Advancing Decision-Making through AI-Human Collaboration: A Systematic Review and Conceptual Framework

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Abstract

The interplay between humans and artificial intelligence (AI) in decision-making has become increasingly intricate and significant. Despite rapid advancements, the literature remains fragmented, with limited integrative frameworks to explain how AI-human dynamics and decision-making typologies shape outcomes. This study addresses this critical gap by conducting a systematic review and bibliometric analysis of 1,004 articles, culminating in a novel conceptual framework. The framework identifies two critical dimensions, AI-human dynamics and decision typologies, that shape decision outcomes and introduces four distinct paradigms of AI-human collaborative decision-making: autonomous execution, guided resolution, collaborative exploration, and augmented discovery. By synthesizing these paradigms, this research advances the theoretical understanding of hybrid decision-making systems and provides actionable insights for organizations navigating complex and AI-driven environments. By elucidating the mechanisms and trade-offs inherent in AI-human collaboration, this work lays a robust foundation for future research on adaptive decision systems in an era marked by accelerating technological change.

INTRODUCTION

Artificial intelligence (AI) is recognized as a transformative force reshaping employees, teams, and organizations (Cascio & Montealegre, 2016). AI decision-making is defined as the process of using artificial intelligence (AI) to support, enhance, or revolutionize the decision-making process, effectively incorporating AI technology into the decision-making process (Russell & Norvig, 2022; Brynjolfsson & McAfee, 2017). This new decision-making framework includes leveraging various AI technologies such as machine learning, natural language processing, and data analytics to process and analyze large volumes of data, identify patterns, and generate actionable insights (Goodfellow, Bengio, & Courville, 2016; McKinsey Global Institute, 2018; Ng, 2016; Kim, Lee, & Hwang, 2021; Lee et al., 2023).

Organizations are increasingly adopting AI to enhance decision quality, driven by demands for speed, accuracy, and adaptability in volatile environments (Akhtar et al., 2019; Vrontis et al., 2022). For example, AI applications range from machine learning algorithms predicting market trends (Fountaine et al., 2019) and AI-driven analytics optimizing supply chain operations (Choudhury et al., 2020), to AI-based tools supporting financial decision-making (Davenport & Ronanki, 2018). A study conducted by Oracle and Future Workplace (2019) revealed a growing influence of AI, with 50 percent of employees presently applying various forms of AI to assist in decision-making.

Despite these significant advantages, integrating AI into decision-making processes not only promises to boost efficiency and effectiveness but also introduces new complexities and challenges that require a deeper understanding of its mechanisms and outcomes (Choudhury et al., 2020). The rapid adoption of AI tools has not been as smooth as anticipated (Arslan et al., 2022), and the technological inflexibility potentially may lead to organizational disruptions, thereby diminishing the advantages of AI in decision-making and escalating governance costs (Basu et al., 2023). Given the extensive applications of AI in decision-making, the emerging research field of AI-empowered decision-making has garnered more attention from both scholars and practitioners. To promote academic development in this field, some researchers have attempted to review or analyze relevant literature to guide future research. For example, Borges (2021) identified key sources of value creation, such as decision support, customer engagement, automation, and the development of new products and services, emphasizing AI's potential to transform organizational strategy. Pietronudo (2021) argues that while AI's ability to rationalize decision-making and foster creativity has been acknowledged, its impact on organizational processes remains multifaceted, leading to both expected and unexpected outcomes. At the same time, scholars have proposed hybrid models that combine human intelligence with AI to address complex problems. These models suggest that AI can expand the range of potential solutions, thus complementing human decision-making (Raisch & Fomina, 2023). A framework for integrating human and AI decision-making emphasizes key factors such as search space specificity, decision speed, and transparency, while also addressing challenges like AI bias and the need for accountability in algorithmic decision-making (Shrestha et al., 2019). Additionally, research on AI's impact on the workforce reveals its significant influence on job roles, required skills, and employee attitudes. As AI continues to reshape organizational practices and labor markets, understanding its long-term effects on innovation and workforce dynamics is crucial (Bankins et al., 2024).

While prior studies explore narrow aspects of AI's role, such as automation (Brynjolfsson & McAfee, 2017), decision support (Shrestha et al., 2019), or ethical implications (Raisch & Krakowski, 2021), they lack a holistic perspective. Existing reviews either focus on technical capabilities, human-AI interaction models, or organizational impacts in isolation, leaving a fragmented understanding of how these dimensions interact (Raisch & Fomina, 2023; Bankins et al., 2024). This fragmentation obscures the mechanisms through which AI reshapes decision processes and inhibits the development of actionable frameworks for practitioners.

This study addresses two critical gaps in the existing literature. Theoretically, prior research has suffered from fragmentation due to the absence of integrative frameworks that explain how AI-human collaboration varies across different decision contexts, such as structured versus unstructured problems, and power dynamics, including AI-led versus human-led processes. While several systematic reviews have tackled decision-making in complex contexts such as multiobjective optimization (Pajasmaa et al., 2025), few have specifically focused on the evolving dynamics of AI-human collaboration across decision typologies. Practically, organizations face challenges in aligning AI adoption with decision-making needs, often overemphasizing automation at the expense of creativity and ethical considerations. To bridge these gaps, we conducted a systematic review and bibliometric analysis of 1,005 articles, which culminated in the development of a novel AI-Human Decision Matrix. This framework categorizes decision-making into four paradigms, autonomous execution, guided resolution, collaborative exploration, and augmented discovery, based on two dimensions: AI-human dynamics (ranging from dominance to empowerment) and decision typology (spanning open to closed). By mapping these paradigms to various organizational contexts, our study not only provides a strategic tool for optimizing AI adoption but also offers meaningful insights for addressing ethical and operational challenges in the rapidly evolving landscape of decision-making.

To structure our inquiry, we propose the following research questions: (1) How have scholars conceptualized and classified the roles of AI in organizational decision-making across various contexts? (2) What are the dominant patterns, paradigms, and trends in AI-human collaborative decision-making revealed through bibliometric analysis? (3) How can we develop an integrative framework that maps AI-human dynamics against different decision typologies to inform both academic inquiry and practical application?

By addressing these questions, this study aims to synthesize fragmented insights into a coherent framework, deepening our understanding of hybrid decision-making systems and informing responsible AI deployment in complex organizational environments.

