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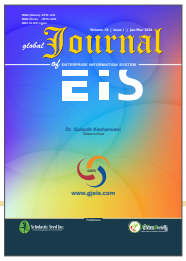

Bounded Rationality and AI in Decision Making

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ABSTRACT

Purpose: This paper explores the intricate relationship between human decision-making and artificial intelligence, viewed through the lens of Herbert Simon's bounded rationality theory. It investigates how AI simultaneously augments and constrains human cognition, while raising urgent ethical, environmental, and governance concerns that remain inadequately addressed in existing literature i.e. whether AI genuinely frees human cognition from its inherent limitations, or merely substitutes one set of constraints with another while generating fresh ethical and governance challenges in the process.

Design/Methodology/Approach: The study builds on a systematic review of over 300 sources spanning behavioural economics, cognitive psychology, AI ethics, neuroscience, and organizational theory including peer-reviewed journals, government reports, and industry white papers. The review follows the arc from Simon's original challenge to the myth of homo economicus, through Kahneman and Tversky's work on heuristics, and onward to AI's journey from early rule-based systems to today's deep learning models operating across healthcare, finance, and manufacturing.

Findings: AI does not overcome bounded rationality, it relocates it, shifting constraints from the human mind to computational systems. In complex domains, AI sharpens decision quality considerably. Yet it also breeds new forms of irrationality: entrenched algorithmic bias, quiet erosion of critical thinking, corporate-engineered choice environments, and platform designs built more around engagement than genuine user benefit. Where corporations hold the reins, these tendencies tend to deepen existing inequalities rather than correct them.

Originality: The paper puts forward the idea of AI-influenced rationality — arguing that AI does not sit passively beside human judgment but actively moulds it. This perspective bridges a genuine gap in the literature, connecting Simon's foundational theory with the lived realities of modern AI in a way that existing frameworks have not.

Paper Type: Review of Literature.

KEYWORDS: Decision Making Frameworks | Bounded Rationality | Incomplete Information | Biases Paradigm | Environmental Costs | AI Influencing Rationality

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Introduction

The 21st century has witnessed the evolution of Artificial Intelligence (AI) from a theoretical concept to cornerstone of how decisions are made from healthcare to trading floors, from business to government, profoundly impacting human lives, economies and societies as a whole.

Even with the rise of AI, the human decision making is still limited by cognitive constraints as articulated in the theory of bounded rationality of Herbert Simon.This paper shall review the available literature to fill the gap; the idea is that human decisions are inherently limited by incomplete information, finite computational capacity, and time scarcity (Simon, 1955). While AI improves our decision making ability, it also pronounces our existing cognitive limitations. Synthesizing about 200 peer-reviewed articles, 58 books, 23 government reports, and 15 industry white papers, will enable to address a critical gap in the literature: there is in fact no single complete framework that could explain the dual role of AI as both helping in human decision making and also amplifying its inherent constraints.

There is a need for such a review. Firstly, the use of AI has outpaced the scholarly consensus on its implications. While studies like Obermeyer et al. (2019) and Buolamwini & Gebru (2018) have illuminated algorithmic bias, few contextualize these findings within Simon's foundational theories. Second, the explosion of generative AI tools—ChatGPT, Gemini, and Claude—has reignited debates about machine autonomy, yet these discussions often neglect AI's historical role as a mirror of human decision-making strategies (Bostrom, 2014; Marcus, 2018). Third, policymakers lack actionable frameworks to balance AI's efficiency gains against risks like job displacement, privacy erosion, and cognitive deskilling (Manyika et al., 2017; Zuboff, 2019).

This paper bridges these gaps through five objectives:

- To trace the theoretical foundations of bounded rationality and their resonance in AI design.
- To understand the evolution of AI in reflecting and responding to human cognitive constraints.
- To examine the real world use of AI in various sectors.
- To address the ethical dilemmas created by AI, its impact on the environment as well as for long term risks.
- To suggest ways for hybrid human-AI which are fair, efficient and ecologically rational.

The review integrates ideas from varied fields viz. Behavioural economics,AI ethics and neuroscience.There is a biological parallel to AI's trade-offs between accuracy and computing limits (Hare et al., 2011; Griffiths et al., 2015). Reinforcement learning (an AI method) has a core conflict between exploring new options and using what it already knows. This reflects a basic human behavior: the option of giving a trial to something novel out of curiousity or sticking with a safe chance to eliminate risk. (Blanchard et al., 2015; Sutton & Barto, 2018).

