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Research on Governance Trust Mechanism of Social Enterprises Based on Generative Artificial Intelligence Assisted Decision-Making

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Abstract. Social enterprises play an important role in public service supplementation, community development, and sustainable business practices. Their governance processes face pressures related to mission preservation, transparent resource allocation, and multi-stakeholder trust maintenance. Generative artificial intelligence can process unstructured information such as annual reports, project materials, meeting records, and stakeholder feedback, providing support for proposal generation, risk identification, and explanatory output in governance decision-making. Focusing on the governance trust mechanism of social enterprises under generative AI-assisted decision-making, this study constructs an analytical framework linking AI-assisted decision-making level, governance process quality, and governance trust outcomes. It further verifies the framework through public textual data, scenario-based experimental ratings, and a repeated-measures regression model. The results show that the AI-assisted decision-making group scores higher than the manual decision-making group in governance trust, decision transparency, and explanatory adequacy. Among the mechanism variables, explanatory adequacy makes the strongest contribution to governance trust, followed by risk controllability. The findings indicate that the value of generative AI in social enterprise governance lies mainly in improving information integration efficiency, explanatory clarity, and risk identification capability. The study also provides methodological references for building responsible AI-assisted governance mechanisms in social enterprises.

Keywords: Social enterprise, corporate governance, generative artificial intelligence, assisted decision-making, governance trust mechanism

1. Introduction

Social enterprises play an increasingly important role in public service supplementation, community development, support for vulnerable groups, and sustainable business practices. Their operation is shaped by economic performance, social mission, and stakeholder expectations at the same time. Corporate governance studies have long focused on board supervision, accountability allocation, and organizational performance, while social enterprise governance further emphasizes mission

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preservation, legitimate resource use, and the stable maintenance of multi-stakeholder trust [1]. Generative artificial intelligence can process unstructured materials such as annual reports, meeting minutes, project evaluations, and public feedback, while supporting governance judgment through proposal generation, risk warning, and explanatory output [2]. In social enterprise governance, AI-assisted decision-making should be examined through decision transparency, explanatory adequacy, participatory fairness, and risk controllability, so that its influence on governance trust can be explained through both governance theory and computational methods.

2. Literature review

2.1. Social enterprise governance and multiple stakeholder trust

The key issue of social enterprise governance lies in coordinating commercial sustainability, social mission, and stakeholder participation. Stakeholder theory emphasizes that organizational governance should respond to the differentiated demands of various actors in resource contribution, value distribution, and responsibility sharing, which provides a foundation for analyzing governance trust in social enterprises [3]. The sources of trust in social enterprises include not only financial performance, but also whether project selection is mission-consistent, whether resource use is transparent, and whether beneficiary groups are included in the governance process. Multi-stakeholder participation can strengthen organizational legitimacy, while expanded participation may also increase coordination costs when information disclosure is insufficient and responsibility arrangements remain unclear [4]. Governance trust is jointly shaped by decision evidence, interactive procedures, and risk responses.

2.2. Research on generative artificial intelligence assisted decision making

The value of generative AI-assisted decision-making mainly lies in complex information processing, contextual reasoning, and governance text generation. Large language models can extract key issues from unstructured texts and transform policy requirements, project goals, and stakeholder opinions into comparable governance alternatives [5]. In corporate governance settings, this technology can improve the efficiency of information integration and provide support for risk identification and proposal explanation for boards, management teams, and project groups. Generative AI output is probabilistic in nature, so model results may be influenced by training data, prompt design, and the completeness of input materials [6]. The credibility of assisted decision-making therefore needs to be constrained through human review, evidence tracing, and accountability confirmation.

2.3. Technological embedding path of the governance trust mechanism

The formation of governance trust requires technological capability to be embedded into organizational institutions and decision-making procedures. Research on explainable artificial intelligence emphasizes that model outputs can be included in credible judgment only when they have clear evidence, traceable sources, and understandable logic [7]. When social enterprises use generative AI, the technological embedding path should cover data authorization, text processing, proposal generation, human review, stakeholder feedback, and risk recording. Algorithmic governance research indicates that responsibility allocation and supervision mechanisms influence organizational members' acceptance of intelligent systems [8]. Responsible AI further requires

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technological application to remain aligned with ethical principles, organizational accountability, and social value goals [9].

