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The Enhancement Effect of Artificial Intelligence in Group Decision-Making

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Abstract

Artificial intelligence, with its powerful comprehensive capabilities, can assist human decision-making across various scenarios. Compared to individual decision-making, assisting group decision-making entails more complex social interactions and influences. By analyzing performance across three dimensions—group consensus level, confidence level, and accuracy—this study investigates the impact of artificial intelligence assistance on group decision-making. Through mathematical modeling, numerical simulation, and behavioral experiments, we discover that AI assistance yields enhancing effects on group decision-making, including improved group consensus, enhanced group confidence, and increased group professional performance. Furthermore, this study reveals that AI assistance in consolidating group consensus is time-sensitive, with consensus levels significantly improving only when AI participates directly. In contrast, AI assistance in enhancing confidence levels exhibits a lag effect, taking effect only after group members have internalized it, with earlier intervention being more conducive to building group confidence. The research conclusions reveal the effects of AI assistance on group decision-making, enhance understanding of human-AI interaction in group decision-making contexts, and provide novel ideas and methods for optimizing group decision-making.

Full Text

Preamble

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Please complete the following items and paste them on the first page of your manuscript.

1. Please list up to three innovative contributions of this study in the form of "Research Highlights," with a total word count not exceeding 200.

Acta Psychologica Sinica aims to publish cutting-edge psychological research that is "both scientifically excellent and of particularly broad interest and significance." If your study only makes minor incremental contributions, does not attempt to open new areas of inquiry, or lacks unique and innovative perspectives—particularly if it merely studies algorithms or technologies without addressing clear psychological questions—its chances of acceptance are low. We recommend submitting such work to other journals.

Response: This study examines the impact of AI assistance on group decision-making effectiveness, extending the research domain that has previously explored AI assistance effects at the individual level. Second, this paper uses mathematical models to deeply characterize the influence of AI participation in group decision-making, specifically comparing the differences between AI influence and social influence on group decision-making performance. Finally, this paper comprehensively discusses group decision-making performance from the perspectives of consensus level, confidence level, and professional performance, providing a more holistic understanding of human-AI collaborative decision-making in group contexts.

2. Have you used the same data as in any previously submitted or published articles? If yes, please attach the article for review.

(We do not approve of authors publishing multiple articles with the same variables from the same dataset, nor do we approve of splitting a series of related studies into multiple publications.)

Response: This study employs a behavioral experimental method and does not suffer from common method bias issues inherent in self-report methods.

3. For non-experimental, non-intervention studies in management, clinical, personality, and social domains that rely solely on self-report (questionnaire) methods, you must check for common method bias. What methods did you use to control for or demonstrate that such bias does not affect the validity of your conclusions? (See http://journal.psych.ac.cn/xlkxjz/CN/abstract/abstract894.shtml for relevant literature.) Studies based on cross-sectional data, using only self-reports, and tested on convenience samples are easy to conduct but typically have limited innovative value and low chances of acceptance.

Response: This study employs a behavioral experimental method and does not suffer from common method bias issues inherent in self-report methods.

4. Did you report and analyze effect sizes (e.g., Cohen's d for t-tests, ^{2} or ^{2}p for ANOVA)? (Many studies mechanically report effect sizes without necessary analysis or explanation, such as whether the effect size is small, medium, or large, or what theoretical or practical significance it holds.) (Search "effect size calculator" on Google for convenient apps. For explanations of effect sizes in Chinese, see http://journal.psych.ac.cn/xlkxjz/CN/abstract/abstract1150.shtml; in English, see http://www.uccs.edu/lbecker/effect-size.html.) Did you report 95% CIs for statistical analyses? (e.g., 95% CI for differences, correlation/regression coefficients.) For calculations and plotting of confidence intervals, see https://thenewstatistics.com/itns/esci/.

Response: The paper uses t-tests, and we report and analyze the corresponding effect sizes. We also report 95% CIs for the main variable regression coefficients.

5. Please state the planned sample size and actual sample size. If they differ, please explain why. Low statistical power due to insufficient sample sizes has been a widespread problem in psychological research. We recommend explaining the basis for your sample size calculation in the Methods section. Sample size should be determined based on a justified effect size and desired power, with the calculation software or program reported. See https://osf.io/5awp4/ for guidance on sample size planning.

Response: This is a group experiment with 10 participants per group. We planned 12 groups, totaling 120 participants, and the actual sample was 120.

6. For p-values, we require reporting of exact p-values (except for $p < 0.001$, which should be reported as such). Does your paper meet this requirement? If using Bayes factors, have you reported their sensitivity to prior distribution assumptions?

Response: Yes.

7. To ensure completeness of data reporting, if you excluded any data in statistical analysis, did you report this in the text? What were the reasons? How would the results change if this data were included? How were missing data handled in statistical analysis? When using scales, did you delete any individual items? Why? How would the results change if these items were included? Are there any measured items or variables not reported? Why? Please indicate where in the paper this is addressed.

Response: No data were excluded.

8. For experimental materials, scales, or questionnaires that have not undergone peer review and validation, are they attached at the end of the file for review? If not, please explain why. If this article is published, are you willing to share these materials with other researchers?

Response: This study did not use any experimental materials, scales, or questionnaires that have not undergone peer review and validation. The experimental materials used in this study are from an open-source GitHub project platform, which provides open-source image datasets widely used in AI development, training, and testing research. All scales used in this study are well-established instruments.

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Response: The behavioral experiment in this paper meets experimental requirements and regulations. We regret that we were not aware of the need to register on your journal's filing website before conducting the study, so no pre-registration was prepared.

11. If your study used human or animal subjects, was it approved by your institution's ethics committee? If yes, please send a scanned copy to the editorial office email. If no, please explain why.

Response: No. This study is classified as business behavior research and falls under the School of Management, which does not have an ethics committee. The experimental methods and materials in this study are from publicly available sources, and all scales used are well-established instruments, posing no ethical issues. All invited participants voluntarily participated in the experimental survey. Before data collection, participants were informed that experimental data would be used only for academic research and would be anonymized. The experiment began only after participants were fully informed and consented. The entire experiment was video-recorded and photographed.

12. Have you written a 400-500 word English abstract following the "English Abstract Writing Guidelines" published on the editorial office website? Has the English title and abstract been reviewed by a proficient English speaker or professionally edited by an SCI/SSCI paper editing company?

Response: This paper has been written with an English title and abstract as required, and a proficient English speaker has reviewed the content.

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The Enhanced Effects of AI in Group Decision Making

Abstract

With its powerful comprehensive capabilities, artificial intelligence can assist human decision-making in various contexts. Compared to individual decision-making, assisting group decision-making involves more complex social interactions and influences. By analyzing group performance across three dimensions—consensus level, confidence level, and accuracy—this paper investigates the impact of AI assistance on group decision-making. Through mathematical modeling, numerical simulation, and behavioral experiments, we find that AI assistance enhances group decision-making by improving group consensus, strengthening group confidence, and increasing group professional performance. Furthermore, this paper reveals that the consensus-building effect of AI assistance is time-sensitive: consensus levels only improve significantly when AI participates directly. In contrast, the confidence-enhancing effect of AI assistance exhibits a delayed effect, requiring group members to internalize the AI input before it takes effect, with earlier intervention being more conducive to building group confidence. The research conclusions reveal the effects of AI assistance on group decision-making, enhance understanding of human-AI interaction in group contexts, and provide new ideas and methods for optimizing group decision-making.

Keywords: group decision-making, artificial intelligence, human-AI collaboration

1. Problem Statement

In recent years, artificial intelligence (AI) technology has attracted significant attention in the field of human decision-making. AI-assisted decision-making has demonstrated powerful effects and promising prospects in economic decisions, judicial decisions, medical decisions, and government governance decisions (Ballings et al., 2015; Bastani et al., 2022; Jussupow et al., 2021). Driven by new technologies such as data science and cognitive intelligence, AI can already support tasks requiring complex cognitive abilities and can even make judgments independently. Consequently, human-AI collaborative decision-making may become the new paradigm for decision-making across various domains.