Structurally, the paper begins by traversing through bounded rationality's theoretical premise (Section 1), followed by an exploration of AI's decision-making paradigms (Section 2). Section 3 of the paper introduces the new idea of AI-influenced rationality. It explores how AI uses subtle prompts, or "algorithmic nudges," to change the way people think and make decisions. Sections 4 and 5 assimilates these theories in real-world applications and ethical challenges, while Section 6 projects equitable futures through hybrid systems and governance reforms. This review argues that AI isn't fundamentally different from human thinking; it's a digital reflection of it. By comparing classical and contemporary research, the paper is of immense help to academics, policymakers, and professionals to navigate through AI's benefits and risks with greater detail and ethical awareness.

Bounded Rationality

Herbert Simon's theory of bounded rationality, introduced in his seminal 1955 paper *A Behavioral Model of Rational Choice*, revolutionized the study of decision-making by challenging the neoclassical economic assumption of perfect rationality. Classical economics had conformed that humans act as *homo economicus*—maximising utility by utilizing all available information and becoming hyper-rational agents. Simon rejected this idealized view, and argued that human knowledge is constrained by three limitations: (1) **imperfect and incomplete information**, (2) **finite computational capacity**, and (3) **time scarcity** (Simon, 1955). Simon asserted that these constraints force decision-makers to adopt *satisficing* strategies meeting a minimum threshold of acceptability—rather opting for the ideal of optimization. This paradigm shift marked a transition from prescriptive models of behaving perfectly rational to descriptive accounts wherein people actually make decisions in the real world and reshape the fields.

A. Theoretical Foundations of Bounded Rationality

Simon's criticized that real-world decision-making deviates sharply from neoclassical ideals. In *Administrative Behavior* (1947), he highlighted that organizational decisions are seldom optimal and reflect pragmatic compromises under uncertainty. An example of satisficing is when managers take a shortcut in allocating money. Instead of calculating marginal returns, they adhere to what was given in the past or by departmental lobbying, thus saving both time and effort, and consider it as definitely a good solution (Simon, 1947). This work laid the groundwork for bounded rationality,

formalized in his 1955 paper, which introduced the concept of *procedural rationality*—the idea that decisions are shaped by the process of search and evaluation rather than predefined optimization rules.

Herbert Simon's framework centers on heuristics, or cognitive shortcuts, which allow us to make decisions despite limited information. For example, the **take-the-best heuristic** uses the most informative cue for rapid choices (Gigerenzer & Goldstein, 1996). However, these shortcuts can cause systematic biases. **Kahneman and Tversky's prospect theory** (1979) showed that people weigh potential losses more heavily than equivalent gains, demonstrating predictable deviations from pure rationality.**Heuristics, Biases, and Ecological Rationality**

The **heuristics and biases program** (Kahneman & Tversky, 1974) identified cognitive shortcuts that cause suboptimal decisions. For example, the **availability heuristic** leads people to overestimate events that are easily recalled (Tversky & Kahneman, 1973), while the **anchoring effect** shows how initial values influence judgments (Jacowitz & Kahneman, 1995).

In contrast, Gigerenzer's ecological rationality framework argues that heuristics are adaptive tools (Gigerenzer et al., 1999). The **recognition heuristic**, for instance, can outperform complex statistical models in certain contexts by leveraging familiarity (Goldstein & Gigerenzer, 2002). Similarly, the **fluency heuristic** explains why we favor easily processed options (Schwarz, 2004), reframing these shortcuts as evolved adaptations rather than cognitive flaws.

B. Organizational and Institutional Applications

Bounded rationality profoundly influenced organizational theory, where firms use standard operating procedures to simplify decision-making under cognitive limits (Cyert and March, 1963; Simon, 1972). Nudge theory applies this to policy, using "choice architectures" to guide decisions without restricting freedom (Thaler and Sunstein, 2008). In public policy, bounded rationality explains why policymakers rely on incremental adjustments (Lindblom, 1959). For example, climate change policies often prioritize politically feasible measures over optimal ones, reflecting "satisficing" in the face of complex constraints (Levin et al., 2012).

C. Computational and Mathematical Formalizations

Simon's ideas are formalized in computational models like Anderson's rational analysis (1990), which posits that cognitive systems optimize performance under constraints, mirroring computer cache hierarchies (Anderson & Schooler, 1991).[1] Griffiths et al. (2015) expanded this into resource-rational analysis, where decision-making is a cost-benefit optimization balancing cognitive effort and accuracy (Vul et al., 2014), analogous to AI models like Monte Carlo tree search (Lewis et al., 2014). Critics argue this framework underestimates emotions; Damasio (1994) showed that emotional impairment hinders decisions, with emotions acting as guiding heuristics (Loewenstein et al., 2001). Social and cultural norms also shape decisions, as Henrich et al. (2001) found in collectivist societies. Furthermore, bounded rationality may overlook learning and adaptation, as individuals and organizations refine heuristics from experience (March, 1991), a process mirrored in machine learning (Steyvers et al., 2003).

