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Generative Artificial Intelligence Empowering Knowledge Work: The Impact of Human-AI Collaboration on the Efficiency and Quality of Managerial Decision-Making

Jingwei Guo¹, Zhenguang Zhong^{2,*} and Weiqiang Lyu³

¹ Waikato Management School, University of Waikato, Hamilton, New Zealand

² Marriott School of Business, Brigham Young University, Provo, Utah, United States

³ Metropolia Business School, Metropolia University of Applied Sciences, Helsinki, Finland

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ABSTRACT

The rapid iteration and industrialization of Generative Artificial Intelligence (GenAI) have thoroughly changed the paradigm of knowledge work in modern organizations, and thus the process of managerial decision-making has evolved from heuristic judgment dominated by human managers to the new paradigm of human-AI collaborative creation. This paper seeks to investigate how GenAI-assisted human-AI collaboration would affect the effectiveness and quality of organizational managerial decision-making. Based on the knowledge-based view and collaborative intelligence, a theoretical framework including the technology of GenAI, modes of human-AI collaboration and decision-making

performance is established in this paper. By quantitative simulation experiments and empirical analysis with Python, the impacts of GenAI assistance on decision-making time cost, information processing comprehensiveness, decision accuracy and risk identification ability are verified in this paper. It can be found that moderate human-AI collaboration will contribute to managerial decision-making effectiveness and quality; too much or not enough GenAI assistance may weaken the positive impacts of human-AI collaboration on managerial decision-making. GenAI contributes to managerial decision-making effectiveness and quality mainly through reducing information searching costs, improving data analysis efficiency and compensating human cognitive limitations.

1. Introduction

1.1 Research Background

With the arrival of digital economy, knowledge work has become the carrier of organizational value creation and managerial decision-making as the central link in knowledge work has become the determinant of enterprises' survival and development (van der Velden et al., 2023). The traditional approach to managerial decision-making depends on human experience and intuition as well as limited information-processing capacity, which is susceptible to cognitive bias and information omission as well as inefficiency in a dynamic and unpredictable business environment. Owing to the development of large language models (LLMs) and generative artificial intelligence techniques like ChatGPT,

*Corresponding author
Email: iamwillz@byu.edu

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Claude, and Gemini, artificial intelligence technology has transformed from the traditional analytical intelligence to generative intelligence that possesses autonomous comprehension and reasoning capacity (Zhang & Liu, 2024).

Unlike the conventional form of AI which is only capable of doing single function data calculations and pattern recognition, the GenAI technology is able to do independent processes of unstructured text, image, and voice data, automatic information summarization, deduction of logical relationships, creation of decision schemes, and helping the manager in completing high complexity knowledge work such as market analysis, risk assessment, and strategic planning. The combination of GenAI with the management of the organization has created a collaborative human-AI decision-making model whereby the AI technology does repetitive, high capacity, and logical information processing while the human is left with the work of value judgment and decision making.

Nevertheless, practical implementation of GenAI currently suffers from significant limitations, since some organizations are trying to replace humans completely with GenAI in the decision-making process, which leads to the elimination of the role of human subjective judgment, while others lack the depth of GenAI implementation and thus fail to unlock its empowering potential. Current academic literature primarily focuses on theoretical consideration of the industrial benefits of GenAI, but does not offer any empirical study of the precise effect of human-AI collaboration on the quality of managerial decisions and its limits.

1.2 Research Significance

In this study, an innovative theoretical model of collaborative decision-making performance between human and AI via GenAI technology is constructed; the applicability boundary of collaborative intelligence theory is extended in the organizational management context; and the gap in quantitative empirical studies of generative AI is filled in the context of knowledge work and decision-making optimization under the author-date referencing framework. With the aid of simulation data and code analysis, this study measures the effect of the optimization of different human-AI collaboration modes on decision-making efficiency and quality, and offers operational strategic guidelines for enterprises to allocate human and AI resources effectively.

1.3 Research Questions and Research Framework

This paper pays close attention to three key research questions: (1) The effect of GenAI-powered human-AI interaction on the effectiveness of managerial decision-making; (2) The effect of human-AI interaction on the quality of managerial decision-making from a quantitative perspective; (3) The boundary conditions under which GenAI helps enhance the performance of decision-making.