METHODOLOGY

Data Collection

Literature data is sourced from the Web of Science (WoS) Core Collection, concentrating on the Social Sciences Citation Index (SSCI) and the Science Citation Index Expanded (SCI-EXPANDED). As highlighted in prior studies (Jiang et al.,2024; Pouris & Pouris, 2011; Mongeon & Paul-Hus, 2016; Borges, 2021; Adriaanse & Rensleigh, 2013), the Web of Science (WoS) database serves as the primary source for data collection. The rationale for selecting the WoS database is multifaceted: First, it encompasses the most significant and influential journals in the field (Pouris & Pouris, 2011). Second, given the interdisciplinary nature of AI Decision-making, which includes information technology and strategic management, WoS is particularly well-suited for our objectives due to its comprehensive coverage across diverse disciplines (Adriaanse & Rensleigh, 2013). Third, WoS is recognized as one of the most prestigious and respected repositories of scientific information in the social sciences (Mongeon & Paul-Hus, 2016), and its utility has been extensively demonstrated in prior review articles related to management decision-making (Borges, 2021).

The screening process is illustrated in Fig. 1. In this study, we focused on journal articles published between 2010 and 2024. The academic literature in the field of AI and Decision-making began in the 1990s, but articles related to AI applications became prominent only after 2010. Therefore, we selected this time frame from 2010 to 2024 to align with the notable growth in AI and machine learning applications in management. The primary search terms were constructed using Boolean operators (AND/OR) to link two groups of keywords. The first group included terms such as “decision quality,” “decision efficiency,” “decision effectiveness,” or simply “decision.” The second group contained keywords referencing AI-related technologies, such as “artificial intelligence,” “machine learning,” or “AI.” The search was restricted to English-language journal articles, as these are widely regarded as representative of the most influential and reputable research. This process resulted in a total of 28,492 articles.

Given the multidisciplinary nature of AI research, we refined the results to ensure relevance to management studies. Specifically, we limited the Web of Science categories to include only publications related to management, business, economics, and business finance. This refinement resulted in a total of 1,005 articles.

Data Analysis

The bibliographic records were exported from the Web of Science (WoS) database to VOSviewer 1.6.19 for bibliometric analysis. Compared to other bibliometric tools, VOSviewer offers better visualization capabilities (Van Eck & Waltman, 2010). VOSviewer focuses on the knowledge structure of specific domains, enabling researchers to identify and visualize hidden patterns and trends by extracting information from a large number of bibliographic records (Cobo et al., 2011). Each record includes details such as authors and their affiliations including countries, titles, abstracts, keywords, publication years, source journals, and references. Based on the bibliographic data, analyses of keyword co-occurrence, trend dynamics, and country-wise literature contributions were conducted.

Keyword co-occurrence

A keyword co-occurrence analysis was conducted to identify relationships among themes within the literature. The co-occurrence network visualization map indicated that these clusters formed a broad and interconnected topic network within the studies (Gupta & Khan, 2024). The software detected links between similar keywords and grouped them into clusters, each represented by a distinct color. Keywords within the same cluster reflect similar or closely related themes (Ali & Gölgeci, 2019; van Eck & Waltman, 2009). The results of this analysis are presented in Fig. 2.

The existing themes in AI-related decision-making literature were categorized into four clusters. The red cluster (N = 10 terms/keywords) focuses on automated decision-making, comprising research on decision-making. The green cluster (N = 11 terms/keywords) is labeled as augmentation and collaboration, comprising research on decision-making. The blue cluster (N = 15 terms/keywords) is identified as strategic discovery and innovation. The yellow cluster (N = 10 terms/keywords) highlights aspects such as predictive analytics and data analytics.

The initial red-colored cluster (N = 10 terms/keywords) is “Autonomous Execution” consists of "Decision-making", "Automation", "Adoption" and "Trust", which are frequently repeated keywords. In the yellow cluster (N = 10 terms/keywords), Guided Resolution, the most frequently repeated keywords are "Efficiency", " Predictive Analytics" and " Data Analytics ". The third cluster in green (N = 11 terms/keywords) is Collaborative Exploration (AI-dominated Open Decision-Making), composed of the most frequently repeated keywords: "Augmentation", "Creativity", "Rational" and "Decision support systems". Lastly, "Artificial Intelligence (AI)", "Innovation", and "Complexity" are the most frequently repeated keywords in the blue cluster (N = 15 terms/keywords) Augmented Discovery.

Authorship analysis

Table 1 highlights the leading contributors in articles related to AI decision management, focusing on their publication volume and citation impact. Among the 226 authors analyzed, the ten most highly cited authors are presented, with nine of them receiving over 200 citations. Table 2 demonstrates that Shivam Gupta stands out as the most prolific author, with 10 publications and 457 citations. He is followed by Yogesh Dwivedi, who, despite having published fewer papers (7), achieved the highest citation count of 544. Other notable contributors include Patrick Mikalef (6 publications, 265 citations), Mehrbakhsh Nilashi (5 publications, 281 citations), and Ajay Kumar (5 publications, 274 citations). The remaining authors each have four publications, with Vinit Parida leading this group with 338 citations, followed by Yash Raj Shrestha, Dimitris Bertsimas, Krogh Georg Von, and Arpan Kumar Kar, who demonstrate varying degrees of citation impact.

Table 1
Top-cited authors for bibliometric reviews

Author	Papers	Papers citations
Yogesh Dwivedi	7	544
Shivam Gupta	10	457
Vinit Parida	4	338
Yash Raj Shrestha	4	322
Dimitris Bertsimas	4	307
Krogh Georg Von	4	304
Mehrbakhsh Nilashi	5	281
Ajay Kumar	5	274
Patrick Mikalef	6	265
Arpan Kumar Kar	4	193

In addition to citation performance analysis, we employed a co-authorship network mapping to identify the primary groups of contributors to AI decision management literature. The co-authorship network encompasses 21 authors who have each published at least four bibliometric review articles and received at least one citation. This analysis reveals two major clusters, as illustrated in Fig. 6, with Gupta Shivam emerging as the central figure in terms of both publication count and citation influence.

RESULTS

To provide an overview of existing research on AI decision-making, we use bibliometric analysis to conduct a comprehensive literature review. Artificial intelligence significantly enhances the speed and effectiveness of decision-making by assisting humans in selecting among various options and generating different alternatives for human choice. Various types of AI decision-making are applied in different social and business contexts. This demonstrates the complementary relationship between humans and AI in the decision-making process (Von Krogh, 2018).

Through the results of bibliometric analysis, after synthesizing the four clusters presented in Fig. 4, we identified and classified an AI decision matrix with the horizontal axis labeled "Human-AI Dynamics" and the vertical axis labeled "Decision-making Paradigm." This matrix allowed us to recognize four distinct AI decision-making types: "Autonomous Execution," which refers to AI-dominated closed decision-making where the system operates independently to reach a conclusion; "Guided Resolution," which refers to AI-empowered closed decision-making where AI supports but does not fully control the decision process; "Collaborative Exploration," which refers to AI-dominated open decision-making where AI leads the exploration and decision-making process in an open-ended context; and "Augmented Discovery," which refers to AI-empowered open decision-making where AI assists human decision-makers in exploring and discovering new possibilities in uncertain environments.

