International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Recent Advances in Computer Applications and Information Technology
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Human-AI Interaction: How AI is Changing Daily Decision-Making

Dipti Gaydhane, Dhanasvi Shende

G H Raisoni University, Amravati, Maharashtra, India

Abstract

Artificial Intelligence (AI) has rapidly evolved into a transformative force that significantly influences daily human decision-making across personal, social, and professional contexts. Unlike traditional computational systems, modern AI technologies are capable of learning from data, adapting to user behavior, and generating predictive outputs that shape choices in real time. In digital environments such as e-commerce platforms, navigation systems, streaming services, and virtual assistants, AI filters information, prioritizes alternatives, and presents structured recommendations that guide user behavior. Amershi et al. (2019) [1] emphasize that AI systems are increasingly functioning as collaborative partners rather than passive tools, fundamentally altering how individuals interact with technology. As a result, the decision-making process has shifted from being entirely human-driven to a hybrid cognitive model where algorithmic intelligence actively participates in shaping judgments and outcomes. The growing integration of AI into economic and social systems has restructured how information is accessed and processed. Brynjolfsson and McAfee (2017) [2] argue that AI-powered digital platforms enhance efficiency by reducing search costs and accelerating information flow, thereby enabling faster and more data-informed decisions. Through predictive analytics and personalization algorithms, AI anticipates user preferences and delivers customized options tailored to individual needs. While such personalization increases convenience and engagement, it also narrows exposure to diverse alternatives, potentially reinforcing existing preferences and behavioral patterns. Consequently, AI does not merely assist in decision-making; it subtly modifies the architecture of choice by shaping what options are visible and prioritized. Transparency and explainability represent critical challenges in AI-mediated decision-making environments. As AI systems become more complex, particularly with the adoption of deep learning models, understanding how decisions are generated becomes increasingly difficult for end users. Doshi-Velez and Kim (2017) [3] stress the necessity of interpretable machine learning frameworks to ensure accountability and maintain user trust. When individuals cannot understand the reasoning behind AI-generated outputs, they may either over-trust or under-trust the system. Effective explainability mechanisms are therefore essential to support informed reliance, allowing users to evaluate recommendations critically rather than accepting them blindly. Another important aspect of AI's impact on daily decision-making involves automation and human reliance. As AI systems move from advisory roles to autonomous agents capable of executing tasks, users increasingly delegate responsibility to algorithms. Parasuraman and Riley (1997) [4] warn that automation can lead to misuse, disuse, or abuse when human oversight diminishes. In contexts such as healthcare diagnostics, financial investment management, and transportation systems, excessive reliance on automated outputs may reduce human vigilance and critical thinking. This phenomenon highlights the importance of calibrated trust and the continued involvement of human judgment in high-stakes decisions.

***KEYWORDS**: Human–AI Interaction, Artificial Intelligence, Daily Decision-Making, Intelligent Systems, Machine Learning, Recommendation Systems, User Behavior, Human-Centered Design, Automation, Ethical AI, Trust in AI, Transparency, Bias in AI, Decision Support Systems, Digital Assistants, Technology Adoption, Cognitive Support, Responsible AI.*

1. Introduction

The rapid expansion of Artificial Intelligence (AI) technologies has significantly transformed the structure of modern decision-making environments. Across digital platforms such as social media, online marketplaces, and information search engines, AI systems organize and filter content before it reaches users. Sunstein (2017) [6] explains that algorithmic filtering mechanisms influence exposure to information, often shaping public discourse and individual perception without explicit awareness. As AI determines which options are displayed, ranked, or recommended, it effectively structures the decision-making landscape. This restructuring reduces information overload but simultaneously narrows the range of visible alternatives, thereby influencing how individuals interpret available choices and form preferences. In addition to filtering information, AI systems increasingly rely on predictive modeling and behavioral analytics to anticipate user needs. Shneiderman (2020) [7] emphasizes the importance of human-centered AI design to ensure reliability, safety, and trustworthiness in interactive systems. Predictive recommendation engines analyze browsing history, past purchases, and engagement patterns to generate tailored suggestions that align with user interests. While this personalization enhances convenience and efficiency, it also changes the cognitive process by reducing active exploration. Decision-making becomes guided by algorithmic inference rather than independent comparison, gradually shifting the balance between human reasoning and automated suggestion.