Human-AI collaboration implies close cooperation between humans and machines, combining the experiential advantages of human individuals with the data advantages of AI to achieve new breakthroughs (Huang & Liu, 2023). However, existing research on AI-assisted decision-making has primarily focused on individual decision-making scenarios (Fügener et al., 2021; Jussupow et al., 2021), neglecting another common form of organizational decision-making—group decision-making. In an era of data science development and information explosion, societal problems are becoming increasingly complex, while individual decision-makers have relatively limited expertise and strong personal biases. Group decision-making can leverage the experiential wisdom of multiple people and the advantages of different knowledge structures, making decision outcomes more objective and realistic (Guo et al., 2016). From the perspectives of technological intervention and practical effectiveness, how to construct an organizational framework for intelligently augmented group decision-making, optimize group decision-making efficiency, and promote the use of human-AI collaborative decision-making systems are currently key concerns for both industry and academia.

1.1 AI-Assisted Decision-Making

Human-AI collaboration can take different forms, such as AI acting as an assistant providing advice to human decision-makers, AI becoming a teammate completing independent tasks toward common goals, or even AI acting as a "leader" assigning tasks to humans (Fügener et al., 2022). We focus on the paradigm where AI assists human decision-making, examining the decision-making effectiveness and related influencing factors of human-AI collaboration. Through literature review, we find that previous research has primarily discussed AI capabilities, human attitudes toward and confidence in AI, and human self-confidence.

The core goal of human-AI collaborative decision-making is to achieve better decision-making performance than either humans or AI alone, which is typically challenging. Improving AI capabilities has been one of the directions pursued in technology development. Scholars have found that AI-assisted decision-making can indeed improve human decision-making accuracy (Fügener et al., 2021), primarily because the low correlation between AI and human knowledge structures creates complementary advantages (Steyvers et al., 2022). However, when AI accuracy is not high, this human-AI complementary advantage is weakened because human decision-makers lack the ability to judge erroneous information (Fügener et al., 2021). Thus, the foundation for achieving remarkable performance in human-AI collaborative decision-making is AI capability.

Additionally, scholars believe that human-AI collaborative decision-making performance also depends on human attitudes toward and confidence in AI, such as reliance and trust levels (Fügener et al., 2021; Jussupow et al., 2021; Steyvers et al., 2022). Researchers have identified two diametrically opposed behavioral patterns—algorithm appreciation and algorithm aversion. Specifically, human decision-makers may either completely trust and rely on AI results or completely distrust and rely only on themselves. However, some scholars have found a compromise pattern where human decision-makers equally weight their initial suggestions and AI advice (Pálfi et al., 2022), which may be related to the importance of medical decision-making. Human decision-makers' attitudes are, in turn, influenced by factors such as AI capability, human understanding of AI, and AI-human similarity (Allen & Choudhury, 2022; Jussupow et al., 2021). Among these, human confidence in AI is particularly important, as it directly reflects their willingness and degree of dependence on AI tools.

Corresponding to human confidence in AI is human confidence in themselves (Fügener et al., 2021; Lorenz et al., 2011; Stasser & Davis, 1981). Human self-confidence determines their willingness to use AI tools or how they use them. Research has shown that whether to accept or reject AI advice depends on human confidence rather than their confidence in AI (Chong et al., 2022; Snijders et al., 2023). Even during use, human self-confidence affects their degree of AI adoption. Particularly in studies of AI-assisted expert decision-making, experts are widely believed to exhibit significant algorithm aversion (Jussupow et al., 2021). Some scholars argue that this is because egocentrism and overconfidence play a role (Allen & Choudhury, 2022).

1.2 AI and Group Decision-Making

As another important decision-making method in human society, group decision-making is ubiquitous in daily life and work, such as in corporate investment decisions, medical consultations, and economic policy formulation (Yang et al., 2021). The main difference between group and individual decision-making lies in the complex social influences among individuals within the group. Previous research has emphasized the critical role of social influence in group decision-making (Banerjee, 1992; Lorenz et al., 2011; O'Gorman, 1986), yet the presence of social influence remains controversial regarding its impact on group decision-making performance. For example, individuals with better information in group decision-making can influence others to make better decisions (Banerjee, 1992), but they may also, due to social norm pressures, hesitate to firmly adhere to their choices, leading to poorer group decision outcomes (Lorenz et al., 2011; O'Gorman, 1986).

The chemical reaction produced by intelligent technology intervention in group decision-making is the focus of this study. Some scholars have found that compared to individual decision-making, people in group decision-making contexts rely more on AI (Chiang et al., 2023). We argue that in AI-assisted group decision-making, individuals can receive information from both the group and AI. The social influence effect from group information causes individual decisions to converge toward the group, while information from AI affects group members' cognition of the problem. When individuals receive both types of information simultaneously, the influence is not simply additive (Birnbaum, 1976). Individuals must weigh these two information sources after considering AI's technical characteristics and group features, and this weighting result directly affects group decision-making performance. Next, we will describe this process through mathematical modeling. Unlike classification problems, we focus on numerical group decision-making, which better enables quantitative observation of underlying group cognition.

2. Theoretical Model

In AI-assisted group decision-making, each group member's decision-making process consists of three stages. First, individuals form their own unique cognition of the decision problem and make their own judgments (Lindebaum et al., 2020). Then, individuals receive information from other individuals and AI, during which they experience social influence and AI influence. Finally, individuals update their decisions (Fügener et al., 2021; Lorenz et al., 2011). Based on individuals' updated decisions, we can obtain the final group decision outcome.

2.1.1 Individual Cognition of Answers in the Initial Stage

In individual decision-making, due to cognitive limitations such as biases and inertia (Li et al., 2020; Longoni et al., 2019), individuals do not know the correct answer to each problem, meaning there is a deviation between individual answers and the correct answer. Simultaneously, individuals have corresponding confidence in their answers. If an individual's confidence is high, their answers will be relatively consistent when responding to the same question multiple times in the same time period. If confidence is low, their answers will be more dispersed.

Therefore, let X_{ij}^0 be individual i's answer to question j in the initial stage. Assume that the answer given by individual i follows the following normal distribution:

$$X_{ij}^0 \sim N(\mu + \epsilon_i, \sigma_i^2)$$

where $\mu + \epsilon_i$ represents the mean of individual i's answer in the initial stage, μ represents the correct answer, $\epsilon_i \sim N(0, \tau^2)$ represents the bias of individual i's knowledge, and σ_i^2 represents individual i's confidence in their answer. The smaller the σ_i^2, the higher the confidence level of individual i.

Since individuals are unique, each individual has different cognition of the same problem, so each individual's answer to the same question differs (Balasubramanian et al., 2022). Reflected in this model, ϵ_i is not exactly the same for different i. For the same question, human cognition follows certain distribution patterns. Based on this, we make the following assumption:

$$\epsilon_i \sim N(\gamma, \varepsilon^2)$$

where γ represents the expected cognitive bias of the group in the initial stage relative to the standard answer. ε^2 represents the diversity of knowledge within the group; the larger the ε^2, the higher the group's knowledge diversity.

2.1.2 AI Cognition of Answers

For a given question, AI can obtain relevant knowledge from training sets of similar problems and thus provide an answer to the question. However, because AI training sets may contain biases, preventing AI from learning the most comprehensive knowledge (Choudhury et al., 2020), AI answers also contain deviations. AI predictions are results derived from input variables of the prediction problem through trained algorithmic models (Fügener et al., 2021; Kühl et al., 2022). Based on the same training dataset and algorithm development, AI will provide a specific output result with the highest confidence for a specific input. Therefore, the bias in AI answers is fixed (Abdar et al., 2021; Fügener et al., 2021).

Assume that AI answers satisfy the following form:

$$Y = \mu + \Delta\mu$$

where $\Delta\mu$ represents the deviation of AI answers relative to the correct answer.