3. Experimental methods

3.1. Research framework and variable design

The research framework follows the path of generative AI-assisted decision-making, governance process quality, and governance trust outcomes. Generative AI-assisted decision-making is treated as the independent variable and is measured through recommendation quality, information integration capability, risk warning capability, and explanation capability. These dimensions correspond to decision feasibility, integration of multi-source materials, completeness of risk identification, and clarity of explanation. Governance trust is treated as the dependent variable. The measurement does not rely on fully self-designed items. Instead, it is adapted from Mayer and Davis's management trust scale and Jian, Bisantz, and Drury's Trust in Automated Systems Scale. The former measures trust in the ability, benevolence, and integrity of governance actors, while the latter measures perceived reliability and credibility of automated support systems. The mechanism variables include decision transparency, explanatory adequacy, participatory fairness, and risk controllability. Decision transparency and participatory fairness are adapted from the procedural justice and informational justice dimensions of Colquitt's Organizational Justice Scale, while explanatory adequacy is adapted from the five-point structure of the Explanation Satisfaction Scale. All items use a five-point Likert scale. After the pilot test, Cronbach's alpha and confirmatory factor analysis are used to retain items with acceptable reliability and factor loadings [10].

3.2. Data collection and experimental scenario construction

Data collection includes two parts: public textual data and experimental rating data. Public textual data are collected from social enterprise websites, annual reports, social impact reports, ESG or sustainability reports, project evaluation documents, public meeting minutes, partnership announcements, and stakeholder feedback texts. The time span is set from 2021 to 2024. Sample screening follows three criteria. First, the organization should have a clear social mission and continuous operation records. Second, it should disclose governance or social impact materials for at least two consecutive years. Third, its project descriptions, stakeholder information, and resource allocation content should support text coding. The experimental scenarios are constructed according to common governance tasks of social enterprises, including public welfare project resource allocation, social impact evaluation, partner selection, and risk event response. Each scenario contains a manual decision-making plan and a generative AI-assisted decision-making plan. The same group of evaluators rates both plans, and randomized presentation order is used to control order effects. Evaluators include social enterprise managers, employees, partners, and beneficiary representatives. The expert group reviews plan quality, explanation completeness, and risk identification level, producing a matched dataset of textual features, mechanism variables, and governance trust scores.

3.3. Model construction and experimental procedure

Model construction begins with cleaning, denoising, tokenizing, and vectorizing public governance texts. Annual reports, social impact reports, project materials, and stakeholder feedback are then

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transformed into computable text vectors [11]. To determine whether AI-generated recommendations deviate from the original governance materials and social mission, a text embedding model is used to calculate semantic consistency between AI recommendations and governance materials, as shown in Formula (1).

$$SC_j=\cos\left(E\left(R_j\right),E\left(M_j\right)\right)=\frac{E(R_j)\cdot E(M_j)}{\|E(R_j)\|\|E(M_j)\|} \quad (1)$$

In Formula (1), SC_j represents the semantic consistency of governance plan j, $E\left(R_j\right)$ represents the text vector of the AI-generated recommendation, and $E\left(M_j\right)$ represents the text vector of the original governance material or social mission statement. A higher semantic consistency score indicates a stronger match between the AI recommendation and the organization's mission and governance materials. A repeated-measures regression model is then used to test the effects of AI-assisted decision-making and mechanism variables on governance trust. Since the same evaluator rates both the manual plan and the AI-assisted plan, evaluator random effects and task fixed effects are included, as shown in Formula (2).

$$GT_{ict}=\beta_0+\beta_1 A_{lc}+\beta_2 DT_{ict}+\beta_3 EA_{ict}+\beta_4 PF_{ict}+\beta_5 RC_{ict}+\theta Z_i+\mu_t+u_i+\varepsilon_{ict} \quad (2)$$

In Formula (2), GT_{ict} represents the governance trust score given by evaluator i under condition ccc and task t. A_{lc} indicates whether the condition is AI-assisted decision-making. DT, EA, PF, and C represent decision transparency, explanatory adequacy, participatory fairness, and risk controllability. Z_i represents control variables such as evaluator identity, experience, and familiarity with AI. μ_t represents task fixed effects, and u_i represents evaluator random effects. The experimental process includes text collection, text coding, AI plan generation, human review, scale rating, reliability testing, and model estimation.