We defined four types of AI decision-making by using the horizontal axis to represent AI-dominated versus human-dominated decisions, and the vertical axis to represent open versus closed decision-making. The difference among the four AI decision types is based on whether the final decision is made by humans with the support of AI or made by AI with humans' supervision, and whether the decision involves a well-defined, structured problem or a diverse, flexible problem with multiple possible answers. By evaluating the effectiveness and applicability of different decision-making models, we can identify scenarios where AI-dominated decisions are more suitable or when human judgment and feedback are necessary. Consequently, we propose four types of AI decision-making: "Autonomous Execution" (AI-dominated closed decision-making), "Guided Resolution" (AI-empowered closed decision-making), "Collaborative Exploration" (AI-dominated open decision-making), and "Augmented Discovery" (AI-empowered open decision-making). These types aid in understanding the roles and impacts of different AI decision-making models.

The largest cluster represents the "Autonomous Execution" type of AI decision-making, characterized by AI-dominated closed decision-making. The core of this decision-making model lies in delegating certain tasks or operations based on closed decision-making to machines, enabling more comprehensive, rational, and efficient processing. The second largest cluster embodies the "Guided Resolution" type of AI decision-making, where AI plays a supportive and enabling role in the decision-making process rather than making decisions autonomously. The third largest cluster represents the "Collaborative Exploration" model of AI decision-making. In this model, AI leads the process through alternative decision-making, assuming responsibility for the final decision, while humans provide support and feedback to help AI optimize and adjust decisions. The last cluster represents the "Augmented Discovery" type of AI decision-making, focusing on leveraging AI to enhance human capabilities, thereby driving discovery and innovation in open decision-making.

Building upon prior literature, we categorize the decision-making process of each type into three distinct stages, problem identification, information collection and processing, and decision implementation (Simon, 1960; March, 1994). These stages serve as a framework to analyze and distinguish the contributions of each study within the clusters, enhancing our ability to relate them to broader decision-making dynamics.

Within the decision-making process, individuals must navigate complex environments to acquire critical decision-related information, analyze contextual factors and potential outcomes, and determine whether favorable conditions for action exist (Klein, 1998; Gigerenzer & Goldstein, 1996). Significant variation exists among individuals in their understanding and practice of decision-making, driven by factors such as cognitive capabilities (Kahneman, 2011), accumulated experience (Argyris & Schön, 1978), organizational support (Mintzberg et al., 1976), and external environmental uncertainty (Tversky & Kahneman, 1974). The final stage of decision-making is implementation which becomes particularly critical in high-risk and complex scenarios, where effective resource allocation and team collaboration are essential to increase the likelihood of success (Cyert & March, 1963; Bazerman & Moore, 2013). Fully committing to the execution phase fosters the attainment of organizational or individual objectives, enabling broader progress (Gollwitzer, 1999; Heath & Heath, 2010). The different types of AI decision-making exhibit distinct characteristics across the three stages of information collection, information processing, and decision implementation. Below, we describe the features and differences of the four decision-making types. Table 2 summarizes the four clusters and decision types.

Table 2
Clusters and Decision Types

Decision Types	Autonomous Execution (Red)	Guided Resolution (Green)	Collaborative Exploration (Yellow)	Augmented Discovery (Blue)
Keywords	Automation; Adoption; Decision making; Determinants; Acceptance.	Augmentation; Rational; Collaboration; Uncertainty; Decision support systems.	Efficiency; Prediction; Simulation; Strategic judgment.	Innovation; Strategy; Complexity; Discovery; Implementation.
Definition	AI-dominated closed decision-making where the system operates independently to reach a conclusion.	AI-empowered closed decision-making where AI supports but does not fully control the decision process	AI-dominated open decision-making where AI leads the exploration and decision-making process in an open-ended context.	AI-empowered open decision-making where AI assists human decision-makers in exploring and discovering new possibilities in uncertain environments
Information Collection	AI leads the entire data collection process by automating the real-time gathering, processing, and integration of data from various structured sources, ensuring high quality and consistency through techniques like data fusion, monitoring, and cleaning.	AI significantly enhances human decision-making by efficiently processing and analyzing large datasets across various sectors, such as healthcare and finance, thereby extending cognitive capabilities and improving the accuracy and speed of complex analyses.	AI synthesizes data from diverse, unstructured sources to detect trends and shifts, while human input ensures adaptive strategy adjustments, exemplifying the importance of cross-domain data fusion and real-time analytic in gaining competitive advantages.	AI empowers humans by rapidly analyzing complex and unstructured data to uncover latent patterns and emerging trends, significantly enhancing the comprehensiveness, precision, and efficiency of data collection, as demonstrated in social sciences research.

Decision Types	Autonomous Execution (Red)	Guided Resolution (Green)	Collaborative Exploration (Yellow)	Augmented Discovery (Blue)
Information Process	AI uses advanced techniques to analyze large datasets, identify patterns, make predictions and generate actionable insights.	AI empowers data-driven decision-making by providing analytical insights through its computational power, while humans maintain interpretative control, exemplified in business management and supply chain optimization where AI's analysis supports strategic human judgment.	AI utilizes advanced methodologies such as machine learning, deep learning, and reinforcement learning to uncover latent patterns and create predictive models, enabling actionable forecasts and innovative solutions to open-ended challenges, as demonstrated by Netflix's content strategy optimization.	The information processing phase involves intensive collaboration between AI and humans, where AI's predictive modeling is refined by human expertise and creativity, integrating emotional intelligence with data-driven decision-making to foster innovation, as seen in personalized medical treatment planning.
Decision Implementation	AI not only processes information but also autonomously makes and executes decisions with minimal human involvement, ensuring rapid, real-time adjustments and optimizing processes.	AI offers data-driven support, while humans integrate these insights with their expertise and situational judgment, balancing rational and emotional considerations, as seen in healthcare and emergency management contexts.	AI autonomously generates actionable recommendations and leads decision execution, while human oversight ensures iterative refinements, exemplified in new product development where AI designs prototypes and humans validate and adjust outcomes.	The decision implementation phase epitomizes human-AI collaboration, where humans integrate AI-generated analyses with intuition, experience, and value-based judgments to execute decisions, exemplified in artistic creation where AI provides inspiration and artists refine outputs to reflect personal style and emotion, showcasing AI-empowered open decision-making.