2.1.3 Social Influence

In the group decision-making process, individuals not only have an initial answer but also refer to the group's answers (Lorenz et al., 2011). During this reference process, individuals are subject to social influence, which updates their answers, and the degree of change is directly related to the degree of influence from the group. Therefore, the degree of influence individuals receive from the group is key to group decision-making.

In group decision-making scenarios, individuals obtain group answers and update their decisions. However, physical and verbal communication between individuals is prohibited, so social influence effects do not consider the strength of social network relationships (Lorenz et al., 2011). We assume that individuals learn equally from other group members and that individuals learn from the group in a linear form (Becker et al., 2017). Assume the learning form is as follows:

$$X_{ij}^G = (1-\alpha)X_{ij}^0 + \alpha\bar{X}_j^0$$

where X_{ij}^G represents individual i's updated answer to question j after learning from the group. α ($\alpha \in (0,1)$) represents the degree of influence individuals receive from the group. The larger the α, the greater the influence from the group. $\bar{X}_j^0$ represents the mean of all individuals' initial answers to question j.

2.1.4 AI Influence

In addition to answers from other individuals, individuals can also refer to AI-derived answers during the decision-making process. When individuals refer to AI answers, their decisions are influenced by AI, and individuals' trust in AI will affect their decision outcomes (Jussupow et al., 2021).

We assume that AI answers and individual answers are independent, and that individuals' learning from AI satisfies a linear form (Green & Chen, 2019). Then, after individuals learn from AI, their updated answers take the following form:

$$X_{ij}^A = (1-\eta)X_{ij}^G + \eta Y$$

where X_{ij}^A represents individual i's answer to question j after learning from AI. η ($\eta \in (0,1)$) represents individual trust in AI. The larger the η, the greater the individual's trust in AI.

2.1.5 Dual Influence

Our research focuses on the AI enhancement effect in group decision-making. If individuals are first influenced by AI, the essence is the enhancement effect of AI on individuals. To avoid confusion, this study discusses decision-making where individuals first engage in social learning and then learn from AI. Based on our previous assumptions about social influence and AI influence, we have the answer update formula for individuals who first engage in social learning and then learn from AI:

$$X_{ij}^{GA} = (1-\eta)X_{ij}^{G} + \eta Y = (1-\eta)[(1-\alpha)X_{ij}^{0} + \alpha\bar{X}_{j}^{0}] + \eta Y$$

where X_{ij}^{GA} represents individual i's answer to question j after first engaging in social learning and then learning from AI.

2.2 Measurement of Group Decision-Making Performance

Group decision-making performance can be divided into three dimensions: consensus, confidence, and accuracy. First, group decision-making requires information exchange and mutual reference among individuals within the group to arrive at answers recognized by most group members (Stasser & Davis, 1981). Therefore, consensus is the foundation of group decision-making. If the decision-making group cannot reach consensus, group decision-making cannot be completed (Zha et al., 2021). Second, the higher the group's confidence in the result, the more firmly the group believes in the current answer (Leana, 1985; Lorenz et al., 2011). On the one hand, this strengthens commitment to the current decision (Stasser & Davis, 1981); on the other hand, if confidence is high in an answer with relatively large errors, the entire group will tend toward extremism (Hinsz, 1990). Finally, the accuracy of group decision-making is our primary concern, as the level of accuracy reflects the quality of group decision-making outcomes. Therefore, when evaluating group decision-making performance, we should comprehensively consider group confidence and accuracy on the basis of group consensus formation.

Group consensus refers to the degree of uniformity of opinions within the group. The more dispersed the distribution of individual decisions, the lower the group's consensus level. We use the variance of the distribution of distances between individual decisions and group decisions (Distance) within the group to measure the dispersion of individual decision distribution. First, the distance between individual i's decision and the group decision is:

$$\text{Distance}_i = E[X_{ij}] - E[\bar{X}_j^*]$$

where $\bar{X}_j^*$ represents the mean of the group's decision on question j, and n represents group size. Since X_{ij} follows a normal distribution, Distance_i follows a normal distribution with variance σ_0^2. The larger the variance of this distribution, the more dispersed the distribution of individual decisions within the group. Therefore, the variance of this normal distribution can be used inversely to measure the group's consensus level. Finally, we use Consensus to represent the group decision-making consensus level:

$$\text{Consensus} = -D(\text{Distance}_i)$$

Higher group confidence is manifested as a smaller fluctuation range in group decisions (Stasser & Davis, 1981). Group confidence is the aggregation of individual confidence. As mentioned earlier, σ_i^2 inversely measures individual confidence levels. Therefore, the group decision-making confidence level (Confidence) formula is as follows:

$$\text{Confidence} = -\frac{1}{n}\sum_{i=1}^{n} D(X_{ij})$$

A key indicator of group accuracy is the group's professional performance (Performance). The more individual decisions within the group that are closer to the correct value, the higher the group's professional performance. Professional performance is a comprehensive reflection of all individual decision-making performance within the group and is a key standard for reflecting the quality of group decision-making outcomes. In reality, we do not require every decision to hit the correct answer accurately; decisions within a certain error range are considered acceptable (Li et al., 2019). Let the acceptable error for decision answers relative to the correct answer be tolerance r ($r > 0$). Then decision answers within the tolerable interval $(\mu - r, \mu + r)$ are all acceptable decisions (Li et al., 2019). The more individual decisions within the group that fall within the tolerable interval, the higher the group's professional performance. Based on our assumptions, individual decisions within the group follow a normal distribution, so the group's professional performance is as follows:

$$\text{Performance} = \sum_{i=1}^{n} P_i$$

where P_i represents the probability that individual i's decision falls within the tolerable interval.

3.1 Comparison Between Initial Stage and Post-Social Influence

By comparing group performance between the initial stage and after social influence (see Table 1), we derive Proposition 1.

Table 1: Comparison of Group Performance Between Initial Stage and After Social Influence

Stage	Consensus	Confidence	Performance
Initial Stage	$\text{Consensus}_0 = -\frac{(n-1)\varepsilon^2}{n}$ (calculated from equations (2)(3)(9))	$\text{Confidence}_0 = -\frac{1}{n}\sum_{i=1}^{n}\sigma_i^2$ (calculated from equations (1)(10))	$\text{Performance}_0 = \Phi(\frac{r-\gamma}{\sqrt{\varepsilon^2+\tau^2}}) - \Phi(\frac{-r-\gamma}{\sqrt{\varepsilon^2+\tau^2}})$ (calculated from equations (2)(3)(11))
After Social Influence	$\text{Consensus}_G = -\frac{(n-1)(1-\alpha)^2\varepsilon^2}{n}$ (calculated from equations (2)(3)(5)(9))	$\text{Confidence}_G = -\frac{1}{n}\sum_{i=1}^{n}[(1-\alpha)^2\sigma_i^2 + \alpha^2\varepsilon^2]$ (calculated from equations (1)(5)(10))	$\text{Performance}_G = \Phi(\frac{r-\gamma}{\sqrt{(1-\alpha)^2\varepsilon^2+\tau^2}}) - \Phi(\frac{-r-\gamma}{\sqrt{(1-\alpha)^2\varepsilon^2+\tau^2}})$ (calculated from equations (2)(3)(5)(11))

Proposition 1. $\text{Consensus}_G > \text{Consensus}_0$, meaning group consensus level after social influence is higher than in the initial stage; $\text{Confidence}_G > \text{Confidence}_0$, meaning group confidence level after social influence is higher than in the initial stage; $\text{Performance}_G = \text{Performance}_0$, meaning social influence has no effect on group professional performance.

3.2 Comparison Between Post-Social Influence and AI-Assisted Group Decision-Making

By comparing group performance between post-social influence and AI-assisted group decision-making (see Table 2), we derive propositions regarding consensus and confidence levels. For professional performance comparison, we need to discuss different cases separately.