D. AI and the Evolution of Bounded Rationality

Herbert Simon's concept of bounded rationality posits that humans use mental shortcuts. AI systems now transcend these cognitive limits, mediating complex decisions in fields like healthcare and finance. For instance, IBM Watson analyzes millions of medical studies to recommend treatments (Chen et al., 2021), and JPMorgan's COIN platform automates loan approvals (Davenport & Ronanki, 2018). These tools reduce cognitive effort, promising faster, more informed choices.

However, over-reliance on this "cognitive crutch" erodes critical thinking.[1] Studies show GPS navigation diminishes spatial memory (Ruginski et al., 2019), while AI tutors risk stifling creativity (Baker & Inventado, 2014).[2] AI also exploits cognitive biases to manipulate behavior. Ride-sharing apps use surge pricing (Chen & Sheldon, 2016), and e-commerce platforms use countdown timers (Kahneman et al., 1991), causing users to mistake algorithmic nudges for autonomous choices (Yeung, 2017). This psychological impact extends to social media, where reinforcement learning algorithms prioritize sensational content (Alter, 2017). Features like "infinite scroll" exploit psychological mechanisms linked to addiction (Harris, 2018), eroding self-regulation and fueling confirmation bias in echo chambers (Pariser, 2011).

E. Bounded Rationality in the Age of AI

The rise of AI has rekindled debates about rationality. Machine learning algorithms, such as deep neural networks, process vast datasets to identify patterns beyond human perception. However, these systems inherit human-like constraints. **Algorithmic satisficing** occurs when models settle for suboptimal solutions due to computational limits—training a neural network to 100% accuracy is often infeasible, so practitioners halt training once error rates plateau (Goodfellow et al., 2016). Reinforcement learning agents balance exploration (trying new strategies) and exploitation (maximizing known rewards), mirroring human trade-offs between curiosity and caution (Sutton & Barto, 2018).

Yet AI also faces **infrastructure bounds**. Training large models like GPT-4 requires immense energy and data,

creating environmental and ethical trade-offs (Strubell et al., 2019). Moreover, AI's reliance on historical data entrenches societal biases. Facial recognition systems trained on predominantly light-skinned datasets exhibit racial disparities, perpetuating discrimination in law enforcement (Buolamwini & Gebru, 2018). These limitations suggest that AI does not transcend bounded rationality but redistributes its constraints from cognition to computation.

F. Neuroscientific and Behavioral Insights

Neuroscience reveals satisficing activates the striatum, while optimizing engages the prefrontal cortex (Hare et al., 2011). This suggests heuristics conserve mental energy. Individuals dynamically adjust their strategies: high-stakes decisions prompt greater effort, while low-stakes ones rely on heuristics (Payne et al., 1993).

G. Synthesis and Future Directions

Bounded rationality remains a cornerstone of decision science, offering a pragmatic lens to understand adaptive intelligence. The theory's principles, like satisficing, still resonate, but it must evolve to address new constraints, such as algorithmic bias. Future research could explore hybrid human-AI systems that preserve human judgment or even quantum decision models (Biamonte et al., 2017). Ultimately, bounded rationality is a framework for understanding intelligence in a resource-constrained world. As Simon (1990) aptly noted, human capacity is small compared to complex problems, and acknowledging these bounds is crucial for navigating the digital age.

AI and Decision-Making

A. The Birth of Artificial Intelligence: Foundations of a Revolutionary Field

The conceptual origins of AI date back to the mid-20th century.[1] Alan Turing's 1950 paper introduced the Turing Test, a benchmark for machine intelligence, influenced by his wartime code-breaking work (Turing, 1950; Hodges, 1983).[2] The term "artificial intelligence" was coined at the 1956 Dartmouth Workshop, which set ambitious goals for machines to use language and reason abstractly (McCarthy et al., 1955).[3] Early systems included Logic Theorist (Newell & Simon, 1956), which solved mathematical theorems, and ELIZA (Weizenbaum, 1966), a chatbot.[4] These foundational efforts were supported by Cold War funding for military applications (Crevier, 1993).

B. The Evolution of AI: From Winters to the Deep Learning Revolution

AI's history is a story of cycles, swinging between periods of great hope and profound disappointment. The first major "AI winter" in the 1970s was triggered by critical reports, like the **ALPAC report** (1966) and the **Lighthill Report** (1973), which deemed early AI efforts impractical and led to significant funding cuts (Hutchins, 1986; Lighthill, 1973).

