts. This is a fundamental departure from the naive expectation adaptive approach where the agent can rely on variables as dictated by multiple economic models. REH agents are also assumed to have completed their learning processes on predetermined and fixed models based on past periods of economics. REH detached the learning process and the expectation-forming process for the agent, dismissing the need to interlink the two. Perhaps the

A pragmatic view of the rational expectation theory provides the logical progression towards AI-based expectation analysis, replacing REH human agent learning processes with machine learning AI agents. The progression from the 1930 Adaptive Expectation Approach to the 1961 Rational Expectations Hypothesis and the contemporary AI-based Rational Expectation Analysis is perhaps a march from human agents' 'bounded rationality' towards AI-based machine agents' 'unbounded rationality'.

The AI rational expectation agents are modelled for complex learning environments that are non-parametric and non-linear in nature. The resulting AI rational expectations agent allows innovation by juxta positioning non-restrictive assumptions and heterogeneous variable shifting environments. Such a model for rational expectation analysis would be difficult for human agents to grasp and process. An AI-based adaptive agent can perform rational expectation analysis in a 'model-free' environment.

Conclusion

Artificial intelligence (AI) is having a significant impact on the analysis of economic rationality. In traditional economic theory, rationality assumes that the agent makes consistent and rational decisions. However, it is not always possible for agents to act rationally and consistently in economic decision-making because of a myriad of unknowns within the process of solving complex problems. AI, with its capacity to process large data sets with precise predictive capabilities, has the potential to analyze and optimize complex economic decision-making processes within a defined framework with ease. AI can perform real-time analysis leveraging large amounts of data that can reduce time and increase accuracy within a defined complexity. AI can help in developing economic rationality analysis tools that can constantly update and optimise strategies through rapid adapting based on changing economic conditions and new data. AI-based rationality analysis models are susceptible to data biases due to their lack of human skepticism based on pragmatism, leading to, erroneous analysis. AI's decision-making processes are often referred to as a 'black box problem', defining the inability to explain the AI's decision-making process. Notwithstanding the deep learning limitations of AI rationality analysis modelling, AI can still improve utility-maximizing decisions by providing a more objective and comprehensive view of rational expectation analysis. Overt reliance on AI-based rationality analysis frameworks with potential data bias can lead economic rational agents to make irrational decisions. The rapid predictive capabilities of AI can also reduce organisational confidence in human rational decision-making abilities, creating a form of machine dependency within the economic systems.

Wagner (2020) argued that AI agents are incompatible with economic modelling that requires human-centric rational expectations such as belief modelling. If the expectation modelling follows the pattern of any information set leading to information processing and delivering expectations, the AI expectation model would be perfect or imperfect in so far as the perfection or imperfection of the learning information. It can be argued that AI algorithms may just recognise patterns within variables and not necessarily predict change that is from the past flowing into the present for future expectations. Thus, can we categorise AI predictions within the discourse of economic rational expectation theory or is it still the domain of rational human agents?

AI in its present state of learning from supplied data lacks the pragmatism of human consciousness, around which the economic theory of rational expectation is formed. Akos Rona-Tas (2020) argued that the predictive AI algorithm 'mechanically projects the past onto the future'. The sense of past, present and future is intrinsically a human concept, related to the human agency and beyond the learning dimensions of a machine. Thus, if rational expectation is subject to human agency, human judgment is preferred over an algorithm to predict future expectations. While the scholarly discourse on rational expectation with or without human agency continues, the proliferation of algorithms is being formalized for complex social and economic predictions.

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