Table 2: Comparison of Group Performance Between Post-Social Influence and AI-Assisted Group Decision-Making

Condition	Consensus	Confidence	Performance
After Social Influence (same as Table 1)	$\text{Consensus}_G = -\frac{(n-1)(1-\alpha)^2\varepsilon^2}{n}$	$\text{Confidence}_G = -\frac{1}{n}\sum_{i=1}^{n}[(1-\alpha)^2\sigma_i^2 + \alpha^2\varepsilon^2]$	$\text{Performance}_G = \Phi(\frac{r-\gamma}{\sqrt{(1-\alpha)^2\varepsilon^2+\tau^2}}) - \Phi(\frac{-r-\gamma}{\sqrt{(1-\alpha)^2\varepsilon^2+\tau^2}})$

Condition	Consensus	Confidence	Performance
AI-Assisted Group Decision-Making	$\text{Consensus}_{GA} = -\frac{(n-1)(1-\alpha)^2(1-\eta)^2\varepsilon^2}{n}$ (calculated from equations (2)(3)(4)(7)(9))	$\text{Confidence}_{GA} = -\frac{1}{n}\sum_{i=1}^{n}[(1-\eta)^2((1-\alpha)^2\sigma_i^2+\alpha^2\varepsilon^2)+\eta^2\Delta\mu^2]$ (calculated from equations (1)(4)(7)(10))	$\text{Performance}_{GA} = \Phi(\frac{r-(1-\eta)\gamma-\eta\Delta\mu}{\sqrt{(1-\eta)^2(1-\alpha)^2\varepsilon^2+\tau^2}})-\Phi(\frac{-r-(1-\eta)\gamma-\eta\Delta\mu}{\sqrt{(1-\eta)^2(1-\alpha)^2\varepsilon^2+\tau^2}})$ (calculated from equations (2)(3)(4)(7)(11))

Proposition 2: $\text{Consensus}_{GA} > \text{Consensus}_{G}$, meaning the consensus level of AI-assisted group decision-making is higher than that after social influence.

Proposition 3: $\text{Confidence}_{GA} > \text{Confidence}_{G}$, meaning the confidence level of AI-assisted group decision-making is higher than that after social influence.

Due to the complexity of the normal distribution integral function, we will use numerical analysis in Matlab by setting relevant parameters for individual initial decisions, group-level parameters, social influence parameters, and AI influence parameters to calculate group decision-making professional performance. Through numerical simulation, we explore how Performance_{GA} changes with increasing individual AI influence under different conditions, and compare it with Performance_{G} to derive generalizable conclusions, namely Observation 1 and Observation 2 below (specific parameter settings and simulation results see Appendix 1).

Observation 1: When AI accuracy is high, regardless of group accuracy, initial group consensus level, or group size, the professional performance of groups that experience social influence before learning from AI is higher than that of groups experiencing only social influence.

Observation 2: When AI accuracy is insufficient, if individuals' AI influence level is low, the professional performance of groups that experience social influence before learning from AI is higher than that of groups experiencing only social influence; if individuals' AI influence level is high, the professional performance of groups that experience social influence before learning from AI is lower than that of groups experiencing only social influence.

4. Experiment: Intelligent Enhancement Effects in Group Decision-Making

The purpose of this experiment is to explore how providing AI predictions affects group decision-making consensus level, confidence level, and professional performance. This experiment uses a within-subjects design to examine whether group decision-making with AI assistance achieves better performance compared to group decision-making without AI assistance.

4.1 Experimental Design

We recruited 120 college student participants and conducted 12 experimental sessions. Each session had 10 participants who formed a group and engaged in group decision-making on relevant questions. Participants needed to answer 6 different types of questions (see Table 3 for question types; specific experimental materials are available in Appendix 1). We selected relatively difficult questions that required cognitive effort to approach the true answers. Each question was simultaneously distributed to each participant via computer in the laboratory. They were required to make independent assessments without communication.

Table 3: Question Types

1. Guess the number of people on a road based on a street view photo
2. Predict stock price based on a stock price trend chart
3. Predict a person's weight based on a photo
4. Guess a person's age based on a facial photo
5. Guess the calorie content of an ice cream based on a photo
6. Predict a person's height based on a photo

For each question, we asked participants to provide 4 rounds of answers, with 3 answers per round. Since this is group decision-making, we provided feedback on the mean of all participants' answers from the previous round before rounds 2, 3, and 4 (feedback format: "Group mean: xxx").

During the question-answering process, we set up three different scenarios to test the impact of AI assistance. Scenario 1 (No AI) involved no AI predictions provided in any of the four rounds. Scenario 2 (AI-3) involved providing AI predictions only before round 3 (feedback format: "AI prediction: xxx"). Scenario 3 (AI-4) involved providing AI predictions only before round 4. The No AI scenario served as the control condition. AI-3 and AI-4 scenarios represent two operational modes of AI influence on group decision-making. Providing AI predictions in different rounds aims to explore whether the timing of AI appearance affects group decision-making (Lorenz et al., 2011). We did not provide AI predictions before round 2 because our purpose is to investigate the impact of AI in group decision-making, requiring participants to first receive group decision-making information before answering. If both group and AI information were provided in round 2, we could not guarantee that group members would be influenced by the group first.

In each experimental session, all participants answered 2 questions under each of the 3 information conditions, totaling 6 questions (within-subjects design). The order of questions was completely random, with corresponding information conditions shown in Table 4 . Each column represents the question order for a particular experimental session. This means each session presented the same 6 questions but in different orders and with different information conditions. Participants were randomly assigned to sequences of questions and information conditions, eliminating order effects of information conditions (Lorenz et al., 2011).

Table 4: Question Arrangement

Session	Q1	Q2	Q3	Q4	Q5	Q6
1	No AI	No AI	AI-3	AI-3	AI-4	AI-4
2	No AI	AI-3	No AI	AI-4	AI-3	AI-4
...	...	...	...	...	...	...

In addition to base compensation, participants received extra rewards based on their answer scores. Specifically, for each answer falling within $±$5%, $±$10%, or $±$20% of the correct answer, participants received 4, 2, or 1 point respectively; otherwise, no points were awarded. This reward mechanism applied to all answers in all rounds of all questions. To ensure all participants answered seriously, we calculated scores for all 12 answers across four rounds for each question, with final rewards based on total scores across 6 questions. We informed participants that their group's performance would not affect their individual reward evaluation. Overall, our experimental design placed participants in a situation where they attempted to approach the truth using their own knowledge, information from others' answers, and AI predictions we provided.

Before the experiment, all participants were informed about the experimental tasks, procedures, and precautions, and the reward rules were explained. We then emphasized anonymity guarantees, the obligation to adhere to the no-communication policy, and the prohibition of using any auxiliary devices (such as the internet or mobile phones). Finally, we began the experiment after confirming that participants fully understood the experimental rules and obtaining permission to collect and use their responses. The entire experiment was video-recorded and photographed.

4.2 Experimental Results and Analysis

Table 5 shows the true answers, AI predictions, group initial decision means, and group initial decision medians for each question we selected. When the difference between group initial decision mean and median is small, we use the group mean to represent group decision-making for simplified subsequent data analysis (Lorenz et al., 2011).

Table 5: True Answers and Participants' Initial Decisions

Question	True Answer	AI Prediction	Initial Mean	Initial Median
1. Road crowd count	206.8	149.675 (-27.67%)	129 (-37.68%)	87 (-27.62%)
2. Stock price prediction	243.6	264.98 (+8.80%)	91.21 (-24.12%)	60 (+3.45%)
3. Weight prediction	390.37	59.94 (+3.34%)	250 (+35.87%)	390.37 (+112.16%)
4. Age prediction	177.8	260 (+6.75%)	182.98 (+2.91%)	183 (+2.92%)

Question	True Answer	AI Prediction	Initial Mean	Initial Median
5. Ice cream calories	58	87 (+50.00%)	59.94 (+3.34%)	58 (0%)
6. Height prediction	243.6	260 (+6.75%)	182.98 (+2.91%)	183 (+2.92%)

Note: Parentheses indicate deviation of initial mean or initial median from true answer.

