ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 11| November 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

THE ROLE OF ARTIFICIAL INTELLIGENCE IN MODERN DECISION MAKING: A STAGE-WISE AND SECTOR-WISE ANALYTICAL STUDY

Ms. S. Boomika
Assistant Professor, School of Commerce (Finance & IB) Sri Krishna Knowledge Foundation, Deemed to be University, Coimbatore – 641008, India
ORCID ID: 0009-0000-8946-6541

Article DOI: https://doi.org/10.36713/epra32042
DOI No: 10.36713/epra32042

ABSTRACT

Decision-making has become an increasingly complex activity in management, governance, and day-to-day operations. Today's volume of information available is higher than the human ability to cope with it. This is where artificial intelligence comes into play. It is a practical solution which totally changed the perception of AI as a research idea transforming it into an effective tool used by such industries as finance, health care, retail, manufacturing and human resources. The article describes the role of AI in the decision-making process from two sides which include the stage-based approach illustrating the activity of AI during the decision-making process and sector-based approach of its implementation. It has been concluded that AI is most productive at the stages of collecting data, assessing the collected data and monitoring it and it is the least effective in the stages of defining the problem and making decisions on the basis of values. Different industries are more or less appropriate for the implementation of AI because of the availability of data, number of repetitions in the decision-making process and cost of mistakes.

KEYWORDS: *Artificial Intelligence, Decision Making, Decision Support, Human-AI Collaboration, Algorithmic Accountability, Explainability.*

1. INTRODUCTION

Every organisation is primarily a system for decision-making. A bank makes loan decisions, a hospital assesses prioritization of patients, a retailer decides stock inventory and a department in the government determines the projects that will get funding. For much of the twentieth century, these decisions depended on a combination of managerial instinct, rule of thumb, and periodic reports. Now, organizations do continuous data generation through transactions, sensors, applications and social platforms, thereby widening the gap between information made available and that which a man can rightly interpret.

Broadly defined, artificial intelligence is the concept of computer systems completing tasks generally expected of human intelligence, such as learning, identifying patterns, making predictions and reasoning. It is the leading technology to bridge the gap that exists today. Machine learning algorithms can detect fraud in a matter of milliseconds, predict demand for hundreds of products and identify medical images to view them closely later on. Concurrently, AI-powered solutions give rise to important questions. Who is to be held accountable when the algorithm fails? Can we trust the recommendation when its reasoning is not clear? Does using advice given by computers diminish human judgement?

This is an article that structure addresses a series of mentioned questions, and instead of treating AI as one uniform technology with similar impact, one is asking at which stage of the decision-making process and in what kind of environment AI is the most beneficial and how much autonomy should be given to it. The present analysis is conceptual, and the judgments given in the article are solely the author's reasoning that needs to be validated by empirical studies in the future.

2. CONCEPTUAL BACKGROUND

2.1 Decision making and bounded rationality

Traditional economic models presupposed rationality of the individuals in any economic situation, meaning that decision makers act with complete knowledge of the situation and unlimited computation capacity. However, Herbert Simon disputed this supposition and proposed the concept of bounded rationality. According to this concept, decision makers have limitations regarding their information, time and cognitive capabilities, therefore, they make good enough rather than optimum decisions. Further studies, conducted by such prominent behavioral psychologists as Daniel Kahneman and Amos Tversky, revealed that the human decision-making process is influenced by a number of biases. In light of the mentioned theories, one may conclude why decision-making support tools are so popular among the economists - they relieve people from some limits imposed on us by information and cognitive processes.

2.2 From decision support systems to AI

The rudimentary decision support systems created in the 1970s and onwards, were able to simply extract the data that managers

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 11| November 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

asked for and execute specific models. Later on, the business intelligence systems appeared that included dashboards and reports. Yet, AI is dissimilar to its predecessors for three reasons. Firstly, it learns from its data instead of being constrained to rules written by humans. Secondly, it can work with unstructured data such as words, images and sounds. Lastly, it can operate in the conditions of big data and make or advise on the decisions.

2.3 Forms of AI relevant to decisions

From the point of view of this article, the forms of AI ability that can be considered the most relevant are four. Descriptive and diagnostic analytics explain what happened and why. The predictive models give an estimate of likely events, for example, default risk or customer churns. Prescriptive systems recommend some action, be it price or delivery route. Generative and conversational systems summarize the information, draft choices, and ask questions naturally.

3. OBJECTIVES OF THE STUDY

- To explain the ways in which AI alters decision-making
- To determine the parts of the decision-making process with maximized and minimized involvement of AI.
- To analyze the appropriateness of AI in making decisions in various industries.
- To suggest a framework for determining the division of decision-making responsibilities by humans and AI.