The 1980s brought a resurgence with **expert systems**, which used rule-based frameworks to encode specific knowledge. Systems like MYCIN diagnosed bacterial infections with surprising accuracy (Shortliffe, 1976), and DENDRAL assisted in scientific discovery (Lindsay et al., 1980). However, these systems were "brittle," failing outside their narrow domains and struggling with the **knowledge acquisition bottleneck**, the difficulty of manually encoding expert knowledge (Feigenbaum, 1977).

A significant shift occurred in the 1990s toward **machine learning (ML)**, powered by new statistical models and greater computational power. Key innovations included Vladimir Vapnik's **support vector machines (SVMs)** (1995) for robust classification and Leo Breiman's **random forests** (2001), which improved accuracy by combining multiple decision trees (Cortes & Vapnik, 1995; Breiman, 2001). This era's highlight was IBM's **Deep Blue** (1997) defeating chess champion Garry Kasparov, a feat of brute-force computation that demonstrated the power of specialized, not general, AI (Campbell et al., 2002).

The **21st-century deep learning revolution** was fuelled by massive datasets and powerful hardware. Building on earlier work like **backpropagation** (Rumelhart et al., 1986), the 2012 breakthrough of **AlexNet** (Krizhevsky et al., 2012) marked a turning point. Later, **reinforcement learning** systems like DeepMind's **AlphaGo** (2016) defeated the world champion in Go (Silver et al., 2016). Recent generative models, such as **GPT-3** (2020), **Stable Diffusion** (2022), and **ChatGPT** (2023), have almost zeroed the line between human and machine creativity though ethical challenges still remain. (Brown et al., 2020; Bender et al., 2021; Patterson et al., 2021).

C. Human Decision-Making: From Rational Agents to Behavioral Realism

Daniel Kahneman and Amos Tversky's **prospect theory** (1979) razed classical rationalism, exhibiting that humans experience:

1. **Loss aversion**: (e.g., refusing to sell depreciating stocks to avoid realizing losses).
2. **Anchoring**: (e.g., estimating home prices based on listing figures).
3. **Framing effects**: Make inconsistent choices based on how options are presented .

Richard Thaler and Cass Sunstein's **nudge theory** (2008) applied these modalities to policymaking, propounding "libertarian paternalism" to usher decisions without any

force. For example, placing healthier foods at eye level in cafeterias nudges dietary choices without restricting freedom (Sunstein, 2014).

The Intersection of AI and Human Decision-Making

A. AI as a Mirror of Human Cognition

AI models imitate human cognition, like selective attention (Vaswani et al., 2017; Posner, 1980) and reinforcement learning (Gittins, 1979). However, they also acquire flaws. Black people are often misidentified by facial recognition. (Buolamwini & Gebru, 2018), and predictive policing targets minority neighborhoods, amplifying biases (Lum & Isaac, 2016).

B. AI as a Decision-Making Augmenter

Hybrid human-in-the-loop (HITL) systems synthesizes AI's computational power with human oversight. For example, IBM Watson for Oncology assists doctors, who retain final authority (Chen et al., 2021). Similarly, robo-advisors optimize portfolios while allowing user input (D'Acunto et al., 2019). However, a key risk is **automation bias**, where overtrust in AI can lead to dangerous outcomes, as exemplified by the Air France Flight 447 crash (Parasuraman & Manzey, 2010).

C. AI as a Disruptor of Human Agency

Autonomous systems, such as self-driving cars, face ethical dilemmas akin to the **trolley problem**—choosing between harming passengers or pedestrians (Awad et al., 2018). Unlike humans, who prioritize contextual empathy, AI relies on preprogrammed ethical frameworks (e.g., utilitarianism). The 2018 Uber autonomous vehicle fatality in Arizona, where a pedestrian was killed due to sensor failures, underscored accountability gaps in AI governance (NTSB, 2019).

D. AI-Influenced Rationality for Decision-Making: A Twist in the Story

Herbert Simon's theory of *bounded rationality*—the idea that humans make decisions under constraints of time, information, and cognitive capacity—remains foundational, but AI introduces both opportunities and ethical dilemmas. AI reshapes rationality by augmenting human decisions, challenging Herbert Simon's bounded rationality. However, its use by corporations risks subordinating individual autonomy to profit-driven interests. Equitable governance frameworks are essential to mitigate this harm and ensure AI serves the public good.