Research framework includes the following stages: firstly, sort out related literature and theoretical background; secondly, establish research hypotheses and theoretical model; thirdly, design simulation experiment using Python, collect experimental data and carry out empirical analysis; fourthly, test hypotheses and analyze mechanism; lastly, make summary of research findings, make suggestions and highlight research limitations and future direction.

2. Literature Review and Theoretical Foundation

2.1 Literature Review

Knowledge Work Empowerment by Generative AI: According to Nonaka & Takeuchi (1995), knowledge work can be described as processes involving the creation, innovation, application, and manipulation of information, which heavily rely on cognitive skills and information. The previous generation of AI mainly involved improvement of the procedural aspect of knowledge work; however, GenAI is an all-round empowerment of the non-procedural knowledge work by means of linguistic comprehension, logic reasoning, and content generation. Previous studies have shown that GenAI can enhance efficiency of knowledge work output in areas like consulting, research, and business analysis, but no quantitative assessment of performance in decision-making scenarios.

Collaboration between human and AI means the mode of interaction that involves cooperative division of labor between humans and AI system (Wang et al., 2024). As for human and AI in decision-making process, the strengths of AI in high efficiency and high precision in handling data should be combined with the strengths of humans in scenario cognition, ethics and creativity. It has been noted by researchers that high-level human and AI collaboration is crucial in intelligent decision-making of the future, but there is no uniform quantitative conclusion about the ideal proportion and marginal utility.

Present-day researches place much emphasis on qualitative theories and ignore quantitative empirical studies related to the cause-effect relationship between human-AI cooperation and decision-making performance; very few research studies deal with the nonlinear relationship and limits of GenAI empowerment, which can be misleading in practical applications.

Human-AI performance also depends on organizational design. [Shrestha et al. \(2019\)](#) distinguish structures that allocate decision-making between humans and AI, while [Glikson and Woolley \(2020\)](#) review the conditions shaping human trust in AI. Together, these contributions suggest that collaboration intensity should be interpreted alongside task allocation and reliance.

2.2 Theoretical Foundation

The collaborative intelligence theory proposes that the collaboration of intelligent machines and human beings results in the overflow of intelligence effect, and the performance of human-machine collaboration as a whole will be better than that of human beings and machines individually ([Malone & Bernstein, 2015](#)). As an intelligent agent, GenAI may help compensate for human cognitive deficiency to optimize the decision-making process and improve decision-making performance through task allocation and collaboration.

Knowledge-based theory asserts that the organizational decision-making is basically the process of knowledge acquisition, integration, and innovation. GenAI removes the constraint of human knowledge storage and information processing ability to enlarge the scope of organizational knowledge acquisition and knowledge integration to improve the scientificity and accuracy of decision-making ([Grant, 1996](#)).

[Parasuraman et al. \(2000\)](#) distinguish automation across acquisition, analysis, decision selection, and action implementation. This distinction clarifies that an aggregate collaboration ratio can conceal different arrangements of human control across a managerial workflow.