Cluster 1: Autonomous Execution

In the realm of Autonomous Execution, the role of artificial intelligence is to orchestrate every facet of information collection, processing, and decision implementation. Autonomous Execution can be conceptualized as an AI-dominated closed decision-making process. Within Autonomous Execution, artificial intelligence is tasked not only with acquiring and integrating information from diverse sources but also with conducting in-depth analysis and processing of this information to formulate optimal decisions. At last, AI autonomously implements these decisions based on the analytical outcomes, thereby achieving efficient and precise operations. This comprehensive leadership capability positions artificial intelligence as a pivotal element in Autonomous Execution, ensuring the seamless and effective progression of the entire process.

Information Collection Stage

In the Autonomous Execution model, the information collection process is entirely led by artificial intelligence (AI). This process typically relies on data from multiple standardized and structured sources, such as sensors, operation logs, enterprise resource planning (ERP) systems, and Internet of Things (IoT) devices(Rane & Narvel, 2022). AI automates the real-time collection and processing of this data to ensure high quality and consistency. Specifically, the data collection process often involves multiple technical methods, including data transmission, real-time monitoring, and data cleaning. By utilizing technologies such as Natural Language Processing (NLP), sensor data fusion, and rule-based reasoning engines, AI integrates large volumes of dispersed data to ensure its accuracy and reliability (Balasubramanian et al., 2022). For instance, in intelligent manufacturing systems, sensors collect real-time data on equipment parameters such as temperature, vibration, and pressure. AI uses this data to monitor equipment performance and ensure the smooth operation of production processes（Davenport & Ronanki, 2018). In this process, AI not only executes data collection but also plays a central role in ensuring the effectiveness of the data, preventing noise or anomalies from compromising the accuracy of decision-making.

Information Processing Stage

During the information processing stage, it can highlight the core advantages of AI algorithms, including the rapid identification of patterns and trends, as well as the efficient processing of large-scale datasets. AI performs deep processing on the massive data collected to extract useful patterns, trends, or anomalies. AI employs various advanced techniques, including machine learning, deep learning, reinforcement learning, and data mining, to train algorithms and analyze data (Chatterjee & Vrontis, 2022). These techniques help AI identify underlying patterns within the data, make predictions, and recognize patterns. For example, on a production line, AI can use historical data to train models that predict equipment failure times and provide maintenance recommendations (Serradilla et al., 2022). In the information processing stage, it is characterized by AI's ability to efficiently process data and generate useful information for decision-making through model-based algorithms and data analysis, reflecting the characteristics of rational decision-making (Simon, 1979).

For example, in autonomous driving, AI processes data from radar and cameras and uses deep neural network models to classify and analyze images, recognize traffic signs, pedestrians, and other vehicles, and predict future driving conditions. These processed results form the basis for AI's decisions, enabling it to respond effectively in complex traffic environments. AI optimizes the decision-making process through algorithms, avoids human intervention, and improves system decisions' efficiency and accuracy (Shrestha et al., 2019).

Decision Implementation Stage

In the Autonomous Execution practice, AI not only processes information but also fully takes on the responsibility of executing decisions, with minimal human involvement. In this model, AI automatically implements decisions based on the results of prior information collection and processing, adjusting in real-time according to feedback. For example, in industrial manufacturing, robots automatically adjust machine operations based on AI-generated instructions, optimizing the production process (Grigorievich, 2024). Autonomous vehicles execute braking or steering decisions made by AI to avoid accidents (Bathla et al., 2022). At this stage, AI ensures the rapid and efficient execution of decisions through its precise execution capabilities.

In this process, AI is not only the decision-maker but also the executor of those decisions. The advantage lies in AI's ability to respond instantly, with execution speeds far exceeding human capabilities. Additionally, AI can adjust based on real-time feedback, ensuring precision and consistency throughout the execution process. The decision-execution phase emphasizes minimizing human intervention, reducing human error, and improving the efficiency and accuracy of decision-making and execution (Brynjolfsson & McAfee, 2023).

Autonomous Execution further demonstrates that AI systems can address decision-making problems in closed environments, particularly in applications requiring high precision and real-time capabilities. Through information control and execution accuracy, AI maximizes system efficiency. For example, AI systems in fully automated factories can precisely control every detail of the production line, ensuring continuous production and product quality (Sahoo & Lo, 2022).

Cluster 2: Guided Resolution

In the Guided Resolution model, artificial intelligence is strategically positioned as a tool and support system for human decision-making, with the primary objective of augmenting human capabilities rather than supplanting them entirely. Guided Resolution can be understood as AI-empowered closed decision-making. Within this framework, artificial intelligence assists by providing functionalities such as data analysis, pattern recognition, and predictive insights, thereby enabling humans to make more effective judgments and actions within closed decision-making environments. The involvement of AI allows humans to better comprehend complex information and contexts, thus enhancing the accuracy and efficiency of decision-making. Through this collaborative approach, artificial intelligence not only elevates human decision-making capabilities but also ensures that humans maintain a leading role throughout the process, fully leveraging their creativity and judgment. This model of human-machine collaboration underscores the value of artificial intelligence as an auxiliary tool, facilitating the maximization of human potential.

Information Collection Stage

During the information collection stage, AI aids humans in processing vast amounts of data by filtering, categorizing, and optimizing information, thus providing a clearer foundation for decision-making. For instance, in healthcare, AI supports physicians by analyzing patient health data, such as medical images, genetic test results, or electronic health records, to quickly extract key indicators, thereby accelerating the diagnostic process. This model extends human cognitive and analytical capabilities, demonstrating significant advantages in complex, high-precision environments (Topol, 2019; Daugherty & Wilson, 2018).

In the financial sector, AI analyzes market trends and risk factors. Natural language processing (NLP) techniques enable AI to rapidly filter financial news for investment-relevant information, optimizing portfolio strategies (Chui et al., 2018). These tools enhance the efficiency of information collection and ensure the reliability of analysis results through automated data cleaning and standardization (Marr, 2021).

Information Processing Stage

During information processing, AI leverages its computational power to generate analytical results for human reference. While AI plays a dominant role in analysis, humans retain control over interpreting and utilizing the outcomes. For instance, in business management, AI can analyze customer data to generate recommendations for marketing strategies, such as identifying the most effective advertising times and target audiences (Goodfellow, Bengio, & Courville, 2016). This process reflects the core principle of Data-Driven Decision-Making, emphasizing the use of data analytics to provide scientific support for decision-making (Brynjolfsson & McAfee, 2014).

In supply chain management, AI employs optimization algorithms and predictive models to help businesses accurately estimate inventory needs and optimize logistics routes, reducing operational costs. This model combines AI's analytical capabilities with human strategic judgment. For example, under conditions of high market uncertainty, humans may adjust production plans based on AI's forecasts to mitigate potential risks (Agrawal et al., 2018; McKinsey Global Institute, 2020).