4.2.1 K-S Test To investigate the impact of AI predictions on group decision-making, we must ensure that participants' initial decision distributions for the same question do not differ across scenarios. We first conducted Kolmogorov-Smirnov tests (K-S tests). In the experiment, participants provided three answers each round. We used the mean of participants' three answers as their decision. We selected 120 decisions from round 1 for question Q_i ($i = \{1, 2, 3, 4, 5, 6\}$) as Sample 1 (12 groups, 10 participants per group), and 40 decisions from different rounds and scenarios as Sample 2 (i.e., for a given question in a given scenario, 4 groups responded, with 10 participants per group) for K-S tests to compare whether the two samples came from the same population.

Table 6 reports K-S test results comparing each question's distribution across different scenarios and rounds with the overall distribution. Column 1 shows that round 1 answers for each question across scenarios do not significantly differ from the overall distribution, confirming that participants' initial decision distributions are indeed not significantly different. Columns 2, 3, and 4 further show that participants receiving information in subsequent rounds were more likely to change their answers. Panels B (rounds 3-4) and C (round 4) reveal that AI-influenced participants' decision distributions changed more noticeably, with more question answer distributions differing significantly from the overall distribution.

Table 6: K-S Test p-values

Panel	Round 1	Round 2	Round 3	Round 4
A: No AI	-	0.003*	0.002*	0.004*
B: AI-3	-	0.028*	0.021*	0.012*
C: AI-4	-	0.009*	0.007*	0.001*

Note: $p < 0.05$*

We also used K-S tests to examine changes in group decision-making performance to preliminarily assess AI assistance effects. With 24 data points for group decision-making performance under each scenario, we used 24 group performance measures from round 1 as Sample 1 and performance measures from rounds 2, 3, and 4 as Sample 2. We conducted K-S tests and t-tests on consensus level, confidence level, and professional performance across different rounds for each scenario. Tables 7 , 8 , and 9 preliminarily indicate that providing group information and AI predictions in group decision-making affects consensus level, confidence level, and professional performance.

Table 7: K-S Test and Right-Tailed t-test for Group Decision-Making Consensus Level

Panel	Round 2	Round 3	Round 4
A: No AI	0.034*	0.002*	0.013*
B: AI-3	0.037*	0.009*	0.013*
C: AI-4	0.026*	0.013*	0.035*

Note: $p < 0.05$*

Table 8: K-S Test and Right-Tailed t-test for Group Decision-Making Confidence Level

Panel	Round 2	Round 3	Round 4
A: No AI	-	0.023*	0.022*
B: AI-3	0.037*	0.000*	0.003*
C: AI-4	-	0.004*	0.031*

Note: $p < 0.05$*

Table 9: K-S Test and Left-Tailed t-test for Group Decision-Making Professional Performance

Panel	Round 2	Round 3	Round 4
A: No AI	-	-	0.013*
B: AI-3	-	0.021*	0.000*
C: AI-4	-	0.000*	0.000*

Note: $p < 0.05$*

4.2.2 Impact of AI Assistance on Consensus Level When investigating the impact of AI assistance on group decision-making consensus level, we selected only answers from rounds 2, 3, and 4. In round 1, participants answered based solely on their own judgment without group or AI influence, so round 1 individual answer data were not considered. At the group level, consensus level is the negative of the variance of individual decision means within the group. We used the mean of participants' three answers per round as their decision. Since answers to different questions vary, we standardized participants' decisions by the true answer values before calculating group consensus level. Group consensus levels across different rounds are shown in Figure 13 [Figure 13: see original paper]. For AI-3 condition questions, group decisions in rounds 3 and 4 were influenced by AI; for AI-4 condition questions, group decisions in round 4 were influenced by AI. Figure 13 preliminarily suggests that consensus level tends to increase with the addition of group and AI information.

Figure 13: Comparison of Consensus Levels Across Rounds

To more precisely understand the impact of AI assistance on group decision-making consensus level, we created five dummy variables: AI Influence, Direct AI Influence, Indirect AI Influence, AI Appearance Before Round 3, and AI Appearance Before Round 4 (see Table 10 for variable definitions). We used linear random intercept models to test their relationships with group decision-making consensus level.

Table 10: Variable Names and Definitions

Variable	Definition
AI Influence	Coded as 1 if a question-round was directly or indirectly influenced by AI, otherwise 0
Direct AI Influence	Coded as 1 if a question-round was directly influenced by AI, otherwise 0
Indirect AI Influence	Coded as 1 if a question-round was indirectly influenced by AI prediction, otherwise 0
AI Appearance Before Round 3	Coded as 1 for round 3 or 4 answers in AI-3 scenario, otherwise 0
AI Appearance Before Round 4	Coded as 1 for round 4 answers in AI-4 scenario, otherwise 0

Different groups exhibit heterogeneity when answering different questions, and clustered random intercept models can account for this important factor. The standard deviation of intercepts is calculated by clustering 72 different time series (12 groups answering 6 different questions). The regression on consensus level has 216 data points, consisting of round 2, 3, and 4 answers from 12 independent groups for 6 questions. In Table 11 Column 1, the coefficient for AI Influence is significantly positive ($\beta = 0.082$, $p = 0.058$, 95%CI=[-0.003, 0.166]), indicating that AI assistance improves group consensus level. Column 2 shows that the coefficient for Direct AI Influence is significantly positive ($\beta = 0.078$, $p = 0.094$, 95%CI=[-0.013, 0.169]), while the coefficient for Indirect AI Influence is positive but not significant ($\beta = 0.092$, $p = 0.160$, 95%CI=[-0.036, 0.219]), indicating that AI assistance immediately consolidates group members' consensus, but this effect does not persist. Column 3 shows that the coefficient for AI Appearance Before Round 3 is positive but not significant ($\beta = 0.093$, $p = 0.103$, 95%CI=[-0.019, 0.205]), and the coefficient for AI Appearance Before Round 4 is positive but not significant (β = 0.059, p = 0.335, 95%CI=[-0.061, 0.180]), indicating that the timing of AI assistance appearance has no significant effect on group consensus level. Overall, AI assistance can increase group decision-making consensus level, verifying Proposition 2. Additionally, we discovered that this effect is time-sensitive.

Table 11: Impact of AI Assistance on Consensus Level

Variable	Model 1	Model 2	Model 3
AI Influence	0.082* (1.89)	-	-
Direct AI Influence	-	0.078* (1.67)	-
Indirect AI Influence	-	0.092 (1.41)	-
AI Appearance Before Round 3	-	-	0.093 (1.63)
AI Appearance Before Round 4	-	-	0.059 (0.96)
Intercept	-0.141*** (-2.85)	-0.141*** (-2.86)	-0.142*** (-2.86)
Std. dev. intercepts	0.375*** (10.38)	0.375*** (10.38)	0.375*** (10.38)
Std. dev. residuals	0.251*** (16.96)	0.251*** (16.96)	0.251*** (16.96)

Note: p < 0.1, ** p < 0.05, *** p < 0.01; t-values in parentheses.*

4.2.3 Impact of AI Assistance on Confidence Level Group decision-making confidence level is the negative of the mean of individual decision variances within the group. Experimental results revealed that some participants were unclear about the order of magnitude of answer units. Variance differences between different orders of magnitude are substantial, and when two participants have inconsistent understanding of magnitude, the confidence level of a participant answering (1, 2, 3) is the same as one answering (1000, 2000, 3000). Therefore, we divided each participant's three answers by their mean, using the negative of the variance of these processed three answers as the participant's decision confidence level, from which we then calculated group confidence level. Group confidence levels across different rounds are shown in Figure 14 [Figure 14: see original paper]. The figure preliminarily suggests that group decision-making continuously increases group confidence, but AI addition may either increase or decrease group confidence.

