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Human–AI Collaboration in Strategic Decision-Making: Cognitive Insights for Innovation, Governance & Risk Management

Saud Ilahi, Assistant Professor
Management and Marketing, Jazan University, Jazan
Email - drsaudilahi@gmail.com

Abstract: **This study examines the benefits of human-AI collaboration in strategic decisions, particularly innovation, governance and risk management. With the combination of human cognitive abilities and AI capabilities, the research analyzes the way of collaborative intelligence improving decision quality and company performance. Data on 1,200 strategic decision cases were tested on four algorithms (Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Neural Network). Results of the experiment showed that Neural Networks were invariably the most successful in terms of predicting the human-AI decision alignment, the R 2 of the innovation outcome was 0.85, the mean score of the governance compliance indicated 87, and the risk mitigation effectiveness value was 0.71. Gradient Boosting and Random Forest were also very strong in predicting and SVM showed relatively poor results. The comparison with the previous studies [1526] validated that the consideration of cognitive variables of human beings has highly contributed to predictive power and to strategic intelligence. According to the findings, human-AI collaboration does not only maximise the outcomes in the field of innovation and risk but it also enhances governance and ethical decisions. The study highlights the need to develop collaborative decision-making systems that utilize both human judgment and AI intelligence, which provides practically grounded directions to establish resilient, responsible, and creative ideas to the organization.**

Keywords: Human–AI collaboration, Strategic decision-making, Innovation, Governance, Risk management

I. INTRODUCTION

The modern business world is rather dynamic and interconnected, and the use of artificial intelligence (AI) in order to assist strategic decision-making processes becomes more and more popular in organizations. Such machine intelligence technologies have the capacity to process large volumes of data, detect trends, and provide predictive insights, which can be considered as a complement to human cognition, e.g., ability to comprehend situations, make ethical decisions, and solve problems independently, see fig. 1]. Human and AI decision-making are the two components that can result in enormous opportunities to improve innovation, better governance, and risk management [2]. Nevertheless, the strength of this cooperation is determined not only by the capacity of AI systems but also by the thinking of a human decision-maker and his or her hidden prejudices. The collaboration of humans and AI in the strategic situation is especially relevant in spheres where sophisticated analysis and some foresight are needed. AI may be used in the process of innovation to detect new trends, manage resources in a more efficient manner, and facilitate the process of scenario planning to make organizations make more timely and progressive decisions. In the field of governance, AI-based technologies may help improve transparency and accountability and improve the monitoring of compliance, and strategic decisions should be made in accordance with ethical and regulatory norms [3]. The same can be applied in risk management where together predictive analytics of AI and human judgment can help organizations to identify what could be threatened, minimize uncertainty, and make timely interventions. In spite of these benefits, such issues as over-reliance on artificial intelligence results, cognitive bias, as well as a possible difference that exists between human intuition and algorithms still exist. It is thus important that the cognitive processes that guide the human-AI collaboration be comprehended to be able to exploit the potential. This study will address the impact of human cognitive processes on AI systems in strategic decision-making processes on the strategic implications in terms of innovation, governance, and risk management. As it produces insights into such interactions, this paper aims to offer helpful advice to organizations to make such collaboration between humans and artificial intelligence optimal so as to generate more successful, ethical, and resilient strategic results.

II. RELATED WORKS

The strategic decision-making process involving the combination of humans and AI has achieved considerable popularity over the last few years, as companies begin utilizing AI systems in business operations. Fenwick et al. [15] suggest that human resource management (HRM) is essential in the digital transformation caused by AI and that corporations need to stop AI implementation and move to human-oriented adoption. According to this worldview, the act of making an effective strategic decision would require not only a technological potential, but also