4. Results

4.1. Effects of generative AI assisted decision making on governance trust

Based on pilot rating data from 96 stakeholders and 8 experts, the AI-assisted decision-making group scored higher than the manual decision-making group in governance trust, decision transparency, explanatory adequacy, and risk controllability. The mean governance trust score increased from 3.42 to 3.86, with an improvement of 0.44, indicating that AI-assisted plans improved evaluators' acceptance by integrating public materials and clarifying the basis of decision-making. Explanatory adequacy showed the largest increase, rising from 3.18 to 3.81, which suggests that structured explanations generated by AI helped reduce the cognitive cost of understanding governance decisions. The average response time decreased from 18.6 minutes to 9.8 minutes, while the expert quality score increased by only 0.34. This indicates that AI mainly improved efficiency and clarity of expression, while the substantive quality of governance plans still depended on human review. As shown in Table 1.

Table 1. Analysis of data indicators

Indicator	Manual Decision-Making Group	AI-Assisted Decision-Making Group	Difference	Result Explanation
Governance Trust Score	3.42 ± 0.61	3.86 ± 0.58	0.44	Moderate improvement in trust level
Decision Transparency	3.31 ± 0.66	3.92 ± 0.55	0.61	Clearer information sources

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Table 1. (continued)

Explanatory Adequacy	3.18 ± 0.70	3.81 ± 0.60	0.63	More complete decision rationale
Participatory Fairness	3.36 ± 0.64	3.73 ± 0.59	0.37	More balanced presentation of stakeholder opinions
Risk Controllability	3.29 ± 0.68	3.74 ± 0.62	0.45	Improved risk identification
Average Response Time	18.6 min	9.8 min	-8.8 min	Significant improvement in generation efficiency
Expert Quality Score	3.55 ± 0.52	3.89 ± 0.49	0.34	Slight improvement in plan quality

4.2. Effects of governance trust mechanism variables

The results of the mechanism variables show that explanatory adequacy had the strongest effect on governance trust, with a path coefficient of 0.32, a feature importance value of 0.29, and a trust gain of 0.63. This indicates that evaluators were more concerned with whether AI recommendations clearly explained their evidence, sources, and reasoning process. Risk controllability had a path coefficient of 0.27 and a feature importance value of 0.23, showing that risk warning and human review records were important supports for governance trust in social enterprises. The path coefficient of decision transparency was 0.21, mainly reflected in clear information sources and traceable decision processes. The path coefficient of participatory fairness was 0.18, indicating that the presentation of stakeholder opinions had an effect, though it was weaker than the effects of explanation and risk-related dimensions. As shown in Figure 1.

Figure 1. Governance trust mechanism contribution matrix

5. Discussion

Compared with traditional manual decision-making, AI-assisted decision-making performs better in information integration, explanation generation, and response efficiency, while its improvement in

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the substantive quality of governance plans is relatively limited. Among the mechanism variables, explanatory adequacy has the strongest effect on governance trust, exceeding risk controllability, decision transparency, and participatory fairness. This suggests that stakeholders are more concerned with whether AI recommendations clearly explain their evidence and reasoning process. Risk controllability has a stronger effect than participatory fairness, indicating that risk warnings and human review records enhance trust more effectively than merely presenting multiple stakeholder opinions. Therefore, generative AI is more suitable for auxiliary analysis and explanation support, while data quality, human review, and accountability confirmation remain essential.

6. Conclusion

This study examines the relationship between generative AI-assisted decision-making and governance trust in social enterprises. It constructs an empirical framework consisting of independent variables, mechanism variables, and dependent variables, and develops an operational research path through public governance texts, scenario-based experimental ratings, and a repeated-measures regression model. The results show that AI-assisted decision-making can improve governance trust, mainly through explanatory adequacy, risk controllability, and decision transparency. When introducing generative AI, social enterprises should position it as a governance support tool and establish mechanisms for data authorization, output review, risk recording, and human accountability. Future research may expand real social enterprise samples and introduce longitudinal data to further test the stability and external applicability of the model.

Author contribution

Jingyi Xin and Xiaoying Ou contributed equally to this paper.

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