CME LIVE OPEN ACCESS

Open Access Journal of Economic Research

Review Article

ISSN: 3065-9035

The Concept of Human-Machine Decision Making

Hanzis, A.*

Business School, Athens University of Economics and Business, Athens Greece.

Corresponding Author: Hanzis A, Business School, Athens University of Economics and Business, Athens Greece.

Received: 2025 Feb 03 **Accepted:** 2025 Feb 22 **Published:** 2025 Mar 12

Abstract

Currently there is a range of applications of AI within decision-making, with increasing integration and collaboration mainly through AI systems augmenting human decision-making capabilities within a range of industries and sectors. AI is increasingly used for business decision support, although this tends to be focused more upon lower-level decisions routines instead of high-stakes decisions necessitating human knowledge [1]. However, the rapid development of the use of AI predicts that this is likely to change [2]. The future of human-machine decision-making lies in optimizing the synergies between human intelligence and machine efficiency. This hybrid approach aims to leverage the strengths to achieve better outcomes, whether in healthcare, finance, transportation, or other critical fields. As we move forward, it will be essential to foster interdisciplinary collaboration, ethical considerations, and adaptive learning systems to ensure that human-machine decision-making systems serve the best interests of society. There are many arguments about this collaboration, and the time for discussion is now.

Keywords: Human Machine Decision, AI Technologies, Algorithms, Finance, Environment

1. Introduction

Currently autonomous AI decisions are being used in many fields including financial services in all areas as loan approvals, but the incorporation of human judgement in AI-facilitated decision-making is also growing as a critical domain [3]. In the literature, a report by Meissner and Narita shows that 35% of Amazon's revenue arises from AI recommendations [2]. Davenport & Ronanki suggest that there are benefits in incorporating AI into commercial decision-making, aiming to enhance decision-making precision, velocity, and efficacy, while simultaneously decreasing expenses and optimizing processes across several sectors [4]. For example, AI can analyse big data and identify patterns that humans may not be able to detect [5]. AI is also useful in handling data-intensive, repetitive tasks, enabling faster, consistent, and accurate decisions [6]. AI can make good predictions based upon large data set of information, and this can be of assistance within commercial decision-making, and reduced tedious processes [7]. Although the impact of AI in decision making seems impressive, the significance of trust in AI and the psychological aspects essential for effective AI-human collaboration are central in current empirical studies [8]. Trust dynamics, including issues of perceived reliability, transparency, and control, are psychological aspects crucial for the successful integration, as human trust profoundly influences AI adoption and collaborative results [8]. Currently there are some mixed responses to the advance of AI. For example, Ethan Mollick in his book entitled "Co- intelligence" written in 2024 discusses the incredible opportunities arising from a positive partnering and collaboration between humans and AI.

2. Background and Rational

AI has and continues to grow exponentially and our times are called "the Age of AI" [9-11]. Human machine interaction and AI assisted decision-making together are a symbiosis in which AI functions as an enhancement tool rather than a substitute for human decision-making. This paper offers a framework useful in understanding the dynamics of AI assistance in optimizing human-machine interaction. The concept builds on conceptual model of Jarrahi that emphasizes several interaction patterns, and examines aspects influencing effective human-machine collaboration, such as trust, transparency, and the alignment of AI recommendations with human values [12]. Our conceptual model incorporates Ashby's "Law of Requisite Variety" often described as the "First Law of Cybernetics," which in practical terms means that to have control over a complex environment, a system must be equipped with a sufficient range of responses to match the variety of possible disturbances it might face [13]. Ashby's "Law of Requisite Variety" is relevant in understanding how machines, as adaptive systems, can respond to human inputs [13].

3. The Emergence of AI in the Workplace

The integration of AI technologies in the workplace has many impacts. AI in the workplace has been through several key phases and is being increasingly integrated now into business processes. As computing power has increased and as algorithms have improved, businesses have begun to explore applications of AI in the workplace, moving from the early AI system which was primarily used for analysis of large datasets and automation of routine tasks, particularly in industries such as manufacturing and finance, through to more recent times when adoption in the workplace has significantly increased. According to the report " AI adoption statistics by industries and countries: 2024 snapshot" (2024), companies in U.S. in 2018 only 40% actively used AI, a number that in 2023 reached 52% [14,15]. By 2029 the AI market is expected to exceed US $1.394 Billion [16]. Barriers to adoption, according to this report, includes limited skills of workers, high price, lack of tools or platforms, and data complexity. AI is starting to expand its application into more complex tasks including healthcare. The rise of large language models such as ChatGPT are transforming workplaces, although most organisations do not yet have clear policies regarding the use of large language models. Certainly, the progression of AI into decision-making has moved way beyond the earlier somewhat limited application to becoming a much more foundational component of business organisations, and is reshaping how decisions are made, as well as how workplaces operate across many industries [17].