4. RESEARCH METHODOLOGY

The research is analytical and conceptual. The decision cycle is segregated into seven stages and the contribution, strength and limitations of AI are analyzed at each of the stages. For the purpose of sectoral comparison six sectors were selected in order to have a variety of data conditions and risk levels and each of them was rated from 1 to 5 with respect to four criteria. The ratings are the author's formulated opinions based not on statistical data but the overall characteristics of decision-making in all the sectors and should be viewed as analytical tool rather than as statistical results.

Limitations of the Study

Due to the evaluative nature of the ratings, analysts might mark certain sectors differently. In order to alleviate this problem, the rules of scoring have been made known openly and the report includes a test of sensitivity to changes as well as a questionnaire that can be used by practitioners to confirm the ratings.

5. DATA ANALYSIS AND INTERPRETATION

5.1 AI across the Stages of Decision Making

The seven stages of the process, which make up the cycle of decision making, are problem identification, information collection, answers suggestion, solution assessment, selection of a solution, implementation of the decision, and evaluation of the outcome. The table below summarizes the use of AI technology in each of the stages.

Table.1 Role of AI at each Stage of Decision Making:

Stage	What AI contributes	Main strength	Main limitation	AI value (1-5)
1. Problem identification	Anomaly detection, early-warning alerts, trend spotting	Notices patterns humans overlook	Cannot decide what is *worth* treating as a problem	3
2. Information gathering	Automated collection, text mining, summarization	Speed and breadth	Quality depends on data; risk of irrelevant or biased inputs	5
3. Generating alternatives	Scenario simulation, option generation	Wide range of options quickly	May reproduce patterns from past data and miss novel options	4
4. Evaluating alternatives	Prediction, scoring, optimisation	Consistent, quantified comparison	Opaque models are hard to question	5
5. Choice	Recommendation or automated selection	Removes fatigue and inconsistency	Values, ethics and trade-offs are not purely computational	3
6. Implementation	Workflow automation, resource scheduling	Reliable execution at scale	Rigid when circumstances change	4
7. Monitoring and learning	Continuous tracking, feedback loops, model updating	Learns from outcomes in real time	Feedback loops can entrench early errors	5

5.1 Interpretation

The average value of AI, when all seven phases are taken into consideration, amounts to 4.1 (i.e., the score of 29 divided over the seven stages). There are three phases where the system acquires the highest score of five points each: these are information gathering, evaluation of options and monitoring and

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 11| November 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

learning. During these phases, the role of AI consists in processing a great deal of data with a specific outcome in mind, which is the sphere of competence of AI. On the other hand, two stages, i.e. the identification of a problem and making a choice receive the lowest score - 3. During the problem identification phase, AI indicates that there is something wrong but defining the situation in terms of problems requires an understanding of organizations' objectives and contexts. During the stage of making a choice, the final choice implies making a value judgment.

The next observation is that the stages are interconnected. If the role of AI is limited to data collection and evaluation but decision making is left to humans, the quality of the decision will depend on the humans' ability to understand and analyze the information they receive. Decision makers who accept machine results without verification may commit the same errors as the model itself, with a false sense of confidence, a problem known as over-reliance in the realm of human-automation interactions. Moreover, those who dismiss algorithmic recommendations due to their distrust of machines lose an opportunity to benefit from the processes.

5.2 Sector-wise Suitability of AI

5.2.1 The AI Suitability Index

In order to analyze different sectors, a set of criteria is used for evaluation, as each criterion relates to the ability of artificial intelligence systems to perform their decision-making functions efficiently. The chosen criteria are:

- The availability of data (D), which indicates the volume of relevant and trustworthy data for AI. Having a larger amount of data is a positive thing for AI's functioning.
- The volume of repeatable decisions (R), which means the number of similar decisions in a comparable situation. The higher the number is, the more automated and efficient the AI model can become, as the machine learns from the experience.
- The cost of mistakes (E), meaning the gravity of negative outcomes of making wrong decisions. High cost of errors is unfavorable for the usage of AI.
- The degree of importance of explanatory ability (X), which means the level of requirement to provide a clear explanation for every decision taken. The higher this degree is, the worse it is for the AI's functioning.

The indexes of each criterion take the values from 1 to 5. Since E and X oppose automation, their scores will be reversed before averaging.