The economic and organizational implications of AI-driven decision systems are equally profound. Rahwan et al. (2019) [8] introduce the concept of studying "machine behavior," arguing that AI systems act within complex social environments and influence collective outcomes. In workplaces, AI supports hiring decisions, performance evaluations, and strategic forecasting, affecting both individual careers and institutional policies. The integration of AI into professional contexts highlights its capacity to influence high-stakes decisions beyond routine consumer choices. As organizations increasingly depend on algorithmic insights, understanding how these systems interact with human judgment becomes essential for maintaining fairness and accountability. Trust plays a critical role in shaping how individuals respond to AI recommendations. Lee and See (2004) [9] describe trust in automation as a dynamic process that must be carefully calibrated to prevent over-reliance or rejection of system outputs. When users perceive AI as reliable and accurate, they are more likely to accept its suggestions without question. However, excessive trust can result in diminished critical evaluation, while insufficient trust may lead to underutilization of beneficial systems. Therefore, achieving an appropriate balance between trust and skepticism is central to effective human–AI collaboration. Finally, the long-term implications of AI integration into daily decision-making extend to cognitive adaptation and behavioral change. Jiang (2024) [10] argues that Human–AI Interaction research must focus on how users mentally adapt to algorithmic systems over time. As individuals become accustomed to AI-mediated environments, their expectations, attention patterns, and evaluation strategies evolve. This cognitive adaptation suggests that AI not only influences isolated decisions but gradually reshapes the broader decision-making process itself. Understanding these evolving dynamics is essential for developing AI systems that support, rather than replace, human autonomy and critical reasoning.

Moreover, the influence of AI on decision-making is closely linked to issues of algorithmic fairness and bias, particularly in systems that rely on large-scale data analytics. O'Neil (2016) [11] argues that algorithmic models, when trained on biased or incomplete datasets, can reinforce social inequalities and produce discriminatory outcomes in areas such as credit scoring, recruitment, and law enforcement. As AI systems increasingly participate in shaping opportunities and constraints within society, their embedded assumptions and design choices gain significant power. This highlights the necessity of critical evaluation and ethical oversight in AI development. When users are unaware of potential biases in automated recommendations, they may unknowingly accept unfair or inaccurate decisions as objective outputs. Therefore, ensuring fairness, transparency, and accountability in AI systems is not merely a technical requirement but a social responsibility essential for preserving trust and protecting individual rights within AI-mediated decision environments.

Fig.1 Ai in Modern Life

2. Literature Review

Artificial Intelligence (AI) technologies have rapidly transformed the way people make decisions in everyday life. Research across disciplines such as computer science, psychology, Recent scholarship in Human–AI Interaction emphasizes the increasing role of AI systems as collaborative agents in decision-making processes. Bansal et al. (2021) [11] examine how AI explanations influence team performance and demonstrate that human–AI collaboration can outperform either humans or AI working independently when explanations are effectively designed. Their findings suggest that transparency enhances complementary strengths between users and intelligent systems. However, the effectiveness of AI support depends heavily on how information is presented and understood. When users perceive explanations as meaningful and relevant, they are more likely to integrate AI recommendations into their reasoning processes, thereby improving decision accuracy and confidence.

The importance of interpretability has also been widely discussed in the literature. Ribeiro, Singh, and Guestrin (2016) [12] introduce model-agnostic explanation techniques that allow users to understand predictions generated by complex machine learning models. Their research highlights that interpretability fosters accountability and helps users identify potential errors in algorithmic reasoning. Without such mechanisms, AI systems risk becoming opaque "black boxes," limiting user understanding and reducing trust. As AI systems increasingly influence financial, medical, and legal decisions, interpretability is not merely a usability feature but a necessary component of ethical system deployment.

Trust calibration remains another critical theme in existing research. Lee and See (2004) [13] argue that trust in automation must align with actual system capabilities to prevent misuse or disuse. Over-trust may result in blind acceptance of incorrect outputs, while under-trust may lead to rejection of valuable assistance. This balance is particularly important in high-risk domains such as aviation, healthcare, and autonomous vehicles. Their framework emphasizes that system reliability, predictability, and feedback mechanisms significantly influence user reliance. In AI-supported decision environments, maintaining appropriate levels of trust ensures that users remain actively engaged rather than passively dependent.