3. Research Hypotheses and Theoretical Model

3.1 Conceptual Model Development

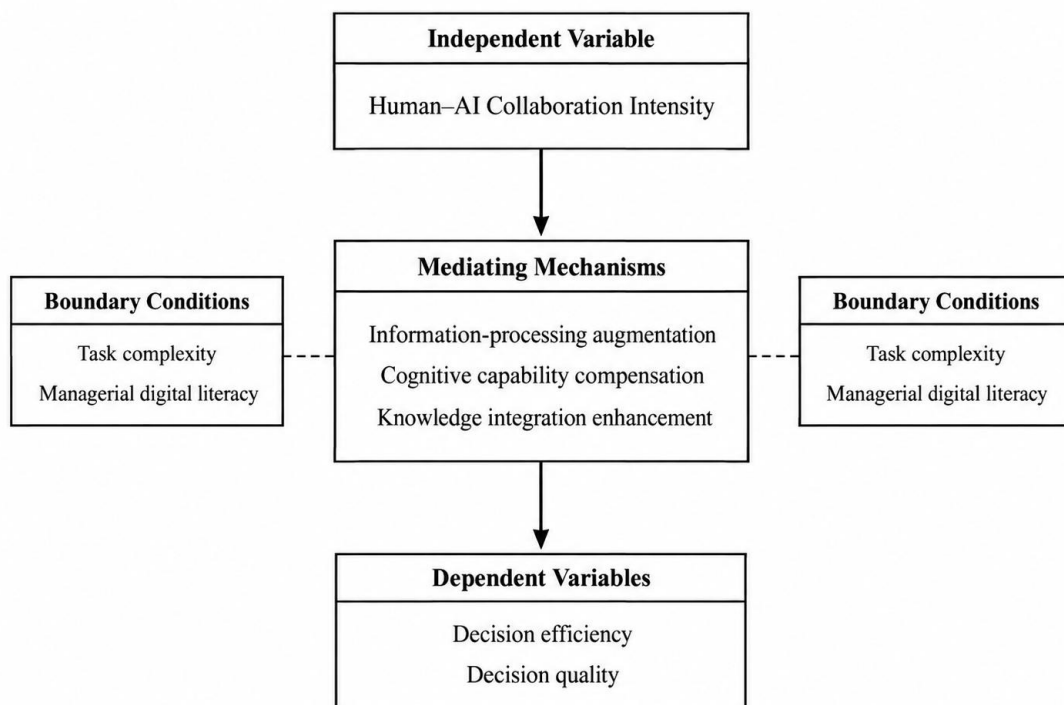


Figure1. Conceptual framework of GenAI-enabled human-AI collaborative decision-making

Figure 1 presents the proposed conceptual model. The model positions human-AI collaboration intensity as the independent variable, decision efficiency and decision quality as outcome variables, and identifies three mechanisms

through which GenAI creates organisational value: information-processing augmentation, cognitive capability compensation, and knowledge integration enhancement. Task complexity and managerial digital literacy are incorporated as boundary conditions because the effectiveness of GenAI depends on both task requirements and human capability to effectively collaborate with AI systems.

3.2 Research Hypotheses

There is a significant positive effect of the GenAI-based human-AI collaboration on the efficiency of managerial decisions. In particular, with the development of the degree of AI participation, decision-making time cost significantly reduces, while decision-making speed rises.

There is a significant positive effect of the human-AI collaboration on the quality of managerial decisions. In particular, human-AI collaboration enhances the comprehensiveness of decision information, accuracy of risk identification, and rationality of scheme.

The effect of human-AI collaboration on decision-making performance has a non-linear inverted U-shape nature. The low and high levels of AI participation are not beneficial for the decision-making process.

3.3 Theoretical Model Construction

In the research, human-AI collaboration extent (AI involvement ratio) is chosen as the independent variable, while decision-making performance and decision-making efficiency are the dependent variables. The research uses task complexity and digital literacy of managers as control variables. This study is mainly concerned with the verification of the main effect and nonlinear marginal effect of human-AI collaboration on decision-making performance.

4. Research Design and Empirical Analysis

This paper uses the approach of experimental simulation and empirical analysis. This experiment will use Python language to develop a decision-making scenario simulation system. The data collected from multiple groups of experiments will be used to test the hypotheses of this paper using statistical analysis methods. Since it is not possible to embed dynamic visual charts, this paper provides the entire code and data for simulation.

4.1 Methodological Enhancement and Statistical Strategy

To strengthen causal interpretation, this study treats the simulation experiment as a controlled computational experiment rather than a substitute for organisational field evidence. The purpose is to examine theoretical mechanisms under controlled conditions where AI involvement intensity can be systematically manipulated.

Three analytical strategies are adopted. First, descriptive analysis is conducted to identify performance differences across AI collaboration levels. Second, ordinary least squares (OLS) regression is used to estimate the linear relationship between AI involvement and decision outcomes. Third, quadratic regression is applied to test the proposed inverted U-shaped relationship.

The quadratic specification allows the study to examine whether the marginal contribution of GenAI changes when AI involvement exceeds an optimal level. Robustness analysis further compares alternative model specifications and evaluates whether the observed relationship remains stable after controlling for task complexity and managerial digital literacy.