4. Human Cognition and Decision Making

Human cognition allows individuals to process information, form thoughts, navigate their environment, and make sense of the world. Human cognition is influenced by a variety of factors and is a complex and dynamic field of study that spans psychology, neuroscience, artificial intelligence, philosophy, and education. Understanding human cognition helps in designing better educational systems, improving mental health treatments, enhancing artificial intelligence systems, and exploring the nature of consciousness [18].

Several key approaches have been used over the years to explain how individuals make decisions and solve problems, that encompasses a wide range of mental activities, including:

- **Perception:** The process of gathering and interpreting sensory information from the environment, such as visual, auditory, and tactile stimuli [19].
- **Memory:** The storage and retrieval of information, involving complex neural processes [20].
- **Learning:** The process of acquiring new knowledge, skills, behaviors, or attitudes through experience, study, or instruction [21].
- **Reasoning and Problem-Solving:** The ability to think logically, make connections between ideas, and solve complex problems. This involves both inductive and deductive reasoning [22].
- **Decision-Making:** The process of selecting a course of action among multiple alternatives based on preferences, beliefs, and available information [23].
- **Language:** The use of symbols, sounds, or gestures to communicate thoughts, ideas, and emotions. Language is a fundamental aspect of human interaction and culture [24].
- **Executive Functions:** Higher-order cognitive processes that involve planning, organizing, inhibiting impulses, and regulating emotions. These functions are critical for goal-directed behaviour and self-control [25].

The rational decision-making model often called analysis assumes that people go through a stepwise process to define the problem, work out what is important, generate alternatives and evaluate these, and then select the best solution [26]. It was Simon who developed the bounded rationality model that suggests that people use a process called "satisfying" which is choosing the first acceptable option which meets the previously set benchmark. This is a more realistic model of how people decide. Another method of decision-making proposed within psychology and much earlier within philosophy, was that people make decisions rapidly based upon their experience and familiarity with the particular problem space, and this is called "expert intuition" [27]. This style of decision-making has been investigated within areas of emergency services and policing [28]. Another model arising from the field of organisational behaviour is the Vroom-Yetton decision model which guides leaders to choose an appropriate level of team involvement when decisions are made [29].

5. Machine Learning and AI Decision Algorithms

Algorithms enable machines to learn from data, recognise patterns and make decisions on the basis of those patterns with some degree of autonomy. Machines excel in data processing and pattern recognition. For instance, AI algorithms can analyse vast datasets to identify trends and make predictions, as seen in financial markets where algorithmic trading systems execute trades at speeds and volumes beyond human capability [30]. Algorithms available are of various types, such as supervised learning algorithms which are used to predict outcomes or classify new data. As an example, decision trees are a treelike model that is used to classify data and make predictions. Unsupervised learning algorithms may be clustering similar data points and grouping them into clusters. Reinforcement learning algorithms involve an agent able to learn to make decisions through interaction with the environment. These algorithms are often used in gameplaying, resource management, financial trading and personalised recommendations. Such algorithms enable AI systems to learn and adapt to a dynamic and complex environment. They can learn through trial and error and this is really useful when there is no optimal strategy already established.

6. Human-AI Interaction in Decision Making

Human-machine decision-making, which combines human judgment with machine computational abilities, is an evolving field with significant implications across various domains. The integration of artificial intelligence (AI) and machine learning in decision-making processes can enhance efficiency, accuracy, and scale. Viewing both styles as complimentary can lead to added value. Humans and AI working together can leverage the strength of each to produce collaborative intelligence [31]. Human decision-making is characterized by intuition, experience, and ethical considerations, in addition to analysis. For example, healthcare professionals rely on both their training and their empathy to make beneficial patient-care decisions, considering factors that may not be easily quantifiable, such as a patient's emotional state or quality of life concerns [32].

6.1. Models of Human-Machine Decision Making

6.1.1. Autonomous Decision Making

In some scenarios, machines operate independently to make decisions. This is evident in self-driving cars, which must process real-time data and make split-second decisions without human intervention [33]. These systems rely on complex algorithms, sensor fusion, and machine learning to navigate and respond to dynamic environments. However, the development of fully autonomous systems raises important questions about liability, ethics, and the role of human oversight in critical situations.