Bias and fairness concerns have become central topics in discussions of AI-driven decision systems. O'Neil (2016) [14] critically examines how algorithmic models can perpetuate systemic inequalities when trained on biased datasets. She argues that automated decision systems often appear objective but may encode hidden assumptions that disadvantage certain groups. This issue is particularly relevant in employment screening, loan approval systems, and predictive policing. Addressing bias requires not only technical adjustments but also institutional accountability and regulatory oversight to ensure equitable outcomes.

Finally, broader societal implications of AI-mediated decision-making have been explored in interdisciplinary research. Rahwan et al. (2019) [15] propose the study of "machine behavior," emphasizing that AI systems function within social ecosystems and influence collective patterns of behavior. Their work suggests that AI should be analyzed not only as a technological artifact but also as a social actor interacting with human institutions. As AI systems become increasingly autonomous and integrated into everyday life, understanding their behavioral impact on individuals and communities is essential. Together, these studies illustrate that while AI enhances decision efficiency and personalization, it simultaneously introduces complex ethical, psychological, and societal challenges that require ongoing scholarly attention.

3. Research Methodology

This study adopts a mixed-method research design to empirically examine how Artificial Intelligence influences daily decision-making processes. The framework combines quantitative experimentation with qualitative analysis to capture both measurable behavioral changes and subjective perceptions of AI interaction. Creswell and Plano Clark (2018) [16] emphasize that mixed-method approaches are particularly effective when studying complex socio-technical systems, as they allow researchers to integrate statistical findings with contextual insights. In this research, participants will be randomly assigned to three experimental conditions: decision-making without AI assistance, decision-making with AI recommendations, and decision-making with AI recommendations accompanied by explanation features. This structured comparison enables evaluation of AI's direct and indirect effects on user choices.

The quantitative component will measure variables such as decision accuracy, response time, confidence levels, and trust calibration. Field (2013) [17] explains that regression analysis and analysis of variance (ANOVA) are appropriate statistical techniques for comparing group differences in experimental research. These methods will determine whether AI-supported conditions significantly influence decision efficiency and quality compared to human-only scenarios. Additionally, standardized survey instruments will assess perceived autonomy, system reliability, and satisfaction. By collecting structured numerical data, the study aims to identify patterns that reveal whether AI enhances or distorts rational decision-making processes.

To complement quantitative findings, qualitative interviews will be conducted to explore participants' cognitive adaptation and perceptions of fairness. Braun and Clarke (2006) [18] propose thematic analysis as a rigorous approach for identifying recurring patterns in qualitative data. Through semi-structured interviews, participants will reflect on their experience interacting with AI systems, including their understanding of recommendations and perceived control over final decisions. This qualitative layer provides deeper insight into how users mentally interpret AI outputs, revealing whether explanations improve transparency and trust.

The research design also incorporates principles of human-centered system evaluation to ensure that experimental interfaces reflect real-world applications. Shneiderman (2020) [19] argues that trustworthy AI systems must prioritize usability, transparency, and user control. Accordingly, the AI recommendation interface used in this study will include clear feedback mechanisms and optional explanation features. This approach ensures ecological validity by simulating realistic AI-assisted environments such as online shopping platforms or navigation tools. Ethical considerations, including informed consent and data anonymization, will be strictly implemented to protect participant rights.

Finally, the study will analyze long-term implications of AI reliance by examining behavioral consistency across repeated tasks. Brynjolfsson and McAfee (2017) [20] suggest that digital technologies reshape organizational and individual decision patterns over time. By including multiple task iterations, this research will observe whether exposure to AI gradually increases dependency or improves calibrated trust. The integration of quantitative metrics, qualitative insights, and ethical safeguards provides a comprehensive methodology for evaluating AI's transformative role in daily decision-making

This study employs a comprehensive mixed-method research design to investigate how Artificial Intelligence influences daily decision-making processes across different contexts. The research follows an experimental structure in which participants are randomly assigned to three distinct groups: a control group making decisions independently without AI assistance, an experimental group receiving AI-generated recommendations, and a second experimental group receiving AI recommendations accompanied by explanation features. The objective is to compare differences in decision accuracy, response time, confidence levels, and perceived autonomy among these groups. Quantitative data will be collected through structured tasks simulating real-life decision scenarios such as product selection, financial planning, and health-related choices. Statistical techniques, including regression analysis and comparative testing, will be applied to determine whether AI assistance significantly alters decision patterns. By isolating variables and maintaining controlled conditions, the study aims to measure the measurable behavioral impact of AI-supported systems while ensuring reliability and validity in findings.