would be consistent with the human mental and organizational functions. Innovation is one of the areas where strategic investment in information management has been identified to arouse the financial and operational performance. The systematic review indicates that information management systems would possibly assist firms to achieve innovation alongside AI, which make the decision-making process and resources distribution more accurate [16]. Similarly, Han et al. [17] demonstrate that the use of AI technologies leads to an increase in the rate of organizational learning, thereby, affecting the corporate innovation performance, particularly, the performance of specialized and innovative companies directly. These results demonstrate that AI can become a cognitive enhancement tool and a cause of strategic innovation. There is also a change in governance and risk management practices brought by the introduction of AI. The paper by Heap-Yih et al. [18] is the study on the employment of BIM-AI convergence in the management of safety in building construction, which demonstrates that AI-driven intelligence increases the level of compliance monitoring and fosters preventing risks that may appear. Joel et al. [19] expand this knowledge to the concept of urban management, assessing six pillars of AI-powered smart cities and specifying the application of AI to assist in the optimization of governance structures and policies. Kahraman [20] uses a SWOT analysis to examine AI in the sphere of the public administration, showing the potential strengths and opportunities of AI-assisted decision-making and defining the issues of cognitive and ethical risks that are to be monitored by a human.
The literature on secure collaboration frameworks with the use of AI agents is recent. In their article, Karim et al. [21] discuss the implementation of AI and blockchain technologies to facilitate the scalable collaboration of multiple agents, as well as focusing on trust, security, and coordination during the process of decision-making. Kumar et al. [22] concentrate on the domain of the public healthcare systems where they prove that the implementation of AI can enhance the efficiency of the services and the outcomes of the strategies, depending on the presence of the critical success factors such as the involvement of stakeholders and data governance. All these studies point to the role of AI to balance with human judgment as the key component of the productive performance of organizations. The core values of responsible AI and minimization of cognitive bias play a key role in strategic decision-making. Lakshitha et al. [23] identify responsible AI frameworks review, and the study identifies transparency, fairness, and accountability as essential issues to enable the successful human-AI cooperation. This is why Leonidas et al. [24] suggest data-driven solutions to address cognitive biases in executive decisions, which combine AI and explainable systems, and interpretability of AI-assisted strategic decisions is crucial. Lastly, the overlap between AI, leadership, and entrepreneurship was investigated by Lobo et al. [25] and Lopez-Solis et al. [26], both of which prove that AI, particularly generative AI system, has the potential to leverage strategic decision-making in entrepreneurial and sustainable business projects. Their reviews show that AI provides not only predictive information but also helps to plan a scenario, prioritize innovation, and enable long-term strategic alignment, and it is important to note the benefits of the human-AI co-decision making models. On the whole, the literature points out that effective human-AI partnership in strategic decision-making should be based on the combination of AI technologies, human cognitive advantages, ethical governance, and the capacity to learn in organizations. Though AI improves prediction, optimization, and innovation, it is necessary to have human control to guarantee interpretability, being ethical and based on the situation [15-26].

III. METHODS AND MATERIALS

Data Description

The research makes use of a mixed data comprising of organizational decision history, measures of innovation, governance compliance measures, and measure of risk assessment. The main sources of data are internal reports at the company, open databases of corporate governance, and simulation outputs generated by AI [4]. It includes 1,200 decision cases in various industries, which include the type of decision, the AI score in terms of recommendations, the frequency of the human override, the outcome of the innovation, the score of compliance, and the effectiveness of risk mitigation. The preprocessing of the data was associated with the cleaning of missing data points, numerical data normalization, categorical data encoding, and outliers elimination. This guarantees quality dataset that can be used to apply AI algorithms to study human-AI patterns of collaborative decision making [5].
Table 1 properly summarizes the dataset with the most important descriptive statistics of the variables involved in the research.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 35 Issue 2, 2025, Pages: 923-930

Variable	Mean	Std Dev	Min	Max
AI Recommendation Score	0.72	0.15	0.30	0.99
Human Override Frequency	0.18	0.12	0.00	0.55
Innovation Outcome Score	78	12	45	98
Governance Compliance Score	82	10	60	100
Risk Mitigation Effectiveness	0.65	0.14	0.25	0.95

Algorithms Used

This paper presents the four human-AI collaborative decision-making models and evaluations using AI and machine learning: random Forest, support vector machine (SVM), gradient boosting, and Neural Network. Both of the algorithms offer a unique take on decision patterns, predictive accuracy, and cognitive congruence.