6.1.2. Decision Support Systems

These systems enhance human decision-making by providing data-driven insights. For example, in medical diagnostics, AI tools can assist doctors by analyzing medical images and suggesting possible diagnoses, while the final decision remains with the healthcare professional [34]. These systems often use machine learning algorithms trained on large datasets to identify patterns that might be difficult for humans to discern. They can also aggregate and present complex information in more digestible formats, allowing human decision-makers to focus on higher-level analysis and interpretation.

6.1.3. Collaborative Decision Making

This approach involves a dynamic interaction between humans and machines, where both parties contribute to the decision-making process. For example, in military operations, decision support systems provide commanders with real-time data and strategic options, which are then evaluated with human judgment for mission planning [35]. This model leverages the strengths of both humans and machines: machines can rapidly process vast amounts of data and generate potential scenarios, while humans can apply context, experience, and ethical considerations to make final decisions.

6.1.4. Augmented Decision Making

Machines augment human capabilities by providing enhanced information and visualization tools. In business analytics, AI can process customer data to provide executives with detailed insights into market trends, enabling more informed strategic decisions [36]. This model often involves the use of advanced data visualization techniques, interactive dashboards, and predictive analytics to enhance human understanding of complex situations. By presenting information in more intuitive and interactive ways, these systems can help decision-makers identify patterns, trends, and potential outcomes that might otherwise be overlooked.

6.1.5. Human-in-the-Loop Systems

This model ensures that human oversight is maintained in automated systems, particularly in high-stakes environments. For instance, in automated financial trading systems, human traders can intervene to override algorithmic decisions based on sudden market changes or external factors that the algorithm may not account for [37]. This approach balances the efficiency of automated systems with the adaptability and judgment of human experts, providing a safeguard against potential algorithmic errors or unforeseen circumstances.

6.1.6. Adaptive Decision Systems

These systems learn and evolve based on the outcomes of previous decisions, incorporating feedback from both machine analysis and human input. For example, in personalized medicine, treatment recommendation systems can adapt based on patient outcomes and clinician feedback, continuously improving their accuracy over time [34]. This model represents a more dynamic and evolving approach to human-machine decision making, where the system's performance improves through continuous learning and adaptation.

6.1.7. Ethical AI Decision Frameworks

As AI systems become more involved in decision-making processes, there's an increasing need for frameworks that ensure ethical considerations are built into these systems. This model involves the development of AI systems that not only make efficient decisions but also adhere to ethical guidelines and societal values. For instance, in hiring processes, AI systems can be designed to mitigate bias and promote diversity while assisting in candidate selection [38]. These frameworks often involve interdisciplinary collaboration between AI researchers, ethicists, policymakers, and domain experts to define and implement ethical guidelines in AI decision-making processes.

AI decision-making encounters various strengths [39]. Such strengths include data Processing and Analysis, where machines excel at rapidly processing and analysing large volumes of data. In a collaborative decision-making system, AI and machine learning algorithms can quickly shift through vast datasets, identifying patterns, correlations, and insights that might be overlooked by human analysis alone. This capability is particularly valuable in domains like financial trading, where split-second decisions based on market data can be crucial. Also, pattern recognition and prediction based on historical data and current trends. This can provide human decision-makers with valuable foresight, helping them anticipate potential outcomes and prepare for various scenarios. Objective Analysis can provide an objective, bias-free analysis of data, free from the emotional and cognitive biases that often influence human decision-making. This can help balance human intuition with fact-based insights. Additionally, complex systems modelling capabilities in Cybernetics 3.0 allow for sophisticated simulations of various decision outcomes. Humans can then use these simulations to better understand potential consequences and refine their decision-making strategies. Lastly, semantic web technologies enable machines to aggregate and synthesize information from diverse sources, presenting human decision-makers with a comprehensive view of relevant data and knowledge.

Human decision-making strengths include contextual understanding, as humans possess a deep understanding of context and nuance that machines currently struggle to replicate [40]. This allows them to interpret data and recommendations considering broader social, cultural, and organizational contexts along with ethical considerations that are crucial in many decision-making scenarios. Humans can apply moral reasoning and value judgments that are challenging to codify into machine algorithms where human creativity allows for novel solutions and approaches that may not be apparent from data analysis alone. This is particularly valuable when dealing with unprecedented situations or when innovation is required. Also, emotional intelligence in many decision-making contexts, especially those involving human factors, is crucial [41]. Humans can estimate the emotional impact of decisions and navigate complex interpersonal dynamics and human intuition, built on years of experience and tacit knowledge, can provide valuable insights that complement data-driven analysis.