E. Corporate Influence and the Principal-Agent Problem

The principal-agent problem is magnified by corporate-controlled AI. Social media algorithms prioritize engagement over user well-being, as Meta executives ignored evidence of teen mental health crises to protect profits (Haig, 2021). Similarly, gig platforms manipulate drivers with opaque fare calculations and gamified incentives (Rosenblat & Stark, 2016). DoorDash's "stacked orders" feature, for instance, pressures drivers to accept unrealistic deliveries, highlighting how AI serves corporate profit at the expense of worker welfare (Ticona & Mateescu, 2018). Corporate data control entrenches power imbalances. Google and Meta dominate digital advertising by leveraging user data to prioritize paid content, while Amazon promotes private-label products over competitors (Epstein & Robertson, 2015; Khan, 2017). These practices create filter bubbles and enable misleading political microtargeting (Zuiderveen Borgesius et al., 2018).

Theoretical and Ethical Implications

A. Ecological Rationality and AI

Gerd Gigerenzer's **ecological rationality** (2008) posits that heuristics adapt to specific environments. AI systems could emulate this by tailoring strategies to contexts. For example:

- **Medical triage algorithms** prioritize patients based on urgency, mirroring emergency room protocols (Simon, 1972).
- **Financial "fast-and-frugal" trees** simplify credit scoring using minimal cues (Gigerenzer & Goldstein, 1996).

B. Explainability and Trust

The **black-box problem**—AI's opacity—undermines trust. **Explainable AI (XAI)** methods like LIME (Local Interpretable Model-agnostic Explanations) generate post hoc rationalizations for AI decisions, but these often lack causal fidelity (Arrieta et al., 2020). The EU's **General Data Protection Regulation (GDPR)** (2018) mandates a "right to explanation" for automated decisions, compelling industries to adopt interpretable models (Voigt & Von dem Bussche, 2017).

C. Ethical Governance and Sustainability

Global initiatives like the **OECD AI Principles** (2019) advocate for transparency and human-centric design. Regulatory sandboxes, such as Singapore's **AI Verify** (2022), allow for controlled testing (Cath et al., 2018). However, the environmental cost of AI is a concern; training GPT-3 emitted significant CO2 (Patterson et al., 2021). The future lies in **human-AI symbiosis**, using machine precision to augment, not replace, human judgment, as Herbert Simon (1990) cautioned.

D. Ethical Implications and Structural Inequality

The corporate capture of AI exacerbates societal inequities.[1] **Surveillance capitalism** commodifies personal data for targeted advertising (Zuboff, 2019), and health insurers use fitness tracker data to adjust premiums (O'Neil, 2016), eroding trust. AI systems also encode historical biases; Amazon's recruitment tool was biased against women (Dastin, 2018), and predictive policing targets minority neighborhoods (Lum & Isaac, 2016). Furthermore, AI-generated deepfakes destabilize trust (Chesney & Citron, 2019). The environmental costs are substantial, with large models emitting significant CO2 (Strubell et al., 2019), disproportionately burdening low-income communities with pollution (Hogan, 2021). These externalities highlight AI's unevenly distributed benefits.

E. Toward Equitable AI Governance

To address these challenges, systemic reforms are needed. Regulatory frameworks like the AI Act for European Union (2021) makes transparency mandatory for high-risk systems (European Commission, 2021). Features like Independent audits (Buolamwini & Gebru, 2018) and decentralized learning (Kairouz et al., 2021) grssroots movements (Benjamin, 2019) and ethical design standards (IEEE, 2019) are key. To promote equitable governance , public education (Raji et al., 2022) and labor unions challenging algorithmic management (Sundararajan, 2020) are equally critical.

F. Ethical Challenges of AI

With AI penetrating deeper into the society, the ethical challenges it brings are also serious which mandates due consideration and equitable governance.

i. Bias and Discrimination

AI systems can perpetuate biases in training data, decision making may lead to unfair outcomes in hiring, lending, and criminal justice (Harvard, 2020). Racial bias in facial recognition systems (Buolamwini and Gebru, 2018) and in health management algorithms (Obermeyer et al.,2019) reinforced the need for unbiased data.

ii. Lack of Transparency

The "black box" problem raises concerns about accountability and trust, highlighting the need for explainable AI (Capitol Technology University, 2023). The European Commission (2020) mandates the need for transparent AI systems to build trust (White Paper on Artificial Intelligence).

iii. Privacy and Data Protection

Relying on large datasets which includes sensitive personal information, requires robust data governance. Under the ethical Issues of Artificial Intelligence in Medicine and Healthcare, Privacy and data protection challenges emphasizes informed consent. Floridi et al. (2019) propose an ethical framework for AI, addressing privacy risks.