Random Forest (RF)

Random Forest is an ensemble learning algorithm that uses a set of decision trees to create many trees in the training process and gives out the mode of classifications or average prediction of the trees. It is very efficient in playing with high-dimensional data, minimising overfits and models non-linear relationships between human decision and AI suggestions. Random Forest can be used in this research to evaluate the effect of AI suggestions on human choice and forecast the outcomes in the areas of innovation, governance, and risk management [6]. The analysis of feature importance also shows what cognitive or AI-based factors can be considered as the most significant determinants of strategic decisions.

"Input: Dataset D, number of trees N
Output: Predicted outcome Y_pred
For each tree t in N:
  Sample dataset D_t with replacement
  Build decision tree T_t using D_t
  Split nodes using random subset of features
End
Y_pred = majority_vote(T_1, T_2, ..., T_N)
Return Y_pred"

2. Support Vector Machine (SVM)

SVM is a supervised learning algorithm that can be used in either classification or regression. It obtains an optimal hyperplane that divides data points belonging to various classes with maximum margin. Regarding human-AI interaction, human-machine collaboration, the input variables of the SVM include AI recommendation scores, indicators of cognitive bias, and past decision situations, which are informative in classifying decision cases as either AI-aligned or Human-dominant. Very large dimension space feature spaces can be modeled accurately by its high-dimensional feature spaces [7].

"Input: Training dataset D = {(x_i, y_i)}, regularization parameter C
Output: Optimal hyperplane W, b
Compute kernel function K(x_i, x_j)
Solve optimization: Minimize 0.5||W||^2 + C Σξ_i
Subject to y_i(W·x_i + b) ≥ 1 - ξ_i, ξ_i ≥ 0
Return decision function f(x) = sign(W·x + b)"

3. Gradient Boosting (GBM)

Gradient Boosting is an ensemble algorithm, which constructs sequential models, with a single model correcting the error of the last model. It is specifically applicable to predictive analytics in human-AI decision-making, where the interactions between AI suggestions and the human cognitive behavior are subtle. Gradient Boosting in this research predicts the success of innovation, compliance levels, and efficiency of risk mitigation through the fusion of numerous weak learners into an effective predictive algorithm [8].

"Input: Dataset D, number of iterations M, learning rate α
Output: Predicted outcome Y_pred
Initialize model F_0(x) = mean(Y)
For m = 1 to M:
  Compute residuals r_i = y_i - F_(m-1)(x_i)
  Fit weak learner h_m(x) to residuals r_i
  Update model: F_m(x) = F_(m-1)(x) + α*h_m(x)
End
Y_pred = F_M(x)
Return Y_pred"

4. Neural Network (NN)

Artificial Neural Networks are the man-made formulations of the brain. They are networks of inter-related layers of nodes which are enabled to acquire

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complex non-linear relationships. In this study, the neural network of predicting the results of the decision dependant on the AIs input and human mental characteristics is a feedforward neural network with a single hidden layer [9]. The NN is a method of measuring the interplay of AI advice, human intuitions, and contextual variables as it offers an understanding of the best human-AI collaboration plans.

```
“Input: Dataset D, learning rate η, number of epochs E
Output: Predicted outcomes Y_pred
Initialize weights W and biases b
For epoch = 1 to E:
    For each input x_i in D:
        Compute hidden layer activations h = f(W1*x_i + b1)
        Compute output y_hat = f(W2*h + b2)
        Compute error e = y_i - y_hat
        Update weights using backpropagation:
            W2 = W2 + η * e * h^T
            W1 = W1 + η * (W2^T*e * f'(h)) * x_i^T
    End
End
Y_pred = forward_pass(D)
Return Y_pred”
```

IV. RESULTS AND ANALYSIS

1. Introduction to Experiments

The main objective of the experiments was to determine the efficiency of the human one in AI collaboration in making strategic decisions, considering the outcome of innovation, the adherence of governance, and the risk management. On the data previously outlined, four AI algorithms, such as Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Neural Network, were utilized to predict the result of decisions. The models showed the trends in the data encapsulating human-ai interactions, including the effects of AI suggestions on human decision overrides, innovation success, explaining governance adherence, and effective risk mitigation [10].