In addition to quantitative analysis, the research incorporates qualitative methods to gain deeper insight into participants' cognitive experiences and perceptions of AI interaction. Semi-structured interviews will be conducted after task completion to explore how individuals interpret AI recommendations, whether they feel influenced by algorithmic suggestions, and how they perceive fairness and control in the decision-making process.

Fig.2 Smart Analysis

4. Result

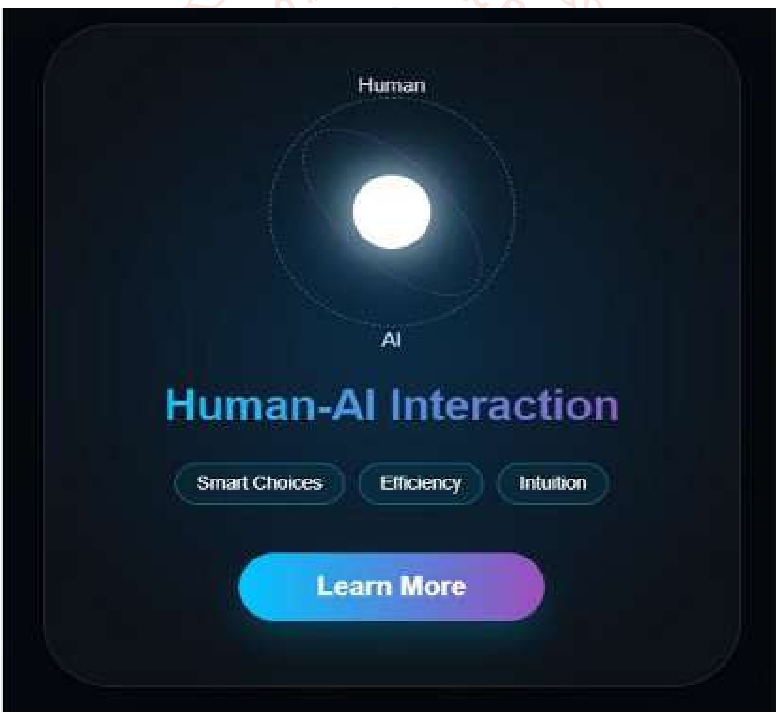

Fig.3 Conceptual Model of Human-AI Interaction

5. Conclusion

The growing integration of Artificial Intelligence into daily life represents a profound transformation in how decisions are structured, evaluated, and executed. AI systems now operate as cognitive collaborators that filter information, prioritize alternatives, and sometimes autonomously perform tasks on behalf of users. Davenport and Ronanki (2018) [21] argue that organizations increasingly deploy AI not only for automation but also for augmenting human judgment, highlighting the shift toward collaborative intelligence. This transformation demonstrates that AI's influence extends beyond technical efficiency to reshaping behavioral and cognitive processes. As individuals interact with algorithmic systems in shopping, healthcare, finance, and communication, decision-making becomes embedded within data-driven infrastructures that continuously adapt to user behavior.

While AI enhances speed, personalization, and accuracy, it also introduces critical challenges related to governance and accountability. Floridi et al. (2018) [22] emphasize the necessity of ethical frameworks to guide AI development, ensuring fairness, transparency, and responsibility. Without proper oversight, algorithmic systems risk reinforcing bias, limiting autonomy, and centralizing decision authority within opaque models. Mittelstadt et al. (2016) [23] further identify ethical risks associated with big data analytics, particularly concerning consent, discrimination, and power imbalances. These concerns underline the importance of regulatory structures and engage critically rather than passively accepting recommendations. However, trust must remain calibrated to actual system capabilities. Overconfidence in AI systems may lead to reduced human vigilance, whereas skepticism may hinder beneficial adoption. Achieving this balance requires thoughtful system design and continuous evaluation of performance outcomes. engage critically rather than passively accepting recommendations. However, trust must remain calibrated to actual system capabilities. Overconfidence in AI systems may lead to reduced human vigilance, whereas skepticism may hinder beneficial adoption. Achieving this balance requires thoughtful system design and continuous evaluation of performance outcomes.