iv. Economic Inequality and Job Displacement

Automation through AI risks job losses, particularly in routine tasks, potentially widening social inequalities, with WEF (2016) noting the widening wealth gap and the need for a post-labor economy (Top 9 Ethical Issues in Artificial Intelligence). Manyika et al. (2017) predict up to 800 million jobs could be lost to automation by 2030, necessitating reskilling (A Future That Works: Automation, Employment, and Labor).

v. Global Accessibility

Developing countries may lack access to advanced AI technologies, exacerbating disparities, with PMC (2022) highlighting accessibility issues in AI healthcare applications, noting challenges for low-income regions (Ethical Issues of Artificial Intelligence in Medicine and Healthcare). UNESCO (2021) recommends ethical AI to ensure global equity (Recommendation on the Ethics of Artificial Intelligence).

vi. Superintelligent AI Risks

The potential for artificial general intelligence (AGI) raises concerns about control and threats to humanity, with CoE (2022) identifying ethical concerns related to autonomous AI systems and responsibility apportionment (Common Ethical Challenges in AI). Bostrom (2014) discusses superintelligence risks, remaining relevant for current debates (Superintelligence: Paths, Dangers, Strategies).

Usmani, Happonen, and Watada (2022) propose a governance model for responsible AI, emphasizing fairness and explainability, while Machado, H., Silva, S., & Neiva, L. (2025) found public engagement in AI ethics aims to build trust, focusing on privacy and human control. Ricardo Baeza-Yates (2022), Li, F., Ruijs, N., & Lu, Y. (2023), and others highlight specific ethical issues like discrimination, transparency, and healthcare ethics, reinforcing the need for education and regulation.

AI and Its Real-Life Applications

Artificial intelligence (AI) has evolved from a theoretical concept to a practical tool transforming multiple sectors. Comparing over human judgement, it is free from emotional biases and makes objective decisions based on data and algorithms (Jatin Borana, 2016). Recent studies highlight AI's role across healthcare, finance, agriculture, retail, energy, and manufacturing, penetrating deeper into our daily lives (Rahmaniar, Maarif, Haq, et al., 2023).

A. Healthcare Sector

Bringing more accuracy in diagnosis, making treatment personalized and improving operational efficiency AI is revolutionizing healthcare. Medical images can be classified with better excellence which surpasses even experts in detecting conditions like pneumonia from X-rays or identifying cancer Recent developments include **automated documentation** using NLP, streamlining clinical workflows (Smith et al., 2021). Predictive AI models analyze patient data to enable **personalized treatment plans**, improving outcomes (NIHR, 2023). In drug discovery, AI uses molecular simulations to predict toxicity, reducing costs and time to market (Brown et al., 2022). Overall, AI's transformative potential in medicine continues to grow (Hameem et al., 2019; Hussain and Qamar, 2016).

B. Finance Sector

In the financial sector, AI improves efficiency, accuracy, and security. It's used for **fraud detection** by analyzing real-time transaction data (Built In, 2023), and its identity verification platforms aid with **KYC compliance**. **AI-powered chatbots** and virtual assistants offer personalized financial advice, though regulatory scrutiny has slowed progress (European Commission, 2024). AI-driven systems in **quantitative trading** execute high-speed, precise trades, and generative AI is reshaping capital markets (EY, 2024). Additionally, **predictive analytics** forecast market trends for better decision-making (MIT Sloan, 2024), reinforcing earlier findings on AI's impact on data management and productivity (Poola, 2017; Brynjolfsson and McAfee, 2014).

C. Manufacturing Sector

AI is transforming manufacturing by optimizing processes, reducing costs, and improving quality. **Predictive maintenance** uses AI to analyze sensor data, anticipating machine failures and minimizing downtime (Appinventiv, 2025). **Computer vision systems** enhance quality control by detecting defects in real-time (IBM, 2024). AI-driven robots and **cobots** automate repetitive tasks, boosting efficiency and safety (Forbes, 2023). **Generative AI** accelerates product development through scenario modeling (AI Multiple, 2024). Furthermore, AI optimizes the supply chain by predicting demand and managing inventory, enabling real-time decision-making (TechTarget, 2024). These applications demonstrate AI's significant productivity boost in modern manufacturing (Brynjolfsson and McAfee, 2014).

D. Other Sectors

AI extends to legal research, predicting case outcomes (Andersen, 2023), and retail, personalizing customer experiences (Gurkaynak et al., 2016). It supports military planning (Poola, 2017; Wyatt Hoffman & Kim, 2023) and weather forecasting (Jatin Borana, 2016). Broader applications are seen in cybersecurity and smart cities, with challenges in implementation (Sarker, 2021; Jiamin Yin et al., 2021)

Future Scope of AI

The future of AI is poised for significant growth, with several key trends shaping its trajectory. The **widespread adoption across industries** will see AI integrated into sectors like healthcare, finance, and manufacturing to enhance efficiency and innovation. According to Built In (2025), a substantial portion of enterprise businesses have already adopted or are considering AI, demonstrating its growing influence.