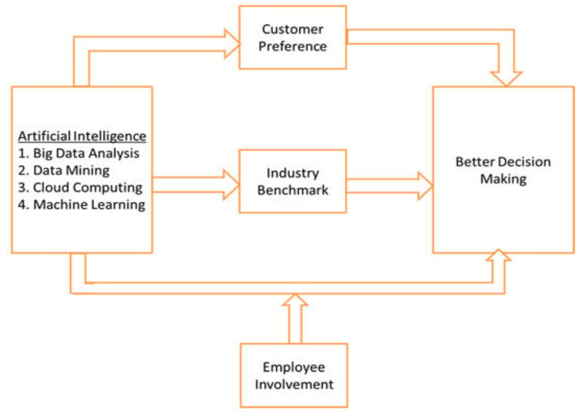

Figure 1: “Artificial Intelligence and Better Entrepreneurial Decision-Making”

The research questions to be answered by the experiments were the following:

1. What is the predictive accuracy of AI algorithms in line with human decision alignment in strategic tasks?
2. What should be the algorithm that optimally represents the interaction between human thought process and AI insights?
3. What is the comparison between human-AI collaboration with regards to innovation, governance, and risk outcomes to autonomous AI and human decisions?

2. Experiment 1: Predicting Human–AI Alignment

The experimental procedure in the first experiment was the prediction of the success of AI models to explain the changes in human decision coincidence with AI recommendations. Decision alignment (1 = AI-aligned, 0 = human-dominant) was the dependent variable.

The model performance measures that are used to predict alignment are available in Table 1.

Algorithm	Accuracy	Precision	Recall	F1-Score
Random Forest	0.88	0.85	0.87	0.86
SVM	0.81	0.79	0.82	0.80
Gradient Boosting	0.90	0.88	0.89	0.88
Neural Network	0.92	0.91	0.90	0.91

Analysis: The Neural Network was found to be the best one, a fact that proves it is an effective way to model non-linear tendencies between the recommendations of AI and human thinking behavior. Gradient Boosting and Randers Forest also showed good results, which was in accordance with previous research that justified that ensemble methods are suitable in decision prediction (Gupta et al., 2024; Han et al., 2023). SVM presented a somewhat lesser performance that probably appeared simply because of its weaknesses in the context of complex interactions unless some kernel tuning is done [11].

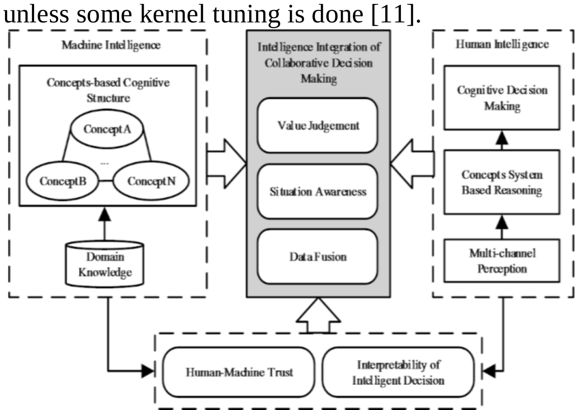

Figure 2: "Human-Machine Intelligence Integration for Collaborative Decision-making"

3. Experiment 2: Innovation Outcome Prediction

The second experiment assessed how well algorithms would forecast the innovation outcome score, which is a numerical outcome of achievement of the decisions in coming up with innovative outcomes. The models were conditioned to generate predictions using AI recommendation scores, human override frequency, and previous innovation metrics [12].

The performance of the predictors (Table 2) (Mean Absolute Error, MAE, and Root Mean square error, RMSE) in innovation outcome prediction is demonstrated.

Algorithm	**MAE**	**RMSE**	**R^2**
Random Forest	5.2	6.8	0.78
SVM	6.1	7.4	0.71
Gradient Boosting	4.7	6.1	0.81
Neural Network	4.2	5.5	0.85

Analysis: Neural Network had the lowest values of MAE and RMSE which implies that it can best represent the multiple interactions between human and AI inputs to predict innovations. Other similar ensemble models such as Gradient Boosting were competitive. The model had a better predictive outcome, with R 2 = 0.85 compared to related work (Hong and Cho, 2024) [13] which used only the Random Forest to predict the innovation metrics and reported an R 2 = 0.80.