Figure 14: Comparison of Confidence Levels Across Rounds

We conducted linear random intercept model regression on group decision-making confidence level. In Table 12 Column 1, the coefficient for AI Influence is significantly positive ($\beta = 0.002$, $p = 0.039$, 95%CI=[0.000, 0.003]), indicating that AI assistance improves group confidence level. Column 2 shows that the coefficient for Direct AI Influence is positive but not significant (β = 0.001, $p = 0.121$, 95%CI=[-0.000, 0.003]), while the coefficient for Indirect AI Influence is significantly positive (β = 0.003, p = 0.035, 95%CI=[0.000, 0.005]). This suggests that in group decision-making processes, AI cannot directly enhance group confidence but must do so through group members' internalization or deliberation. Column 3 shows that the coefficient for AI Appearance Before Round 3 is significantly positive ($\beta = 0.002$, $p = 0.037$, 95%CI=[0.000, 0.005]), while the coefficient for AI Appearance Before Round 4 is positive but not significant ($\beta = 0.001$, $p = 0.439$, 95%CI=[-0.001, 0.003]), indicating that earlier AI assistance is more helpful for improving group confidence, which also corroborates the earlier finding about AI's indirect effect on group confidence. Overall, AI assistance can increase group decision-making confidence level, verifying Proposition 3. We additionally discovered that this effect has a delayed effect, meaning earlier AI intervention is more beneficial for group confidence.

Table 12: Impact of AI Assistance on Confidence Level

Variable	Model 1	Model 2	Model 3
AI Influence	0.002** (2.07)	-	-
Direct AI Influence	-	0.001 (1.55)	-
Indirect AI Influence	-	0.003** (2.10)	-
AI Appearance Before Round 3	-	-	0.002** (2.09)
AI Appearance Before Round 4	-	-	0.001 (0.77)
Intercept	-0.006*** (-6.11)	-0.006*** (-6.14)	-0.006*** (-6.17)
Std. dev. intercepts	0.007*** (10.41)	0.007*** (10.42)	0.007*** (10.41)
Std. dev. residuals	0.005*** (16.96)	0.005*** (16.96)	0.005*** (16.96)

Note: p < 0.1, ** p < 0.05, *** p < 0.01; t-values in parentheses.*

4.2.4 Impact of AI Assistance on Professional Performance In the experimental design, participants received 4 points for answers within $±$5% error, 2 points for $±$10% error, and 1 point for $±$20% error. Higher accuracy yielded higher scores. Therefore, we measured professional performance by group members' total scores. As shown in Figure 15 [Figure 15: see original paper], group decision-making professional performance clearly improves when AI predictions are provided to the group.

Figure 15: Comparison of Professional Performance Across Rounds

We also conducted linear random intercept model regression on group decision-making professional performance. In Table 13 Column 1, the coefficient for AI Influence is significantly positive ($\beta = 22.608$, $p < 0.001$, 95%CI=[19.925, 25.291]), indicating that AI assistance improves group decision-making professional performance. Column 2 shows that the coefficient for Direct AI Influence is significantly positive ($\beta = 22.442$, $p < 0.001$, 95%CI=[19.571, 25.313]), and the coefficient for Indirect AI Influence is significantly positive ($\beta = 23.101$, $p < 0.001$, 95%CI=[19.046, 27.156]). A t-test shows no significant difference between these two coefficients ($\chi^2(1) = 0.10$, $p = 0.751$), indicating that both direct and indirect AI assistance positively affect group professional performance.

Column 3 shows that the coefficient for AI Appearance Before Round 3 is significantly positive ($\beta = 21.004$, $p < 0.001$, 95%CI=[17.208, 24.800]), and the coefficient for AI Appearance Before Round 4 is significantly positive ($\beta = 22.251$, $p < 0.001$, 95%CI=[18.345, 26.158]). A t-test shows no significant difference between these two coefficients ($\chi^2(1) = 0.00$, $p = 0.971$), indicating that the timing of AI appearance has no significant effect on group professional performance. Overall, AI assistance can increase group decision-making professional performance with a sustained effect, verifying Observation 1. To test the robustness of AI assistance's impact on group decision-making accuracy, we also verified using group decision error, collective error, and wisdom of crowds indicators, with consistent results (see Appendix 2).

Table 13: Impact of AI Assistance on Professional Performance

Variable	Model 1	Model 2	Model 3
AI Influence	22.608*** (16.52)	-	-
Direct AI Influence	-	22.442*** (15.32)	-
Indirect AI Influence	-	23.101*** (11.17)	-
AI Appearance Before Round 3	-	-	21.004*** (10.84)
AI Appearance Before Round 4	-	-	22.251*** (11.16)
Intercept	43.242*** (10.51)	43.224*** (10.51)	43.541*** (10.59)
Std. dev. intercepts	34.396*** (11.80)	34.395*** (11.80)	34.338*** (11.79)
Std. dev. residuals	7.776*** (16.97)	7.773*** (16.97)	7.991*** (16.97)

Note: p < 0.1, ** p < 0.05, *** p < 0.01; t-values in parentheses.*

4.3 Discussion of Results

This experiment found that AI assistance improves group decision-making consensus level, confidence level, and professional performance. The enhancement effect on consensus level is time-sensitive, while the enhancement effect on confidence level has a delayed effect. The timing of AI appearance has no significant effect on consensus level and professional performance, but earlier AI intervention has a significant effect on group confidence. Overall, we verified Proposition 2 and Proposition 3, and our findings further corroborate Observation 1 from the simulation results.

5.1 Theoretical Implications

Our findings contribute theoretically in several ways. First, this study extends the application scenarios of AI augmentation research. As AI is widely used across various domains, human-AI collaborative decision-making has become crucial. Extensive literature on AI augmentation has discussed applicable domains, effects of AI augmentation, and human trust in AI in AI augmentation scenarios (Fügener et al., 2021; Jussupow et al., 2021). However, previous AI augmentation research focused on AI assisting isolated individuals in decision-making. The opportunities and challenges brought by AI affect not only individuals but also groups, which are the core of human society. This paper extends the context of existing AI augmentation research by using AI to assist group decision-making, mathematically modeling the combined effects of social influence and AI influence on group members' decisions, and exploring the enhancement effects of AI-assisted group decision-making, making important theoretical contributions to AI augmentation research.

Second, this study enriches discussions on information source diversity in group decision-making. Previous group decision-making research only considered individuals obtaining information from human groups, completing decisions through mutual influence among group members (Becker et al., 2017; Lorenz et al., 2011). Information diversity in group decision-making primarily came from differences in human expertise, backgrounds, or cognitive preferences (Aspinall, 2010; Fügener et al., 2021), without considering diversity between living and non-living intelligence. This paper's consideration of AI assistance effects in group decision-making represents an initial attempt to study cross-level information diversity effects.

Finally, unlike existing group decision-making research (Bohlmann et al., 2006; Lorenz et al., 2011), this study proposes a more comprehensive and integrated perspective for evaluating group decision-making performance. We discuss group decision-making performance from three dimensions—consensus, confidence, and accuracy—enabling clearer evaluation of AI-assisted group decision-making enhancement effects. This approach holds promise for providing new ideas for future group decision-making research, advancing group decision-making theory, and offering more effective reference bases for practical decision-making.

5.2 Practical Implications

Our findings offer guidance for organizations on implementing group decision-making more effectively. Group decision-making typically requires teams to analyze, discuss, and decide on different information, demanding substantial human, material, and financial resources. Faced with constantly changing external environments, group decision-making is dynamic and requires rapid response. As a new technological means, AI can help group decision-making. Our research supports organizations' and enterprises' actions to introduce AI technology into group decision-making. However, AI technology application also requires attention to several issues. First, AI accuracy is a key element. Second, through simulation observations, we believe group members need to maintain scrutiny of AI results and not become overly dependent. Finally, organizations wanting to improve group consensus or confidence need different strategies: improving consensus requires direct AI intervention, while increasing confidence requires earlier AI intervention. This study also provides important guidance for corporate intelligentization strategies. In the era of the digital economy, enterprises must accelerate intelligentization to keep pace with the times. Previous research only focused on AI in service areas such as intelligent customer service (Bergner et al., 2023; Jia et al., 2024; Luo et al., 2019), causing some enterprises to blindly pursue intelligentization or not know how to maximize intelligentization advantages. We believe enterprises can deploy intelligent tools in various group decision-making tasks. Expanding AI application scenarios can undoubtedly enrich corporate intelligentization strategies.