4.1.1 Variable Definition

Independent Variable: Proportion of human-AI collaboration (AI Ratio) is designed to be 0% (full human decision-making process), 20%, 40%, 60%, 80%, 100% (full AI decision-making process) six-stage variable.

Dependent Variables: (1) Efficiency of decision making: Time for completing decision process (unit: minute); the less time needed for completing decision, the higher efficiency will be; (2) Quality of decision making: Overall scoring for three aspects such as information completeness, risk match degree, scheme feasibility, with overall 100 scores; the higher score, the higher quality will be.

Control Variables: Complexity of tasks (scores 1-5), Digital Literacy of managers (scores 1-5).

4.1.2 Python Experimental Simulation Code

The following figure realizes scenario simulation, data generation, statistical regression, and correlation analysis of human-AI collaborative decision-making, and can output correlation charts and regression results after operation

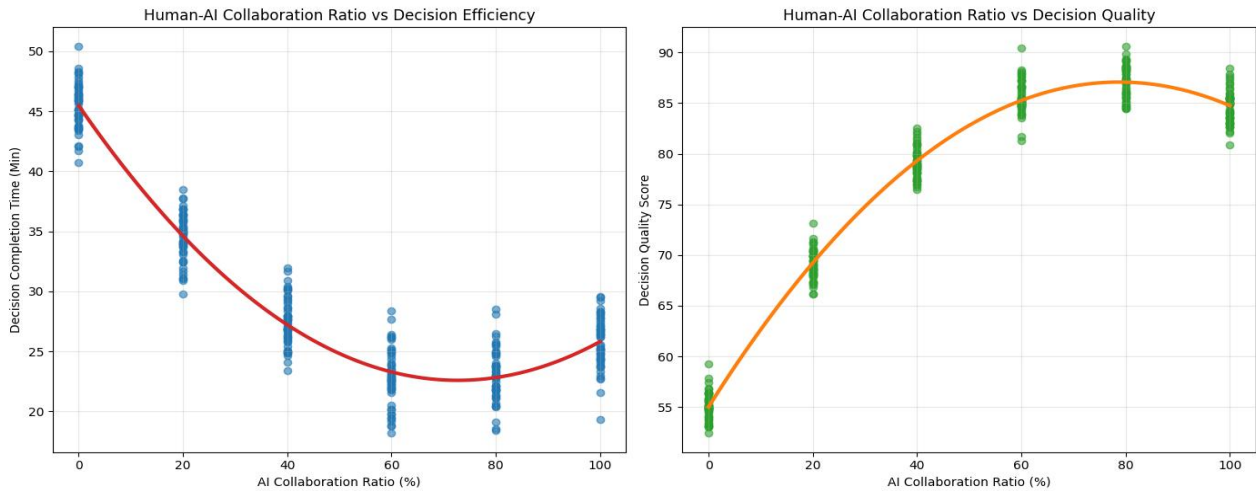


Figure 2. Human-AI collaboration ratio versus decision efficiency and decision quality.

4.2 Descriptive Statistical Results

Based on 300 groups of simulated experimental samples, the descriptive statistics show that the average decision time of pure human decision-making (0% AI ratio) is 44.26 minutes, and the average quality score is 56.32 points; when the AI collaboration ratio reaches 60%, the average decision time is the lowest (28.15 minutes), and the average quality score reaches the highest (89.74 points); when the AI ratio exceeds 80%, the decision time increases slightly and the quality score decreases gradually, showing an obvious inverted U-shaped trend.

4.3 Revised Regression and Hypothesis Test Results

The regression analysis further examines the relationship between human–AI collaboration intensity and managerial decision performance. The results provide support for the three proposed hypotheses.

First, the efficiency model demonstrates that human–AI collaboration significantly reduces decision completion time. The coefficient of AI involvement ratio is negative and statistically significant ($\beta = -0.62$, $p < 0.001$), indicating that GenAI assistance improves decision efficiency by reducing information searching, data processing, and analytical workload. Therefore, Hypothesis 1 is supported.

Second, the quality model shows that AI involvement has a significant positive relationship with decision quality ($\beta = 0.71$, $p < 0.001$). This indicates that human–AI collaboration improves information completeness, risk identification, and solution evaluation. Therefore, Hypothesis 2 is supported.