Decision Implementation Stage

In the final stage of decision-making and implementation, AI provides auxiliary support, while humans make decisions by integrating AI-generated insights with their own knowledge and situational judgment. For example, in healthcare, physicians may use AI-generated treatment plans as a reference but adapt them during implementation based on patient conditions, personal preferences, and ethical considerations. This approach integrates Rational Decision-Making with Emotional Decision-Making, where AI provides data-driven support, while humans evaluate the appropriateness of decisions using ethics and professional expertise (Lerner et al., 2015; Topol, 2019).

In emergency management, AI can analyze real-time data to suggest optimal response strategies, such as resource allocation during natural disasters. However, the final action plan requires human deliberation, considering social factors, political decisions, and evolving on-the-ground circumstances (Brynjolfsson et al., 2017; Edmondson & Harvey, 2018).

Cluster 3: Collaborative Exploration

In the Collaborative Exploration process, artificial intelligence assumes a leading role in addressing open-ended and highly complex decision-making problems. Collaborative Exploration can be understood as AI-dominated open decision-making. Its defining feature lies in its capacity to conduct exploratory analyses to uncover unknown patterns or generate innovative solutions. Within this model, artificial intelligence aids in identifying potential opportunities and challenges by processing vast amounts of data and performing complex predictive modeling. This approach is particularly well-suited for contexts requiring extensive data processing and intricate predictive modeling, such as product development, new market exploration, or hypothesis generation in scientific research (Kaplan & Haenlein, 2023; Fleming, 2018). In these domains, artificial intelligence not only rapidly analyzes and integrates data from multiple sources but also identifies hidden trends and relationships, offering unprecedented insights and strategies. Through this mechanism, artificial intelligence enhances the innovativeness and effectiveness of decision-making within the Collaborative Exploration model, thereby advancing organizational adaptability and competitive advantage under conditions of uncertainty and complexity.

Information Collection Stage

During the information collection stage, AI extracts data from diverse and unstructured sources to construct a comprehensive informational foundation. By integrating data across domains, AI can quickly detect market trends and shifts. For example, natural language processing techniques are employed to analyze social media content, providing insights into consumer behavior(Davenport & Guha, 2020). Meanwhile, human input remains vital during this phase, enabling adaptive adjustments to data strategies in response to evolving demands (Chesbrough, 2003). In drug discovery, for instance, AI can synthesize genomic data, experimental findings, and academic literature to identify potential drug targets and therapeutic pathways (Fleming, 2018). This phase emphasizes the importance of cross-domain data fusion and real-time analytics, which collectively enable organizations to build competitive advantages in complex environments.

Information Processing Stage

AI employs advanced methodologies, including machine learning, deep learning, and reinforcement learning, to extract deeper insights and construct predictive models (Chatterjee & Vrontis, 2022). The goal is to identify latent patterns and generate actionable forecasts. For instance, in Netflix’s content strategy, AI analyzes user viewing preferences, historical consumption data, and cultural trends to forecast the most promising combinations of scripts, directors, and actors, thereby optimizing resource allocation for content production (Westcott Grant, 2018). This exploratory analytical capability allows AI to generate novel insights and provide solutions to open-ended challenges.

Decision Implementation Stage

In the implementation phase, AI takes on a proactive role by generating actionable recommendations and often leading the execution of final decisions. Nonetheless, human oversight and iterative refinement remain essential to ensure contextual relevance, ethical alignment, and adaptive flexibility. For instance, in new product development, AI can autonomously generate prototype designs aligned with customer preferences or offer conceptual blueprints that serve as a foundation for refinement by R&D teams. Within this decision-making configuration, AI drives the exploratory and generative tasks, while humans focus on validating, interpreting, and tailoring outputs to organizational objectives (Kaplan & Haenlein, 2023). Emerging studies further underscore the significance of mutual learning between human and AI agents in such settings, revealing how co-learning dynamics not only enhance outcome quality but also shape the evolving structure of collaboration within AI-augmented teams (Lu et al., 2025).

Cluster 4: Augmented Discovery

Augmented Discovery emphasizes the profound collaboration between artificial intelligence and humans within open decision-making contexts. Augmented Discovery can be understood as AI-empowered open decision-making. In this model, artificial intelligence, through its formidable computational power and data analytical support, assists humans in addressing complex problems while preserving the central role of human creativity, ethical considerations, and value judgment. The involvement of AI enables humans to process vast amounts of information and complex variables more effectively, thereby playing a crucial role in domains such as scientific research, artistic creation, and the resolution of intricate societal challenges (Topol, 2019; Lerner et al., 2015; Deranty & Corbin, 2024). In these areas, artificial intelligence not only provides technical support but also aids in identifying potential patterns and trends, helping humans explore new possibilities and solutions. Through this collaborative approach, the Augmented Discovery model enhances the depth and breadth of decision-making while ensuring human agency and responsibility in the face of uncertainty and complexity. This model of human-machine collaboration fosters innovation and societal progress while maintaining ethical and value-oriented human guidance in the decision-making process.

Information Collection Stage

During the information collection stage, AI aids humans in extracting insights from diverse data sources. The primary objective of this phase is to explore uncharted territories and uncover latent patterns. By analyzing complex and unstructured data, such as texts and images, AI helps identify emerging trends. In the field of social sciences, for instance, AI can analyze vast amounts of social media content to reveal intricate patterns of social behavior or the impacts of public policies (Deranty & Corbin, 2024).

This phase exemplifies the empowering role of AI in data collection, wherein its rapid analytical capabilities significantly enhance the comprehensiveness, precision, and efficiency of the process.

Information Processing Stage

The information processing stage exemplifies a deeply synergistic interaction between artificial intelligence and human judgment. In this phase, AI employs predictive modeling techniques to produce preliminary insights, which are then enriched and contextualized by human experts drawing on their domain-specific knowledge and creative reasoning. This co-active process blends emotional intelligence, human creativity, and algorithmic precision, thereby enabling data-driven decisions that are both analytically robust and contextually nuanced (Shrestha et al., 2019). Recent research further highlights the role of natural language processing in supporting complex knowledge synthesis within collaborative environments, enhancing the efficiency and integration of decision-relevant insights in AI-supported settings (Gimpel et al., 2024). For instance, in healthcare, AI systems analyze genomic profiles and patient records to propose individualized treatment options, which physicians then refine by considering clinical realities and patient values to arrive at the final therapeutic decision (Topol, 2019).

Decision Implementation Stage

The decision implementation phase represents the pinnacle of human-AI collaboration. In this stage, humans synthesize AI-generated analyses with their intuition, experience, and value-based judgments to finalize and execute decisions. In the realm of artistic creation, for instance, AI can provide artists with creative inspiration by generating drafts of abstract paintings, which are further refined by artists to reflect their personal style and emotional expression. This process highlights the fusion of creativity and emotion, demonstrating the advantages of AI-empowered open decision-making (Lerner et al., 2015).