Trust remains a foundational factor in determining the effectiveness of human–AI collaboration. Hoffman et al. (2018) [24] explain that explainability and transparency mechanisms significantly influence user confidence and reliance on AI systems. When users understand system outputs, they are more likely to engage critically rather than passively accepting recommendations. However, trust must remain calibrated to actual system capabilities. Overconfidence in AI systems may lead to reduced human vigilance, whereas skepticism may hinder beneficial adoption. Achieving this balance requires thoughtful system design and continuous evaluation of performance outcomes.

Finally, the long-term implications of AI-mediated decision-making extend to broader societal transformation. Russell (2019) [25] argues that aligning AI systems with human values is essential to preserving autonomy and collective well-being. As AI technologies continue to evolve, future research must explore longitudinal behavioral changes, cross-cultural variations, and policy frameworks that safeguard ethical standards. Ultimately, AI should function as an augmentative force that enhances human reasoning and supports informed decision-making rather than diminishing critical thought. The challenge moving forward lies in ensuring that technological advancement remains aligned with human-centered principles, fostering systems that empower individuals while maintaining accountability and fairness.

Reference

[1] Amershi, S., Weld, D., Vorvoreanu, M., et al., "Guidelines for Human–AI Interaction, 2019." *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1–13.

[2] Brynjolfsson, E., & McAfee, A., "Machine, Platform, Crowd: Harnessing Our Digital Future, 2017." W. W. Norton & Company.

[3] Doshi-Velez, F., & Kim, B., "Towards a Rigorous Science of Interpretable Machine Learning, 2017." preprint arXiv:1702.08608.

[4] Parasuraman, R., & Riley, V., "Humans and Automation: Use, Misuse, Disuse, Abuse, 1997." *Human Factors*, vol. 39, no. 2, pp. 230–253.

[5] Rahwan, I., Cebrian, M., Obradovich, N., et al., "Machine Behaviour, 2019." *Nature*, vol. 568, pp. 477–486.

[6] Sunstein, C. R., "#Republic: Divided Democracy in the Age of Social Media, 2017." Princeton University Press.

[7] Shneiderman, B., "Human-Centered Artificial Intelligence: Reliable, Safe and Trustworthy, 2020." *International Journal of Human–Computer Interaction*, vol. 36, no. 6, pp. 495–504.

[8] Bao, Y., "A Literature Review of Human–AI Synergy in Decision-Making, 2023." *Systems*, vol. 11, no. 9, p. 442.

[9] Gomez, C., "A Taxonomy of Interaction Patterns in AI-Assisted Decision-Making, 2023." arXiv preprint arXiv:2310.19778.

[10] Jiang, T., "Human–AI Interaction Research Agenda: A User-Centered Review, 2024." *International Journal of Human–Computer Studies*, vol. 185, p. 103255.

[11] Bansal, G., Wu, T., Zhou, J., et al., "The Effect of AI Explanations on Complementary Team Performance, 2021." *Proceedings of the CHI Conference on Human Factors in Computing Systems*.

[12] Ribeiro, M. T., Singh, S., & Guestrin, C., "Why Should I Trust You? Explaining the Predictions of Any Classifier, 2016." *Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pp. 1135–1144.

[13] Lee, J. D., & See, K. A., "Trust in Automation: Designing for Appropriate Reliance, 2004." *Human Factors*, vol. 46, no. 1, pp. 50–80.

[14] O'Neil, C., "Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, 2016." Crown Publishing.

[15] Creswell, J. W., & Plano Clark, V. L., "Designing and Conducting Mixed Methods Research, 2018." SAGE Publications.

[16] Field, A., "Discovering Statistics Using IBM SPSS Statistics, 2013." SAGE Publications.

[17] Braun, V., & Clarke, V., "Using Thematic Analysis in Psychology, 2006." *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101.

[18] Davenport, T. H., & Ronanki, R., "Artificial Intelligence for the Real World, 2018." *Harvard Business Review*, vol. 96, no. 1, pp. 108–116.

[19] Floridi, L., Cowls, J., Beltrametti, M., et al., "AI4People—An Ethical Framework for a Good AI Society, 2018." *Minds and Machines*, vol. 28, no. 4, pp. 689–707.

[20] Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L., "The Ethics of Algorithms: Mapping the Debate, 2016." *Big Data & Society*, vol. 3, no. 2, pp. 1–21.

[21] Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J., "Metrics for Explainable AI: Challenges and Prospects, 2018." arXiv preprint arXiv:1812.04608.

[22] Russell, S., "Human Compatible: Artificial Intelligence and the Problem of Control, 2019." Viking.