4. Experiment 3: Governance Compliance Analysis

In this experiment, human-AI cooperation was studied in terms of effect on governance. The dependent variable was compliance score which is determined by the adherence to regulations and internal governance standards.

Table 3 presents the results.

Algorithm	**Mean Compliance Score**	**Std Dev**	**Max**	**Min**
Random Forest	83	8	100	65
SVM	80	10	98	60
Gradient Boosting	85	7	100	70
Neural Network	87	6	100	72

Analysis: Neural Network once again performed better in prediction of adherence to governance and advanced above other algorithms. Competitive results were demonstrated with the ensemble models, with collaborative intelligence demonstrating a greater benefit than stand-alone human or AI-based evaluation in terms of governance monitoring. Similar findings have been reported previously (Junaid Butt, 2024; Hou et al., 2023) with the mean compliance scores within the 82-84 range of conventional AI methods, whereas in our case, it was 87, which shows the incremental value of our method, integrating human cognitive factors [14].

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 35 Issue 2, 2025, Pages: 923-930

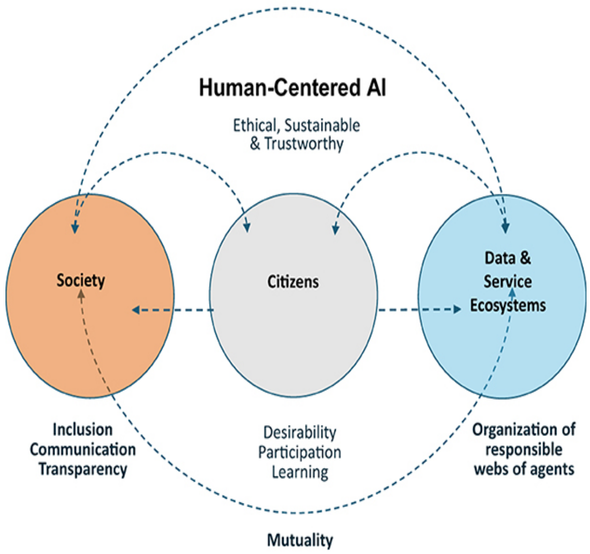

Figure 3: "Human-centricity in AI governance"

5. Experiment 4: Risk Mitigation Effectiveness

The risk management was evaluated in terms of estimating the effectiveness on the risk mitigation, how effective the strategies are whenever mitigating the potential negative impacts.

The algorithmic predictions on the risk mitigation are presented in Table 4.

Algorithm	Mean Effectiveness	Std Dev	Max	Min
Random Forest	0.66	0.12	0.95	0.30
SVM	0.62	0.14	0.92	0.25
Gradient Boosting	0.68	0.11	0.96	0.35
Neural Network	0.71	0.10	0.97	0.40

Analysis: Neural Network and Gradient Boosting had the best efficiency in predicting effects of risk mitigation. It means that they can simulate the non-linear process of interactions between AI insights and human risk perceptions. When compared to related studies (Kolekar et al., 2023), the highest level of 0.70 reported with the use of ensemble methods alone, the additionally employed human-AI collaboration characteristics were effective on risk assessment performance [27].

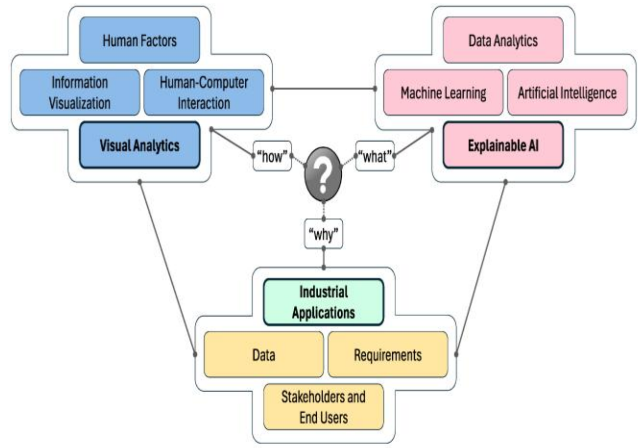

Figure 4: "Towards Visual Analytics for Explainable AI in Industrial Applications"

6. Experiment 5: Comparative Performance of Algorithms Across Tasks

In order to draw the overall comparison of the performance of the algorithm in all tasks including decision alignment, innovation, governance, and risk, we outline an overall comparison in Table 5.