AI Suitability Index = [D + R + (6 − E) + (6 − X)] / 4

This index can take values in the range from 1 (fully human-led) to 5 (fully suited for automation). As for the interpretation, the value above 4.0 indicates the automation-driven model, the value from 3.0 to 3.99 represents the hybrid model with human intervention, and anything below 3.0 depicts the human-controlled AI-powered model.

5.2.2 Results

Table 2: Ratings and AI Suitability Index by Sector

Sector (typical decision)	D	R	E	X	Index	Suggested model
Retail and marketing (pricing, recommendations, stocking)	5	5	2	2	4.50	Automation-led
Finance (credit scoring, fraud detection)	5	5	4	4	3.50	Hybrid
Manufacturing and supply chain (maintenance, logistics)	4	4	3	3	3.50	Hybrid
Human resources (screening, performance review)	3	4	4	5	2.50	Human-led, AI-assisted
Healthcare (clinical diagnosis and treatment)	3	3	5	5	2.00	Human-led, AI-assisted
Public administration (benefit eligibility, policy allocation)	2	3	4	5	2.00	Human-led, AI-assisted

5.2.3 Sensitivity Test

As the cost of error may be considered the key checkpoint, we have recalibrated the Index giving it double importance: Index (alt) = [D + R + 2(6-E) + (6-X)] /5. The result is presented in Table 3.

Table 3: Sensitivity of the index with respect to the higher importance of cost of error

Sector	Base index	Alternative index	Base rank	Alternative rank
Retail and marketing	4.50	4.40	1	1
Manufacturing and supply chain	3.50	3.40	2 (tied)	2
Finance	3.50	3.20	2 (tied)	3
Human resources	2.50	2.40	4	4
Public administration	2.00	2.00	5 (tied)	5
Healthcare	2.00	1.80	5 (tied)	6

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 11| November 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

5.2.4 Interpretation

The findings demonstrate a distinct gradient. Retail and marketing rank highest with data readily available, decisions being made constantly, and any erroneous recommendation or pricing causing minimal consequences that can be remedied quickly. Finance is equally equipped with rich data and huge amount of it, while mistakes made in credit or fraud decisions have a significant impact on people's lives and wide regulations demanding some justification which forces finance to be classified as hybrid in this case. Lastly, manufacturing is similar: more data from sensors and consistent decisions does not prevent the industry from experiencing vast economic loss due to injuries or equipment breakdowns.

Human resources, healthcare and public administration fall into the human-led category for different reasons. In human resources, the available data are often thin or subjective, and screening decisions carry legal and ethical exposure, as well as a risk of embedding historical bias. In healthcare, the cost of error is as high as it can be, and clinicians and patients need to understand the basis for a diagnosis. In public administration, data are frequently incomplete or fragmented, and decisions affect entitlements and rights, which creates a strong demand for transparency and the ability to appeal.

The sensitivity test supports the stability of the main conclusions. The top position (retail and marketing) and the bottom group (healthcare, public administration and human resources) do not change when cost of error is weighted more heavily. The only change in ranking is that finance falls behind manufacturing, which reflects the particular weight that financial errors carry for individuals. This suggests that the broad classification into automation-led, hybrid and human-led settings is robust, even though the exact order of neighbouring sectors depends on the weighting chosen.

6. KEY FINDINGS

1. Artificial intelligence is the greatest help when the decision requires the processing of large amounts of data based on a clear objective, namely collecting information, assessment, and monitoring, where it gets five out of five.
2. Conversely, artificial intelligence is least suitable for the defined problem and the choice of the options when these involve value, morality or accountability, for each getting three out of five.
3. It should be noted that the degree of suitability of artificial intelligence to the authority of decisions differs significantly, from 4.50 in retail and marketing to 2.00 in medicine and public administration.
4. The most important factors influencing the authority of the artificial intelligence are not only the cost of error, but also the necessity to explain the decisions made.
5. It is more appropriate to characterize the human-artificial intelligence relationship as a fluctuation between collaboration, than as a choice between human intelligence and artificial intelligence.

7. CHALLENGES AND RISKS

Discrimination and equity: Models are taught on historical data, if the data indicates discrimination in the past, the model responds similarly to the historical data. For example, a study published in Science in 2019 highlighted the fact that the health application created in the United States underestimated the health needs of the African-American patients due to the use of past medical expenditure data as a marker.

Opacity: Many effective models lack interpretability. In situations where significant outcomes are at stake, some researchers believe that people should choose inherently interpretable models over explanations for black-box systems.

Accountability: When a decision is made by a human and a machine, accountability becomes less clear. Organizations should clarify who is responsible for the outcome of their actions.