DISCUSSION

This study utilizes bibliometric analysis to systematically review the impact of AI on decision-making processes. By leveraging bibliometric methods, key themes and trends within the established academic literature are identified and analyzed.. The analysis has identified four critical themes that characterize AI's role in decision-making: Autonomous Execution, Guided Resolution, Collaborative Exploration, and Augmented Discovery. Building on these themes, a novel framework is proposed, categorizing AI's roles as either enabling or leading within structured (closed) and unstructured (open) decision-making environments.. The integration of AI into decision-making has given rise to a variety of models, each characterized by distinct strengths and limitations.

Autonomous Execution demonstrates AI's ability to lead the entire decision-making process, encompassing data collection, analysis, and execution. It is particularly effective in closed decision environments, where AI minimizes human involvement, delivering efficient and accurate decisions while enhancing system automation and intelligence. This approach is widely applicable across industries requiring consistency and speed, such as manufacturing, logistics, and predictive maintenance. In contrast to Autonomous Execution, Guided Resolution focuses on collaboration, leveraging AI's computational and analytical strengths to support human decision-makers while retaining human authority.. This complementary approach is particularly beneficial in domains such as healthcare, finance, supply chain management, and emergency response. By integrating AI's precision with human intuition and ethical reasoning, the Guided Resolution model addresses complex, closed decision scenarios that require a balance of data-driven insights and contextual judgment.

Collaborative Exploration emphasizes AI's dominant role in open-ended decision-making processes, leveraging its ability to integrate vast datasets and generate innovative solutions. Its application is particularly relevant in scenarios requiring exploration and adaptability, such as scientific research, product innovation, and strategic planning. However, AI's limitations in addressing uncertainties and value-based judgments highlight the need for human involvement in later stages to validate and refine AI-generated insights (Brynjolfsson & McAfee, 2014; Raisch & Krakowski, 2021).

Augmented Discovery highlights a co-creative process where AI complements human creativity and expertise, making it ideal for open, dynamic environments. For example, during global health crises, AI can rapidly analyze transmission models and propose mitigation strategies, while human policymakers evaluate these recommendations through ethical and societal lenses (Davenport & Kirby, 2016). Despite its adaptability, challenges such as over-reliance on AI-generated suggestions and concerns about algorithmic transparency and ethics remain critical considerations (Raisch & Krakowski, 2021).

Building on these observations, our study yields important implications for both theory and practice.

Theoretical Implications

This study makes several contributions to the theoretical understanding of AI decision-making.

First, by proposing the AI-Human Decision Matrix, we categorize AI’s roles in decision-making as either enabling or leading, applied across both structured (closed) and unstructured (open) decision contexts. This framework synthesizes previously fragmented literature and clarifies how AI can complement or substitute human involvement at different stages of decision-making (Akhtar et al., 2019; Raisch & Krakowski, 2021).

Second, the framework advances classical decision-making theories (e.g., Simon, 1960; March, 1994) by introducing a hybrid lens through which to understand AI’s impact on problem identification, information processing, and execution. It extends prior conceptualizations by distinguishing between AI-empowered and AI-dominated roles and mapping these onto specific decision paradigms such as Collaborative Exploration or Augmented Discovery.

Third, our study opens new avenues for theorizing the cognitive division of labor between humans and machines. It reframes AI not merely as a tool for automation or support but also as a potential co-creator of strategic insight in open decision environments (Fleming, 2018; Brynjolfsson & McAfee, 2014).

Finally, the findings underscore critical unresolved theoretical issues that merit further exploration: the need for interdisciplinary integration, longitudinal studies, contextualized analyses, and more nuanced models of human-AI collaboration, particularly as they relate to ethical norms and organizational governance (Arslan et al., 2022; Raisch & Krakowski, 2021).

Practical Implications

From a managerial perspective, the framework offers a practical roadmap for aligning AI deployment with organizational decision complexity.

First, it enables organizations to assess the fit between AI capabilities and decision typologies. By understanding when to apply AI-led automation versus AI-empowered augmentation, managers can optimize efficiency while maintaining human oversight and creativity. This is particularly important given the trade-offs each model entails, for instance, between speed and transparency, or precision and adaptability.

Second, the framework informs the design of governance mechanisms that distinguish between decision contexts requiring AI leadership and necessitating human control. Such differentiation is essential for managing risk, ensuring accountability, and fostering trust in AI-augmented systems (Davenport & Ronanki, 2018; Kaplan & Haenlein, 2023).

Third, the matrix has implications for capability development. As AI becomes more deeply embedded in strategic and operational decision-making, organizations must equip their workforce with not just data literacy but also collaborative fluency, the ability to interact effectively with AI tools in both closed and open problem spaces. AI integration requires a balanced approach that enhances decision performance without compromising values such as fairness, transparency, and accountability (Brynjolfsson & McAfee, 2014; Fleming, 2018)..

Future Research

Led by the insights generated through our framework and literature analysis, we identify three key directions for future research.

First, team-level AI-enabled decision-making remains an underexplored domain. While existing research has predominantly centered on individual or organizational decision contexts, there is a pressing need to investigate how AI integration influences group dynamics, including trust formation, coordination mechanisms, and collective performance (Cascio & Montealegre, 2016; Carmeli et al., 2019). In this regard, recent empirical work by Lu et al. (2025) highlights the pivotal role of human-AI co-learning in shaping team cognition and behavioral adaptation, offering a promising foundation for future inquiry into hybrid team functioning. Particular emphasis should be placed on understanding how AI affects psychological safety, role allocation, and the development of shared mental models within decision-making teams.

Second, longitudinal and cross-contextual studies are needed to understand how AI-human collaboration evolves over time and across industries. These studies could assess the stability of different AI-human decision paradigms, such as Autonomous Execution versus Augmented Discovery, and their long-term impacts on organizational performance, innovation, and employee well-being (Balasubramanian et al., 2022; Basu et al., 2023).

Finally, further exploration of the AI-Human Decision Matrix through empirical validation is expected. Researchers may explore the boundary conditions under which each decision paradigm is most effective and investigate the factors, such as task complexity, data ambiguity, or cultural variation, that moderate the success of each AI-human collaboration mode.

CONCLUSION

In this article, we examine the role of AI in human decision-making through the lens of four AI decision-making paradigms: Autonomous Execution, Guided Resolution, Collaborative Exploration, and Augmented Discovery. This paradigm offers a novel perspective for understanding how AI integrates computational capabilities with human creativity across diverse decision-making contexts, particularly in closed and open decision environments. It highlights the dual role of AI in human decision-making: functioning independently to lead complex decision processes and empowering humans by enhancing their performance in information analysis and creative exploration, thereby advancing decision efficiency and fostering innovation.