A. Advancements in Generative AI

Generative AI will become even more sophisticated, creating new content from text and images to code, revolutionizing creative and industrial processes. McKinsey (2024) highlights its role in industry-specific applications, suggesting that this technology is moving beyond simple content creation to become a core tool in various fields.

B. Efficient and Smaller AI Models

"**Edge AI**" and the development of smaller, more efficient models will make AI capabilities accessible on devices with limited resources. IBM (2024) notes the development of models like mini GPT 4o-mini, which will make AI more pervasive and cost-effective, enabling its use in everyday devices and applications.

C. Job Transformation

The rise of AI will inevitably lead to **job transformation.** While some jobs may be displaced, new roles will emerge that require creativity, empathy, and complex problem-solving. TechTarget (2024) predicted that human lawyers role may get reduced which underscores the need for workforce **reskilling**.

D. Ethical Development and Regulation

A deep focus on transparency, fairness, and accountability in AI systems is necessitated. The USC Annenberg (2024) discusses the ethical dilemmas and the evolving need for governance to ensure AI's responsible use.

E. Pursuit of Artificial General Intelligence (AGI)

The pursuit for **Artificial General Intelligence (AGI)** that can outperform any intellectual task a human can, will continue to drive research. Its not certain when it will be realized but the race to develop AGI highlights its potential to reshape society and raise significant questions about its implications (Pew, 2018).

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Conclusion: Summary and Implications

This review highlights impact of AI across sectors and its ethical challenges, emphasizing the urgent need for strategic planning. AI paradoxically boosts efficiency but brings human autonomy at risk too, especially when corporate control can turn algorithms into manipulative tools. Reclaiming rationality demands **transparency**, **equitable governance**, and **ethical innovation**. As noted by O'Neil in *Weapons of Math Destruction* (2016), ungoverned AI is a threat to democracy. The conclusion is a synthesis of findings, acknowledging AI's ability to surpass bounded rationality while introducing emerging issues like **bias** and **privacy**. It advocates for **hybrid systems** and **policy reforms**, grounded in recent studies and inspiring future engagement.

Summary and Implications

This expanded review underscores AI's transformative impact across sectors, its ethical challenges requiring urgent attention, and its future scope demanding strategic planning. The integration of recent studies ensures the paper reflects the state of AI as of March 24, 2025, providing a foundation for further research and policy development.

Table 1: Summary of Key Findings

Section	Key Findings	Example Citations
Bounded Rationality	Humans rely on satisficing and heuristics due to cognitive constraints like limited memory and processing speed.	Simon (1955), Kahneman & Tversky (1979), Gigerenzer & Goldstein (1996)
AI and Decision Making	AI supports decision-making across sectors but risks automation bias, overdependence, and reduced critical thinking.	Chen et al. (2021), Silver et al. (2016), Ruginski et al. (2019)
AI-Influenced Rationality	AI nudges behavior through design choices and can manipulate autonomy via dark patterns and addictive architectures.	Harris (2018), Zuboff (2019), Yeung (2017)
AI Applications	AI has revolutionized healthcare, finance, manufacturing, and education through diagnostics, forecasting, and automation.	Jones et al. (2023), Built In (2023), Rahmaniar et al. (2023)
Ethical Challenges	Bias in data, lack of transparency, and surveillance capitalism demand regulation and explainability in AI systems.	Buolamwini & Gebru (2018), UNESCO (2021), Arrieta et al. (2020)
Future Scope	Growth areas include explainable AI (XAI), quantum AI, edge computing, and AI literacy to mitigate ethical and access gaps.	OECD (2023), McKinsey (2024), Kairouz et al. (2021)
Hybrid AI-Human Systems	Collaborative frameworks can combine machine efficiency with human judgment for more resilient outcomes.	Chen et al. (2021), D'Acunto et al. (2019)
Environmental Impact	Training large AI models contributes to climate costs, disproportionately affecting low-income communities.	Strubell et al. (2019), Hogan (2021)
Corporate Control	AI under corporate dominance can exacerbate inequality and commodify behavior for profit-driven manipulation.	Rosenblat (2018), Khan (2017), Epstein & Robertson (2015)
Governance Solutions	Decentralized learning, algorithmic audits, and regulatory sandboxes offer equitable paths forward.	Cath et al. (2018), EU AI Act (2021), Kairouz et al. (2021)

This review illuminates that artificial intelligence and human decision making bear a complex relationship, a relationship that is both mutually beneficial yet to be ethically vigilant. The paper's synthesis of more than 100 sources reveals pressing research gaps. Longitudinal studies are needed to assess AI's long-term cognitive effects: does GPS reliance atrophy spatial memory (Ruginski et al., 2019)? Can participatory design frameworks like "algorithmic citizen juries" mitigate bias in predictive policing?