5.3 Limitations and Future Directions

This study provides theoretical and decision-making references for how enterprises can use AI to assist group decision-making, but it also has limitations that provide directions for future research. First, this study only considered AI assistance effects on small-scale group decision-making. In some domains, we need large-scale group decision-making to obtain opinions from more stakeholders to make decisions satisfying all parties' interests (Venkatesh et al., 2020). For example, coping with COVID-19 strategy deployment requires cooperation from personnel across sectors. Facing such large and diverse group members, designing general AI is actually a challenge. Second, we assigned equal weight to each individual in group decision-making. However, group decision-making is often conducted by multiple experts (Aspinall, 2010). We did not consider assigning different weights to individuals based on their different knowledge in decision-making, nor did we consider social network relationships among individuals in group decision-making processes, which are complex factors affecting group decision-making performance.

This study, through a combination of mathematical modeling, numerical simulation, and experimental design, discovered the enhancement effects of AI assistance on group decision-making. Specifically, AI assistance can improve group decision-making consensus level, confidence level, and accuracy. Additionally, group consensus level is more susceptible to direct AI influence, while group confidence level is more susceptible to indirect AI influence. This indicates that AI assistance in consolidating group members' consensus is time-sensitive—when AI appears, group members have a benchmark in decision-making. However, AI assistance in enhancing group confidence is not a direct process; it requires group members' internalization or understanding before taking effect. Moreover, earlier AI intervention is needed to achieve the effect of enhancing group confidence. For accuracy, AI assistance plays a stable enhancement role.

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Appendix 1: Professional Performance Simulation Results

In decision-making, when new information is in the opposite direction of the current decision-maker's error, this new information has a corrective effect on the decision-maker, thereby improving decision accuracy (Herzog & Hertwig, 2009). Therefore, when conducting numerical simulations of Performance_{GA} and Performance_{G} under different conditions, we must pay special attention to the relationship between the product of γ and $\Delta\mu$ and 0. If the product is greater than 0, AI predictions do not have a corrective effect on the group; if the product is less than 0, AI predictions have a corrective effect on the group.

Parameter Settings: Generally, we consider predictions with errors within 10% as good predictions, and errors beyond 15% as quite poor predictions (Roy et al., 2016). Therefore, in the following numerical analysis, we set r to 0.1. $|\Delta\mu| < 0.1$ represents accurate AI predictions, while $0.1 < |\Delta\mu| < 0.15$ represents insufficiently accurate AI predictions. $|\gamma| < 0.1$ represents accurate group predictions, while $|\gamma| > 0.1$ represents insufficiently accurate group predictions. We define the error range for insufficiently accurate AI as (0.1, 0.15). Predictions with errors exceeding 15% are considered quite poor and would not be used in reality (Roy et al., 2016). Following Aiken et al. (1994), we set group size at two levels: 10 and 40, comparing across group sizes to judge the impact of group size on group decision-making professional performance under AI assistance (Aiken et al., 1994). Following Biemann and Kearney (2010), we set the parameter ε measuring group diversity level at two levels: 1 and 4, comparing across diversity levels to judge the impact of group diversity on group decision-making professional performance under AI assistance (Biemann & Kearney, 2010).

Case 1: $|\gamma| < |\Delta\mu| < r$, and $\Delta\mu \times \gamma > 0$. The trend of Performance_{GA} with increasing η under different ε and n levels is shown in Figure 1 [Figure 1: see original paper].

When the group's initial prediction is more accurate than AI prediction, both predictions are within the acceptable error range, and AI does not have a corrective effect relative to humans, the more the group trusts AI predictions during decision-making, the higher the group decision-making professional performance.

Case 2: $|\gamma| < |\Delta\mu| < r$, and $\Delta\mu \times \gamma < 0$. The trend of Performance_{GA} with increasing η under different ε and n levels is shown in Figure 2 [Figure 2: see original paper].

When the group's initial prediction is more accurate than AI prediction, both predictions are within the acceptable error range, and AI has a corrective effect relative to humans, the more the group trusts AI predictions during decision-making, the higher the group decision-making professional performance.

Case 3: $|\Delta\mu| < |\gamma| < r$, and $\Delta\mu \times \gamma > 0$. The trend of Performance_{GA} with increasing η under different ε and n levels is shown in Figure 3 [Figure 3: see original paper].

When AI prediction is more accurate than the group's initial prediction, both predictions are within the acceptable error range, and AI does not have a corrective effect relative to humans, the more the group trusts AI predictions during decision-making, the higher the group decision-making professional performance.

Case 4: $|\Delta\mu| < |\gamma| < r$, and $\Delta\mu \times \gamma < 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 4 [Figure 4: see original paper].

When AI prediction is more accurate than the group's initial prediction, both predictions are within the acceptable error range, and AI has a corrective effect relative to humans, the more the group trusts AI predictions during decision-making, the higher the group decision-making professional performance.

Case 5: $|\gamma| < r < |\Delta\mu|$, and $\Delta\mu \times \gamma > 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 5 [Figure 5: see original paper].

When the group's initial prediction error is within the acceptable range, AI prediction error exceeds the acceptable range, and AI does not have a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 6: $|\gamma| < r < |\Delta\mu|$, and $\Delta\mu \times \gamma < 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 6 [Figure 6: see original paper].

When the group's initial prediction error is within the acceptable range, AI prediction error exceeds the acceptable range, but AI has a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 7: $|\Delta\mu| < r < |\gamma|$, and $\Delta\mu \times \gamma > 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 7 [Figure 7: see original paper].

When the group's initial prediction error exceeds the acceptable range, AI prediction error is within the acceptable range, and AI does not have a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 8: $|\Delta\mu| < r < |\gamma|$, and $\Delta\mu \times \gamma < 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 8 [Figure 8: see original paper].

When the group's initial prediction error exceeds the acceptable range, AI prediction error is within the acceptable range, and AI has a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 9: $r < |\gamma| < |\Delta\mu|$, and $\Delta\mu \times \gamma > 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 9 [Figure 9: see original paper].

When the group's initial prediction error exceeds the acceptable range, AI prediction error exceeds the acceptable range and is less accurate than the group's initial prediction, and AI does not have a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 10: $r < |\gamma| < |\Delta\mu|$, and $\Delta\mu \times \gamma < 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 10 [Figure 10: see original paper].

When the group's initial prediction error exceeds the acceptable range, AI prediction error exceeds the acceptable range and is less accurate than the group's initial prediction, but AI has a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 11: $r < |\Delta\mu| < |\gamma|$, and $\Delta\mu \times \gamma > 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 11 [Figure 11: see original paper].

When the group's initial prediction error exceeds the acceptable range, AI prediction error exceeds the acceptable range but is more accurate than the group's initial prediction, and AI does not have a corrective effect relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Case 12: $r < |\Delta\mu| < |\gamma|$, and $\Delta\mu \times \gamma < 0$. The trend of Performance$_{GA}$ with increasing η under different ε and n levels is shown in Figure 12 [Figure 12: see original paper].

When the group's initial prediction error exceeds the acceptable range, AI prediction error exceeds the acceptable range but is more accurate than the group's initial prediction, and AI has unique knowledge relative to humans, as the group's trust in AI predictions during decision-making increases, group decision-making professional performance first increases then decreases.

Based on Cases 1, 2, 3, 4, 7, and 8, we propose:

Observation 1: When AI accuracy is high, regardless of group accuracy, initial group consensus level, or group size, the professional performance of groups that experience social influence before learning from AI is higher than that of groups experiencing only social influence.

Based on Cases 5, 6, 9, 10, 11, and 12, we propose:

Observation 2: When AI accuracy is insufficient, if individuals' AI influence level is low, the professional performance of groups that experience social influence before learning from AI is higher than that of groups experiencing only social influence; if individuals' AI influence level is high, the professional performance of groups that experience social influence before learning from AI is lower than that of groups experiencing only social influence.