This approach provides a strategic framework for the organizational application of AI while emphasizing the importance of transparency, accountability, and interdisciplinary integration. Future research should further investigate the long-term implications of AI deployment, the dynamics of team collaboration, and the development of regulatory frameworks to enable the responsible and effective use of AI in complex and dynamic environments. By integrating theory and practice, this framework aim f to offer fresh insights for both academic inquiry and industry application, contributing to AI-driven decision-making innovation and promoting sustainable development.

Declarations

Author Contribution

H.L. conducted the literature search, performed data analysis, and drafted the initial manuscript. F.T. provided conceptual guidance, supervised the research process, and critically revised the manuscript. All authors read and approved the final manuscript and agree to be accountable for all aspects of the work.

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Figures

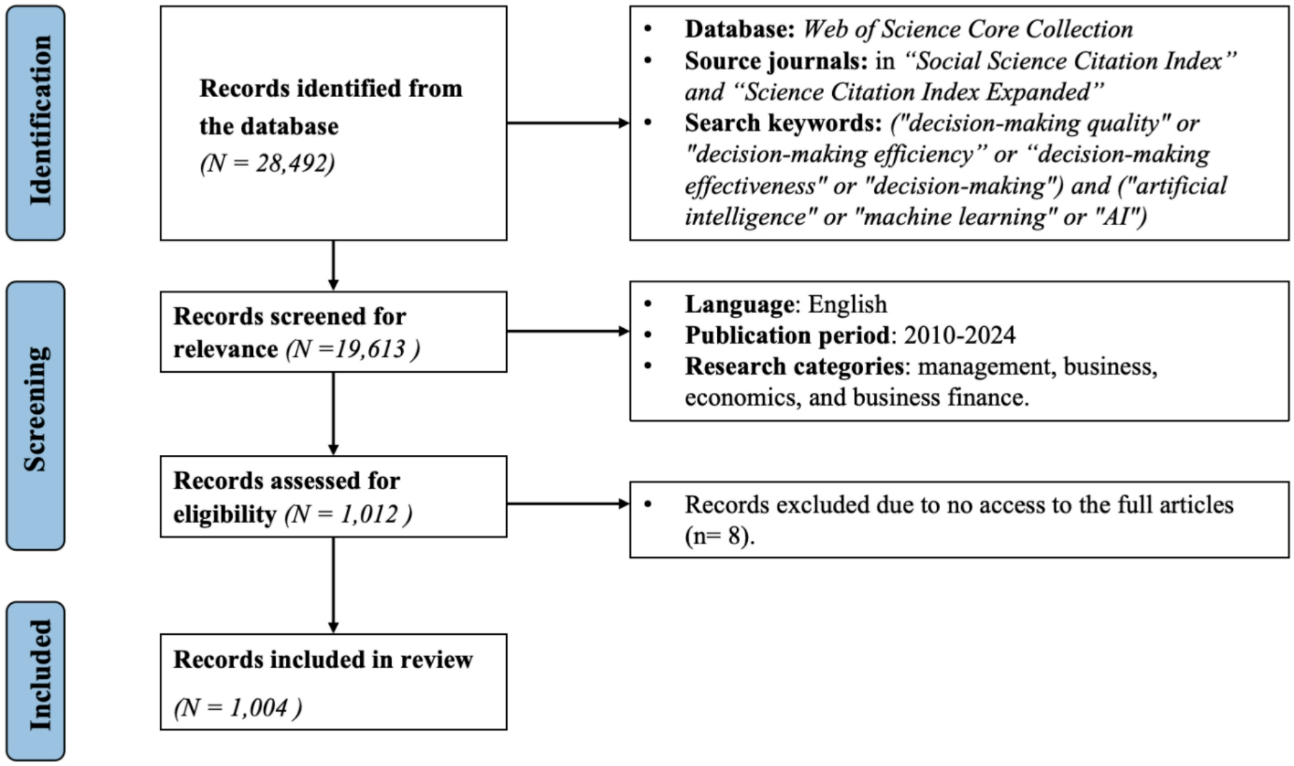

Figure 1

PRISMA Process

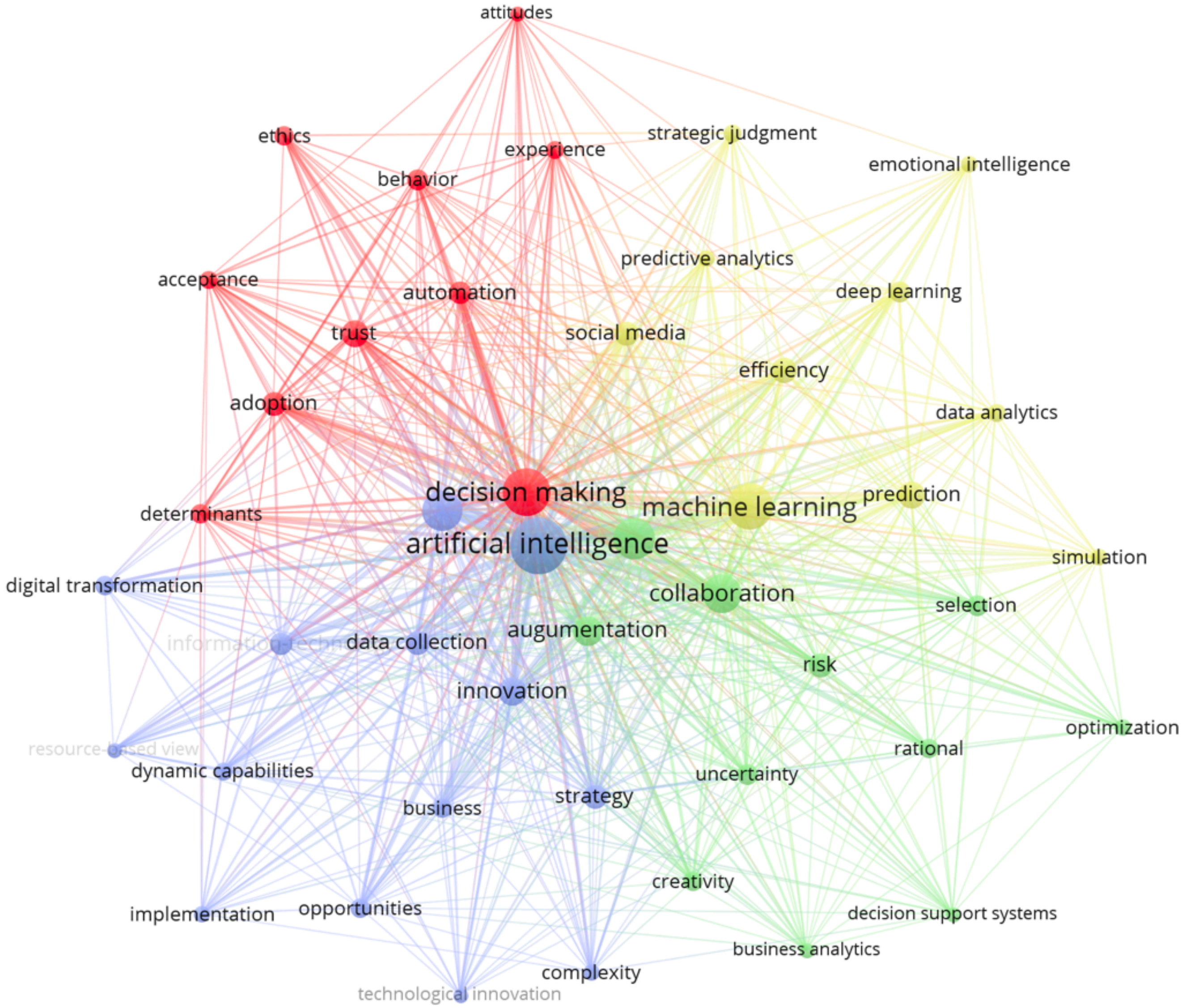

Figure 2

Keywords Network

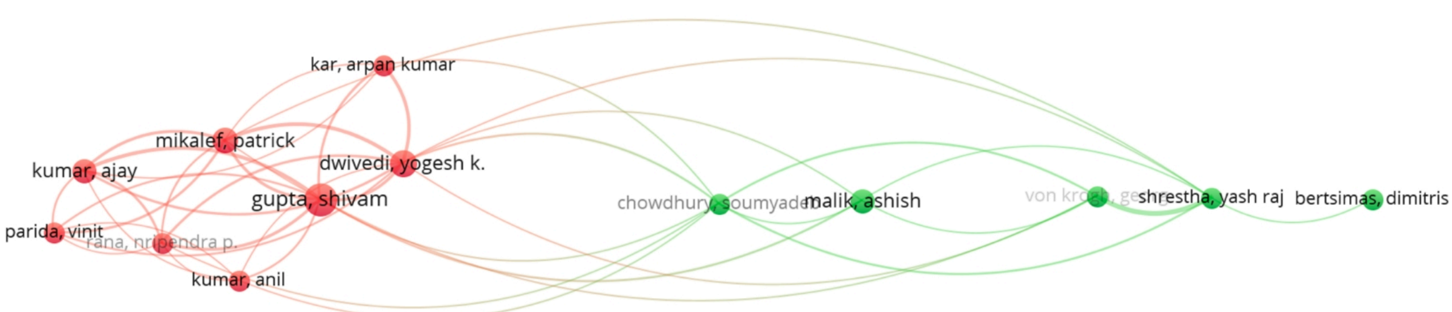

Figure 3

Co-authorship Network

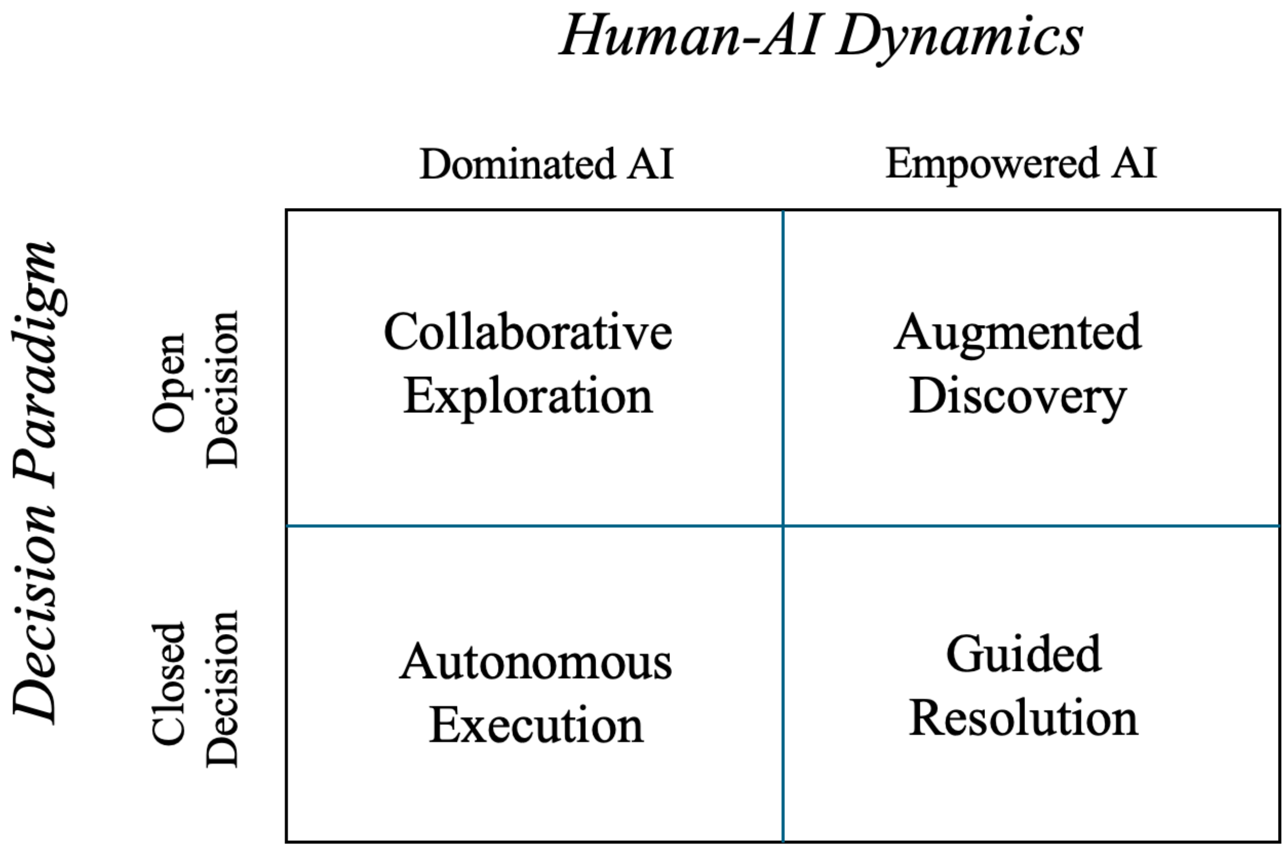

Figure 4

Human-AI Decision-making Matrix