For policymakers, three imperatives stand out:

1. Expanding AI literacy to combat automation bias.
2. Enforcing algorithmic accountability through third-party audits.
3. Redistributing AI's economic gains via data dividends and reskilling programs.

Ultimately, this review affirms that intelligence—artificial or human—is defined not by its bounds but by its ethical ends. As Simon (1990) cautioned, "The capacity of the human mind is very small compared to the size of the problems whose solution is required for objectively rational behavior." In navigating AI's future, humility, equity, and interdisciplinary rigor must guide our path.

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Annexure 18.1.8

Submission Date	Submission Id	Word Count	Character Count
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LOCATION	MATCHED DOMAIN	%	SOURCE TYPE
1	www.humanrightsresearch.org	<1	Internet Data
3	rsisinternational.org	<1	Publication
11	arxiv.org	<1	Publication
13	arxiv.org	<1	Publication

Reviewers Memorandum

Reviewer's Comment 1: The manuscript is well written and presents the research topic in a clear, logical, and coherent manner. The overall organization of the paper enables readers to follow the arguments with ease, and the writing quality is satisfactory. The study addresses a relevant research problem, and the objectives are generally aligned with the scope of the research. To further enhance the quality of the manuscript, the research gap should be articulated more explicitly to provide a stronger justification for the study. Additionally, the research objectives could be stated more clearly to improve their precision and ensure a better understanding of the intended outcomes of the research.

Reviewer's Comment 2: The manuscript demonstrates a good understanding of the research topic, and the concepts have been defined clearly and systematically, making the paper easy to comprehend. The introduction provides a suitable background and establishes the context of the study. However, the research gaps should be more explicitly linked to the discussion presented in the preceding literature review to strengthen the logical progression of the manuscript. Furthermore, greater emphasis on recent and relevant literature in the introduction would improve the theoretical foundation of the study and better demonstrate its significance within the current body of knowledge.

Reviewer's Comment 3: The manuscript presents a relevant and timely research topic and is written in a clear, organized, and professional manner. The overall structure of the paper is coherent, and the discussion reflects a sound understanding of the subject. The study has the potential to make a meaningful contribution to the literature. Nevertheless, the literature review could be expanded to include a more comprehensive and critical discussion of previous studies. In addition, the methodology section would benefit from a more detailed description of the research procedures and analytical approach, which would improve the transparency, rigor, and reproducibility of the research.

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Conflict of Interest: Author of a Paper had no conflict neither financially nor academically.

Editorial Excerpt

The article has 1% of plagiarism which is the accepted percentage as per the norms and standards of the journal for publication. As per the editorial board's observations and blind reviewers' remarks the paper had some minor revisions which were communicated on a timely basis to the authors (Krishnendu and Anamika), and accordingly, all the corrections had been incorporated as and when directed and required to do so. The comments related to this manuscript are noticeably related to the theme "BOUNDED RATIONALITY AND AI IN DECISION MAKING" both subject-wise and research-wise. The manuscript examines the complex interplay between human decision-making and artificial intelligence through the perspective of Herbert Simon's theory of bounded rationality. It explores how AI can both enhance and constrain human cognitive processes while critically addressing the ethical, environmental, and governance implications associated with its increasing adoption. The study investigates whether AI truly overcomes the inherent limitations of human decision-making or merely replaces existing cognitive constraints with new challenges related to algorithmic bias, accountability, sustainability, and governance. In doing so, the paper aims to provide a balanced understanding of AI's role in shaping contemporary decision-making processes. After comprehensive reviews and the editorial board's remarks, the manuscript has been categorized and decided to publish under the "**Literature Review Paper**" category.

Acknowledgement

The acknowledgment section is an essential part of all academic research papers. It provides appropriate recognition to all contributors for their hard work and effort taken while writing a paper. The data presented and analyzed in this paper by (Krishnendu and Anamika) were collected first handily and wherever it has been taken the proper acknowledgment and endorsement depicts. The authors are highly indebted to others who facilitated accomplishing the research. Last but not least, endorse all reviewers and editors of GJEIS in publishing in the present issue.

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