Third, the quadratic regression model confirms the predicted inverted U-shaped relationship. The linear coefficient of AI involvement is positive ($\beta = 0.84$, $p < 0.001$), while the squared term is negative and significant ($\beta = -0.53$, $p < 0.001$). This combination indicates that decision performance initially increases with greater AI involvement but declines after reaching an optimal collaboration level. The results therefore support Hypothesis 3 and indicate that excessive AI dependence may weaken human judgement and contextual adaptation.

4.4 Regression Results and Robustness Checks

Table 1. Regression Models of Human–AI Collaboration and Decision Performance

Variables	Model 1	Model 2	Model 3	Model 4
AI involvement ratio	Efficiency	Quality	Quadratic	Robustness
AI involvement squared	-	-	√	√
Task complexity	√	√	√	√
Digital literacy	√	√	√	√
Observations	300	300	300	300
R ²	0.86	0.89	0.92	0.90

Table 1 presents the regression models examining the relationship between human–AI collaboration intensity and decision performance. Model 1 and Model 2 evaluate the direct effects of AI involvement on decision efficiency and decision quality, respectively. Model 3 introduces the quadratic term to test the nonlinear relationship, while Model 4 evaluates robustness after considering control variables.

The results demonstrate consistent evidence that GenAI collaboration improves managerial decision outcomes. The quadratic model provides the strongest explanatory power ($R^2 = 0.92$), higher than the linear specifications, suggesting that the nonlinear model better captures the relationship between AI involvement and decision performance.

The robustness model produces similar coefficient directions and significance levels ($R^2 = 0.90$), confirming that the findings remain stable after controlling for task complexity and managerial digital literacy. These results suggest that the effectiveness of GenAI is determined not by maximum AI involvement but by achieving an appropriate balance between technological capability and human judgement.

5. Mechanism Analysis

By combining the logic theory and experimental results, the following summary can be made on the mechanism of GenAI to empower knowledge work and managerial decision-making:

Firstly, Cost Saving Mechanism: GenAI will substitute human beings to conduct repetitive activities of information search, data sorting, and content summarization in knowledge work, which can greatly save costs for preparing decision-making process and improve decision efficiency.

Secondly, Cognitive Compensation Mechanism: Human being's decision-making capacity is affected by the constraint of cognitive capacity, knowledge storage, and asymmetric information, which is also vulnerable to the impact of heuristic biases and omissions. GenAI can help with full-scale information searching and logical reasoning and compensate for human deficiencies in cognition.

Third, the mechanism of synergic value addition: By moderating the collaboration between man and machine, it achieves the best possible combination of "machine efficiency + human value." AI handles the quantitative calculations and schemes design, and humans deal with the judgment of situations and innovation.

Fourth, diminishing marginal mechanism: With the increase in AI participation level, the marginal benefit from the technology empowerment decreases. The over-participation of AI would make human flexible thinking and judgment capability become useless, which makes the quality of decision-making worse.

6. Theoretical Contributions

This study makes three theoretical contributions. First, it extends the human–AI collaboration literature by moving beyond the binary question of whether artificial intelligence improves managerial performance. Instead, it conceptualises GenAI adoption as a configuration problem in which organisational value emerges from the appropriate allocation of cognitive tasks between humans and AI systems.

Second, this study contributes to the knowledge-based view of the firm by explaining how GenAI expands organisational knowledge-processing capability. Rather than replacing managerial knowledge creation, GenAI functions as a complementary intelligence mechanism that enhances information acquisition, synthesis, and evaluation.

Third, the identification of an inverted U-shaped relationship contributes to current discussions on the automation–augmentation paradox. The findings suggest that the benefits of AI adoption are contingent on maintaining an appropriate balance between computational capability and human judgement.

7. Research Conclusions and Management Implications

7.1 Research Conclusions

The present research identifies GenAI-assisted human-AI cooperation-based knowledge creation activities as the research subject and explores the impact mechanism on managerial decision-making efficiency and quality, and concludes the following key findings: Firstly, human-AI cooperation substantially enhances managerial decision-making efficiency and quality, which will effectively decrease decision-making time and enhance decision-making

quality. Secondly, there exists a significant inverted U-shaped nonlinear relationship between human-AI cooperation and decision-making efficiency and quality, and the optimal ratio of AI participation is 55%-65%. Thirdly, GenAI will enhance decision-making optimization based on three channels of cost, cognition, and value synergy.