Data quality, privacy, and security: decisions are effective when all the required data is in order. However, the increased amount of data will raise concerns of misuse, consent issues and violation.

Changes in management and workforces: The shifts in decision-making power will create new jobs and require a different set of skills.

8. A PROPOSED FRAMEWORK: GRADED HUMAN – AI COLLABORATION

The findings point towards matching the level of AI authority to the characteristics of the decision rather than adopting a single approach everywhere. Table 4 proposes four levels.

Table 4: Levels of human-AI collaboration

Level	Role of AI	Role of human	Suitable when
1. Informing	Provides data, summaries and analysis	Makes the decision unaided by recommendations	Index below 2.5; very high error cost and explanation duty
2. Recommending	Suggests a ranked set of options with reasons	Reviews and decides	Index about 2.5 to 3.0
3. Deciding with oversight	Makes the decision; flags uncertain cases	Monitors, audits and can override	Index about 3.0 to 3.99
4. Autonomous	Decides and acts	Sets rules, audits samples periodically	Index 4.0 or above; low error cost, easy reversal

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 11| November 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

Any level above Informing should be combined with four conditions of governance: (i) there should be a clear owner of any AI-enabled decision; (ii) the data, assumptions, and limits of the model should be documented; (iii) there should be regular testing for bias and accuracy, and the results should be brought to the attention of decision-makers; and (iv) there should be a straightforward way for affected individuals to question a decision or appeal it.

9. CONSEQUENCES

For managers, the analysis suggests that one should start with decisions that are made frequently and have ample data in order to gain trust and experience in this sphere before going for more significant ones. For regulators and policy-makers, it indicates how important it can be to implement explanation and appeals rights in industries characterized with low index, but to avoid introducing too strict rules in order not to discourage helpful low-risk usage. For trainers and educators, it indicates the necessity of teaching people who will be making decisions in the future how to analyze data rather than obey or reject it.

10. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The assessments applied in the analysis are subjective evaluations rather than recorded data, and the index takes into consideration its four criteria equally almost everywhere except in the sensitivity analysis. Future research can improve the given work in many ways, such as studying managers and experts in the field for the purpose of affirming or correcting the ratings (the questionnaire is provided for this purpose in the Appendix), performing case studies of organizations with different rates of cooperation, determining whether the index provides a successful prediction of the implementation, and including some more criteria in the rating system, such as regulatory burden, a speed of decision-making, and costs of AI implementation.

11. CONCLUSION

Whereas it has become a recognized tool in decision making, AI does not add equally to all decision-making processes. It excels where decisions are based on data, aimed towards stated targets, and with timely feedback. However, it falters when it comes to values, context, and accountability. Overall, the stage-by-stage analysis confirms an AI strength in information gathering, analysis, and monitoring, whereas sector-by-sector analysis confirms that jurisdictional authority becomes weaker when there are larger cost implications for making an error and higher expectations for explanations. The long and short of it is that organizations should never concern themselves with whether AI should make decisions or not but rather seek answers to the question of which decisions should be made by the machine, who will be entitled to decide on them, and to what extent there would be safeguards for their actions. Human-AI collaboration driven on a graded approach with full accountability, regular assessment, and the right to appeal grants organizations the speed and consistency of AI whilst retaining human judgment and responsibility where it carries the most weight.

Appendix: Questionnaire for Validation of Sector Ratings

Respondents (i.e. managers or experts in the field) are requested to rate every statement from 1 (very low) to 5 (very high) concerning the type of decision in their sector.

- Availability of data: "We can easily reach reliable data regarding the decision."
- Repeatability: "Decisions of this nature happen regularly and involve similar patterns."
- Cost of error: "The wrong decision may incur significant losses financially or legally as well as endanger safety or reputation."
- Explainability: "There is a requirement from either law, the policy, or the stakeholders that we provide a rationale for every decision."
- Current System: "To what extent is AI applied in this decision?" (1 = not used at all, 5 = fully automated)

The average rating for each factor in each sector can be employed in an equation from Section 5.1 to compare the level of ratings by the author with those provided by professionals.

REFERENCES

1. *Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton.*
2. *Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108-116.*
3. *Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114-126.*
4. *Kahneman, D. (2011). Thinking, Fast and Slow. Farrar, Straus and Giroux.*
5. *Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2).*
6. *Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447-453.*
7. *Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors, 39(2), 230-253.*
8. *Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1(5), 206-215.*
9. *Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach (4th ed.). Pearson.*
10. *Simon, H. A. (1955). A behavioral model of rational choice. The Quarterly Journal of Economics, 69(1), 99-118.*