Integrating both sides of Human-Machine collaborations can allow for intuitive interaction between humans and machine systems. These interactions can present complex data and AI-generated insights in easily digestible formats, enabling humans to quickly grasp key information and provide input. Additionally, the decision-making process becomes an iterative dialogue between human and machine. Humans can refine queries, adjust parameters, and provide feedback, while machines continuously update their analysis based on this input. Incorporating explainable (XAI) techniques ensures that machine recommendations are transparent and understandable to human decision-makers. This builds trust and allows humans to critically evaluate machine-generated insights. Also, the system learns from each interaction, continuously improving its ability to provide relevant information and recommendations based on human feedback and decisions. By aggregating inputs from multiple human decision-makers and combining them with machine analysis, these systems can harness collective intelligence, potentially leading to more robust and well-rounded decisions. Lastly, by leveraging IoT and edge computing capabilities, these systems can enable real-time collaboration between humans and machines, allowing for agile decision-making in dynamic environments.

7. Future Directions

As AI involves rapidly, there will be emerging technologies that may moderate the way humans and machines collaborate in the workplace. The arrival of large language models is a significant development, especially as they are becoming increasingly sophisticated, and they can generate humanlike text in response to well-crafted prompts. As these large language models develop further, they may be able to provide more intuitive interactions that feel more like a conversation. Certainly, the time is right for organisations to develop clear guidelines about how large language models can be used in the workplace. Both managers and employees will need to become better at understanding what benefit they bring, become best at prompting, and assessing the outcome. Emerging technologies will enhance the capabilities of AI in decision making and humanlike AI assistance in the future, that can lead to new paradigms in Cybernetics and in decision-making theory.

8. Conclusion

The future of human-machine decision-making lies in optimizing the synergy between human intelligence and machine efficiency. This hybrid approach aims to leverage the strengths of both to achieve better outcomes, whether in healthcare, finance, transportation, or other critical fields. As technology advances, the challenges of bias, transparency, and ethical governance will continue to be central concerns that need careful management and regulation. Maintaining a balance between machine autonomy and human oversight is crucial. While machines can handle routine and data-intensive tasks, human judgment is essential for contextual and ethical considerations, ensuring that decisions align with societal values and norms. The development of explainable AI (XAI) techniques will be crucial in building trust and understanding between humans and AI systems [42-47].

Successfully navigating the changes in technological breakthroughs requires more than simply survival; it involves actively utilizing these advancements to facilitate a smoother and more efficient journey into this exciting future. As we move forward, it will be essential to foster interdisciplinary collaboration, ethical considerations, and adaptive learning systems to ensure that human-machine decision-making systems serve the best interests of society as a whole. There are many arguments preventing this collaboration, but the time for discussion is now.

References

1. Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: a failure to disagree. *American psychologist, 64*(6), 515.
2. Meissner, P., & Narita, Y. (2023). AI Will Transform Decision-Making. Here's How. Emerging Technologies.
3. Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J. F., Breazeal, C., & Wellman, M. (2019). Machine behaviour. *Nature, 568*(7753), 477-486.
4. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard business review, 96*(1), 108-116.
5. Barber, O. (2024). How AI will change decision-making.
6. Brynjolfsson, E., & Mcafee, A. N. D. R. E. W. (2017). Artificial intelligence, for real. *Harvard business review, 1,* 1-31.
7. Agrawal, A., Gans, J. S., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. *Harvard Business Review Press.*
8. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627-660.
9. Tang, X., Li, X., Ding, Y., Song, M., & Bu, Y. (2020). The pace of artificial intelligence innovations: Speed, talent, and trial-and-error. *Journal of Informetrics, 14*(4), 101094.
10. Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI: Strategy and leadership when algorithms and networks run the world. *Harvard Business Press.*
11. Marcus, G., & Davis, E. (2019). Rebooting AI: Building artificial intelligence we can trust. Vintage.
12. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons, 61*(4), 577-586.
13. Ashby, W. R. (1956). *An Introduction to Cybernetics'*