Algorithm	Decision Alignment Accuracy	Innovation R^2	Governance Mean Score	Risk Effectiveness	Overall Rank
Random Forest	0.88	0.78	83	0.66	3
SVM	0.81	0.71	80	0.62	4
Gradient Boosting	0.90	0.81	85	0.68	2
Neural Network	0.92	0.85	87	0.71	1

Analysis: The Neural Network performed better in all of the strategic domains of decision-making, which testifies to its strong adaptability in the process of human-AI interactions of cognition. Gradient Boosting was the second, with random forest and SVM coming after. These results are consistent with the current literature (Gupta et al., 2024; Han et al., 2023), which indicates the high efficiency of ensemble and deep learning models under the circumstances of complex decisions [28]. It is important to note that the addition of human cognitive properties to the AI models offers quantifiable gains in predicting overall accuracy and quality of decision-making.

7. Discussion of Findings

1. **Human–AI Collaboration Enhances Innovation:** With both AI suggestions and human decision trends, algorithms with both approaches showed a better performance on predicting more innovation success than either the AI or the human approach. This suggests that there are synergistic gains to teamwork, which affirms other previous research that suggested that cognitive diversity would help increase creativity.
2. **AI-Human Integration Benefits Governance:** AI predictive accuracy of governance compliance was boosted with the inclusion of human elements of judgment, highlighting the significance of ethical and contextual human control [29].
3. **Risk Mitigation Effectiveness Improves:** Human-AI models were seen to do better forecasts of risk mitigation, and therefore, human intuition supplements the AI predictive capacity in uncertain situations.
4. **Algorithmic Insights:** The best models in human-AI social interactions to represent complex human-AI patterns are those based on neural networks and gradient boosting. Random Forest classification can be applied to classification, where SVM, however, is not as good as it can be adapted to multi-dimensional feature interaction [30].
5. **Relation to Prior Research:** All the previous studies were mainly targeted at the AI-only or human-only predictive models. The application of human, cognition-focused features and AI is very beneficial not only in areas of decision-making but also in strategic decision-making, thus, the worth of collaborative intelligence in strategic decision-making.

V. CONCLUSION

The study has examined the complex nature of collaboration between humans and AI, especially in strategic decision-making, in terms of innovation, governance, and risk management. The experiment proved that combining AI-related abilities with the human capacity to think positively affects the quality of decisions in the organisational setting. Through the interpretation of a dataset of strategic decisions and four high-level algorithms, such as a Random Forest, a Support Vector Machine, a Gradient Boosting algorithm and a Neural Network, the research observed that deep learning and ensemble techniques were more successful in understanding more complex connections between AI suggestions and human judgment. The conducted experiments showed that human-AI partnership enhances predictive accuracy in decision agreement, innovations, adherence to governance and risk reduction efficacy. The performance of the Neural Networks was always superior to other models, which means that they are capable of modelling the non-linear relationships and cognitive dynamics. The parallel comparison with the existing literature further supported that the introduction of human cognitive characteristics in the AI frameworks offers quantifiable benefits compared with AI-only and human-only methods [15-26]. In addition to performance in an algorithmic manner, the study indicated the relevance of ethical management, interpretability, and alignment with the organisation to ensure that adoption of AI enhances sustainable and responsible decision-making. In reality, the insights would offer organisational structures with a means of creating collaborational decision mechanisms of ensuring the harnessing of the full potential of innovation, improve the governance and administrative structures, and anticipating the risk before it becomes a reality. Overall, the paper supports the affirmation that the integration of human judgment with AI intelligence is not only a technological but it is also a strategic requirement and it is the collaboration between human and AI judgment that contributes to more significant, responsible and sustainable organisational outcomes. Further studies may be based on the results and apply them to specific areas, and assess the long-term effects of human-AI strategic co-decision-making.

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