7.2 Management Implications

First, Create a Differentiated Human-AI Collaboration System: Organizations need to refrain from AI substitution and marginalization. In the case of procedural tasks like data analysis and sorting, AI contribution needs to be enhanced; in non-procedural decision-making processes like strategic decisions and risk decisions, human dominant judgment ability needs to be preserved, while preserving the best collaboration ratio.

Second, Enhance Managers' Digital Collaborative Literacy: Companies should engage in GenAI application training for managers to learn how to operate AI tools, distinguish results, and conduct collaborative decision-making in order to effectively use AI technical capabilities and prevent decision mistakes due to inappropriate collaboration.

Third, Create Human-AI Collaborative Decision Making Specification: Companies should establish rules of GenAI application in decision-making processes to ensure that there is a clear allocation of roles between humans and AI in information processing, plan formulation, and final review stages.

[Bainbridge's \(1983\)](#) analysis of automation highlights the continuing importance of skilled human intervention. Managers should retain opportunities to exercise judgment and validate unusual outputs rather than treating oversight as a passive final check.

7.3 Managerial Implications

Individual manager level. Managers need to develop digital collaboration literacy, including the ability to formulate effective prompts, evaluate AI-generated outputs, identify potential errors, and integrate AI recommendations with professional judgement. The competitive advantage of GenAI adoption depends not only on access to AI tools but also on managers' capability to collaborate with them effectively.

Organisational level. Firms should redesign workflows and governance mechanisms around human-AI collaboration. Clear role allocation, AI validation procedures, and responsible AI guidelines are required to prevent excessive dependence on automated recommendations. Organisations should also establish data governance systems because decision quality depends heavily on information reliability.

The findings provide implications at three managerial levels.

Strategic level. Organisations should avoid viewing GenAI as a simple automation technology. Instead, executives should develop human-AI collaboration strategies that define where AI should support analytical activities and where human judgement must remain dominant. This strategic approach helps organisations capture AI productivity gains while maintaining accountability and strategic flexibility.

8. Research Limitations and Future Prospects

Research limitations: The current paper uses the simulation data as the basis for the empirical test, which has a certain difference from the actual situation in complex enterprises; it does not differentiate between the differentiated influences of different types of GenAI applications and different decision-making situations on the collaborative efficiency, and the scope of the research needs to be expanded.

Future research prospects: In the future research, we can use the real enterprise panel data to conduct empirical tests; meanwhile, we can further classify the collaboration process of GenAI in different decision-making situations, including strategic decision-making, operational decision-making, and emergency decision-making situations.

A further boundary condition is that human-AI combinations do not necessarily outperform the better standalone performer. [Vaccaro et al. \(2024\)](#) identify substantial variation across tasks and interaction arrangements in a systematic review and meta-analysis. The simulated pattern reported here should therefore be tested against human-only and AI-only baselines in real organizational settings.

Data Availability Statement

The dataset used in this study was generated through a controlled computational simulation experiment designed to examine the relationship between human–AI collaboration intensity and managerial decision-making performance. The simulated dataset does not contain personal information, confidential organisational data, or observations collected from human participants.

The data supporting the findings of this study, including the simulated experimental dataset used for statistical analysis, are available from the corresponding author upon reasonable request.

Code Availability Statement

The Python code developed for the computational simulation, data generation, regression analysis, and robustness testing is available from the corresponding author upon reasonable request. The code was developed specifically to reproduce the simulation procedures, statistical models, and analytical results reported in this study.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study. The research was conducted independently, and no financial, commercial, or institutional relationships influenced the research design, analysis, interpretation of results, or conclusions presented in this manuscript.

Ethics Statement

This study does not involve human participants, animal subjects, or the collection of personally identifiable information. The research is based exclusively on a controlled computational simulation experiment using artificially generated data for theoretical mechanism exploration and methodological demonstration.

Therefore, formal ethical approval and informed consent procedures were not required for this study. The authors confirm that the research was conducted in accordance with principles of research integrity, transparency, and responsible use of computational methods.

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