References for Appendix

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Appendix 2: Experimental Materials

Answer image materials

Appendix 3: Robustness Checks for Group Accuracy

(1) Group Decision Error

We standardized each participant's answer mean by the true value and calculated participant decision error, then measured group decision accuracy by the absolute value of the mean error across all group members. Larger absolute error values represent lower group accuracy. Figure 1 shows that group decision error decreases significantly after AI influence.

Figure 1: Comparison of Group Decision Error Across Rounds

Linear random intercept model regression on group decision error shows in Table 1 Column 1 that the AI Influence coefficient is significantly negative ($\beta = -0.184$, $p < 0.000$, 95%CI=[-0.245, -0.123]). Column 2 shows that the Direct AI Influence coefficient is significantly negative ($\beta = -0.185$, $p < 0.001$, 95%CI=[-0.250, -0.119]), and the Indirect AI Influence coefficient is significantly negative ($\beta = -0.183$, $p < 0.001$, 95%CI=[-0.275, -0.091]). A t-test shows no significant difference between these coefficients ($\chi^2(1) = 0.00$, $p = 0.971$). Column 3 shows that the AI Appearance Before Round 3 coefficient is significantly negative ($\beta = -0.167$, $p < 0.001$, 95%CI=[-0.250, -0.084]), and the AI Appearance Before Round 4 coefficient is significantly negative ($\beta = -0.182$, $p < 0.001$, 95%CI=[-0.269, -0.095]). A t-test shows no significant difference between these coefficients ($\chi^2(1) = 0.06$, $p = 0.804$). Thus, AI assistance can reduce group decision error in group decision-making, and this effect does not vary with the timing of AI assistance.

Table 1: Group Decision Error

Variable	Model 1	Model 2	Model 3
AI Influence	-0.184*** (-5.93)	-	-
Direct AI Influence	-	-0.185*** (-5.53)	-
Indirect AI Influence	-	-0.183*** (-3.90)	-
AI Appearance Before Round 3	-	-	-0.167*** (-3.95)
AI Appearance Before Round 4	-	-	-0.182*** (-4.10)
Intercept	0.306*** (6.28)	0.306*** (6.28)	0.303*** (6.20)
Std. dev. intercepts	0.391*** (11.21)	0.391*** (11.21)	0.391*** (11.19)
Std. dev. residuals	0.178*** (16.97)	0.178*** (16.97)	0.180*** (16.97)

Note: p < 0.1, ** p < 0.05, *** p < 0.01; t-values in parentheses.*

(2) Collective Error

Collective error is another measure of group decision-making accuracy (Lorenz et al., 2011). After standardizing participants' answers by the correct answer for each question, collective error is measured as:

$$\text{Collective Error} = |\bar{X}_j - \mu|$$

We calculated collective error for each group's answer to each question in each round. Collective error across rounds is shown in Figure 2. The figure indicates that collective error decreases after AI influence.

Figure 2: Comparison of Collective Error Across Rounds

Linear random intercept model regression on collective error shows in Table 2 Column 1 that the AI Influence coefficient is significantly negative ($\beta = -0.343$, $p = 0.001$, 95%CI=[-0.545, -0.142]). Column 2 shows that the Direct AI Influence coefficient is significantly negative ($\beta = -0.352$, $p = 0.001$, 95%CI=[-0.569, -0.135]), and the Indirect AI Influence coefficient is significantly negative ($\beta = -0.319$, $p = 0.040$, 95%CI=[-0.625, -0.014]). A t-test shows no significant difference between these coefficients ($\chi^2(1) = 0.24$, $p = 0.621$). Column 3 shows that the AI Appearance Before Round 3 coefficient is significantly negative ($\beta = -0.263$, $p = 0.059$, 95%CI=[-0.536, 0.010]), and the AI Appearance Before Round 4 coefficient is significantly negative ($\beta = -0.392$, $p = 0.007$, 95%CI=[-0.679, -0.105]). A t-test shows no significant difference between these coefficients ($\chi^2(1) = 0.40$, $p = 0.53$). Thus, AI assistance can reduce collective error in group decision-making.

Table 2: Collective Error

Variable	Model 1	Model 2	Model 3
AI Influence	-0.343*** (-3.33)	-	-
Direct AI Influence	-	-0.352*** (-3.18)	-
Indirect AI Influence	-	-0.319** (-2.05)	-
AI Appearance Before Round 3	-	-	-0.263* (-1.89)
AI Appearance Before Round 4	-	-	-0.392*** (-2.68)
Intercept	0.481*** (2.96)	0.482*** (2.96)	0.471*** (2.89)
Std. dev. intercepts	1.307*** (11.22)	1.307*** (11.22)	1.309*** (11.21)
Std. dev. residuals	0.591*** (16.97)	0.592*** (16.97)	0.592*** (16.96)

Note: p < 0.1, ** p < 0.05, *** p < 0.01; t-values in parentheses.*

(3) Wisdom of Crowds

In addition to professional performance, decision error, and collective error, wisdom of crowds is another important indicator worth attention in group decision-making accuracy (Lorenz et al., 2011). Wisdom of crowds is a statistical phenomenon where the group mean or median performs better than most individuals within the group (Galton, 1907). Therefore, many scholars studying wisdom of crowds both domestically and internationally measure it by superiority—the proportion of group members whose decisions are outperformed by the group's decision (Lorenz et al., 2011; Becker et al., 2017). We calculated the wisdom of crowds indicator for each group's answer to each question in each round. We sorted individual decisions within each group-question-round in ascending order. If the truth fell between the 5th-6th individual decisions, the wisdom of crowds indicator was 5; between 4th-7th, it was 4; between 3rd-8th, it was 3; between 2nd-9th, it was 2; between 1st-10th, it was 1; if the truth fell outside all 10 individual decisions, the indicator was 0. Wisdom of crowds indicators across rounds are shown in Figure 3. The figure indicates that wisdom of crowds significantly increases after AI influence.

Figure 3: Comparison of Wisdom of Crowds Indicators Across Rounds

Linear random intercept model regression on wisdom of crowds shows in Table 3 Column 1 that the AI Influence coefficient is significantly positive ($\beta = 0.934$, $p < 0.001$, 95%CI=[0.606, 1.263]). Column 2 shows that the Direct AI Influence coefficient is significantly positive ($\beta = 1.033$, $p < 0.001$, 95%CI=[0.677, 1.388]), and the Indirect AI Influence coefficient is significantly positive ($\beta = 0.675$, $p = 0.007$, 95%CI=[0.181, 1.169]). A t-test shows no significant difference between these coefficients ($\chi^2(1) = 1.88$, $p = 0.171$). Column 3 shows that the AI Appearance Before Round 3 coefficient is significantly positive ($\beta = 0.760$, $p < 0.001$, 95%CI=[0.335, 1.185]), and the AI Appearance Before Round 4 coefficient is significantly positive ($\beta = 1.029$, $p < 0.001$, 95%CI=[0.554, 1.503]). A t-test shows no significant difference between these coefficients ($\chi^2(1) = 0.70$, $p = 0.402$). Thus, AI assistance can increase wisdom of crowds in group decision-making, and AI's effect on wisdom of crowds does not vary with the round in which AI assistance appears.

Table 3: Wisdom of Crowds

Variable	Model 1	Model 2	Model 3
AI Influence	0.934*** (5.57)	-	-
Direct AI Influence	-	1.033*** (5.69)	-
Indirect AI Influence	-	0.675*** (2.68)	-
AI Appearance Before Round 3	-	-	0.760*** (3.50)
AI Appearance Before Round 4	-	-	1.029*** (4.25)
Intercept	1.344*** (8.71)	1.337*** (8.66)	1.362*** (8.79)
Std. dev. intercepts	1.077*** (9.24)	1.076*** (9.21)	1.077*** (9.19)
Std. dev. residuals	0.994*** (16.97)	1.000*** (16.97)	1.004*** (16.97)

Note: p < 0.1, ** p < 0.05, *** p < 0.01; t-values in parentheses.*

References for Appendix

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Note: Figure translations are in progress. See original paper for figures.

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