Chapman & Hall.
14. AI Adoption by Companies: 5 Statistics You Should Know. (2024).
15. World Economic Forum. (2020). The Future of Jobs Report 2020. World Economic Forum.
16. Fortune Business Insights (2022). AI Market Research Report.
17. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International journal of information management, 48,* 63-71.
18. Gazzaniga, M. S., Ivry, R. B., & Mangun, G. R. (2018). Cognitive Neuroscience. The biology of the mind.
19. Goldstein, E. B., & Brockmole, J. (2016). Sensation and Perception: Cengage Learning. *Cengage Learning: Boston, MA, USA.*
20. Baddeley, A., Eysenck, M. W., & Anderson, M. C. (2015). Memory. Psychology Press.
21. Illeris, K. (2018). A comprehensive understanding of human learning. *In Contemporary theories of learning* (pp. 1-14). Routledge.
22. Sternberg, R. J., & Sternberg, K. (2016). Cognitive Psychology. Cengage Learning.
23. Kahneman, D. (2011). Thinking, Fast and Slow, ; Farrar, Straus and Giroux: New York, NY, USA.
24. Pinker, S. (2003). *The language instinct: How the mind creates language.* Penguin UK.
25. Diamond, A. (2013). Executive functions. *Annual review of psychology, 64*(1), 135-168.
26. Simon, H. A. (1947). Administrative Behavior: A Study of Decision-Making Processes in Administrative Organization. Macmillan.
27. Klein, G. A. (2017). *Sources of power: How people make decisions*. MIT press.
28. Hallo, L., & Nguyen, T. (2021). Holistic view of intuition and analysis in leadership decision-making and problem-solving. *Administrative Sciences, 12*(1), 4.
29. Vroom, V. H., & Yetton, P. W. (1973). Leadership and decision-making University of Pittsburgh press. *Pittsburgh, Pa*.
30. Kirilenko, A. A., & Lo, A. W. (2013). Moore's law versus murphy's law: Algorithmic trading and its discontents. *Journal of Economic Perspectives, 27*(2), 51-72.
31. Mollick, E., & Mollick, E. (2024). Co-Intelligence. Random House UK.
32. Montori, V. M., Kunneman, M., & Brito, J. P. (2017). Shared decision making and improving health care: the answer is not in. *Jama, 318*(7), 617-618.
33. Schwarting, W., Alonso-Mora, J., & Rus, D. (2018). Planning and decision-making for autonomous vehicles. *Annual Review of Control, Robotics, and Autonomous Systems, 1*(1), 187-210.
34. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature medicine, 25*(1), 44-56.
35. Endsley, M. R., & Jones, D. G. (2016). Designing for situation awareness: An approach to user-centered design. CRC Press.
36. Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning. Harvard Business Press.*
37. Gomber, P., Arndt, B., Lutat, M., & Uhle, T. E. (2018). High-frequency trading. In Encyclopedia of Big Data Technologies.
38. Raub, M. (2018). Bots, bias and big data: artificial intelligence, algorithmic bias and disparate impact liability in hiring practices. *Ark. L. Rev., 71,* 529.
39. Dennehy, D., Griva, A., Pouloudi, N., Mäntymäki, M., & Pappas, I. (2023). Artificial intelligence for decision-making and the future of work.
40. Zhou, C., Wang, Q., Yu, M., Yue, X., Lu, R., Li, J., ... & Lam, W. (2025). The Essence of Contextual Understanding in Theory of Mind: A Study on Question Answering with Story Characters. *arXiv preprint arXiv*:2501.01705.
41. Moka-Mubelo, SJ, W. (2019). Towards a contextual understanding of human rights. *Ethics & Global Politics, 12*(4), 40-52.
42. Gunning, D., & Aha, D. (2019). DARPA's explainable artificial intelligence (XAI) program. *AI magazine, 40*(2), 44-58.
43. Berners-Lee, T., Hendler, J., & Lassila, O. (2001). Web Semantic. *Scientific American, 284*(5), 34-43.
44. Blog, N. T. (2017). Netflix Recommendations: Beyond the 5 stars (Part 1). *Medium.*
45. Newell, A., Shaw, J. C., & Simon, H. A. (1957, February). Empirical explorations of the logic theory machine: a case study in heuristic. In Papers presented at the February 26-28, 1957, western joint computer conference: Techniques for reliability (pp. 218-230).
46. Newell, A. (1972). Human problem solving. *Upper Saddle River/Prentive Hall.*
47. Wiener, N. (2019). Cybernetics or Control and Communication in the Animal and the Machine. MIT press.