Risk Perception and Trust-Building in AIGC Applications: A Bayesian Structural Equation Model Analysis

Manman Wei[1*], Zhiming Song[1*]

[1] *School of Economics / Jiangsu Normal University Kewen College, Xuzhou, China*
*Corresponding author: sarahsonhengmincamille@gmail.com

Abstract
The rapid diffusion of generative artificial intelligence (AIGC) technologies is accompanied by multiple risks, which profoundly impact public acceptance and trust in the technology. This study integrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Social Amplification of Risk Framework (SARF) to construct a theoretical model encompassing Risk Perception, System Trust, Risk Trust, Behavioral Intention, and Risk Prevention Sensitivity. Based on 696 valid survey responses from Jiangsu Province, a Bayesian Structural Equation Model (BSEM) is employed to empirically analyze the complex interactions among these variables. The results reveal that both Risk Perception and System Trust significantly and positively influence Risk Trust, with System Trust exerting a stronger effect. Furthermore, Risk Trust positively affects Behavioral Intention, while Risk Prevention Sensitivity demonstrates a significant negative inhibitory effect. Based on these findings, the study proposes policy recommendations such as enhancing algorithmic transparency, improving multi-stakeholder governance mechanisms, and strengthening public digital risk literacy to promote responsible innovation and effective governance of AIGC technologies.

Keywords: AIGC; Public Risk Perception; Risk Trust Mechanism; Behavioral Intention; Bayesian Structural Equation Model

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Introduction

Artificial Intelligence Generated Content (AIGC) technology is undergoing rapid development and widespread diffusion. Its core capabilities—such as text generation, image and video creation, and cross-modal content generation—have profoundly transformed the logic of digital content production and cultural communication, while reshaping the value chain of the cultural industry. However, alongside these technological advantages, a range of potential risks has emerged, including algorithmic opacity, lack of content credibility, and the accelerated spread of ethical biases (Liu et al., 2023; Qin et al., 2021). The pace at which these risks spread has far outstripped the responsiveness of governance mechanisms, resulting in a clear imbalance that constitutes the "Solow Paradox" of technological governance (Aleshkovski, 2022). This imbalance has further triggered a "Collingridge dilemma"-style reflection within academia on responsible innovation and risk management—namely, how to effectively identify and prevent systemic risks in the early stages of technological evolution, in order to avoid governance path dependency and social trust crises (Wong & Jensen, 2020). Therefore, establishing a multidimensional risk assessment system for AIGC applications and clarifying the nonlinear transmission mechanisms of risks across technological, social, and institutional networks has become an urgent requirement for achieving responsible innovation and stable societal development.

Risk perception theory suggests that when confronted with uncertain threats posed by emerging and complex technologies, the public often exhibits irrational cognitive biases such as "probability neglect" and "loss sensitivity" (Zhu, 2022). In the context of AIGC applications, such irrational tendencies in Risk Perception are particularly prominent. Given the algorithmic complexity and high degree of uncertainty associated with AIGC technologies, their potential negative impacts are difficult to predict and may be irreversible. As a result, a more complex and subtle dynamic interaction exists between public Risk Perception and technological trust (Lim et al., 2023). Extended studies based on the Technology Acceptance Model (TAM) have confirmed that System Trust—a multidimensional and higher-order construct encompassing both technological reliability and institutional assurance—directly influences the formation of Risk Trust, and ultimately determines whether the public adopts the technology (Kaur & Arora, 2020). The "dual-threshold effect" theory of Risk Prevention Sensitivity further indicates that moderate risk awareness can encourage prudent technology adoption. However, when Risk Prevention Sensitivity exceeds a critical threshold, it may trigger avoidance and resistance toward the technology, thus hindering its broader dissemination (Gu et al., 2022).

However, traditional risk management research has largely been limited to the analysis of linear relationships and simplistic variable exploration, failing to effectively capture the more complex, nonlinear interactive effects among Risk Perception, trust mechanisms, and Behavioral Intention (Lin et al., 2024). Therefore, it is urgent to adopt a complex systems perspective and leverage more advanced and robust modeling approaches to deeply analyze the transmission pathways of AIGC-related risks and the dynamic interaction mechanisms of public trust. In response, this study integrates the extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with the Social Amplification of Risk Framework (SARF) to more comprehensively explain and capturethe dynamic interplay between public Risk Perception and trust-building processes. This approach aims to provide a solid theoretical foundation for constructing a risk management index system tailored to AIGC technologies.

Current academic research on technological Risk Perception and trust management has made significant progress. For instance, Yuqing (2024) confirmed that trust plays a significant mediating

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and moderating role between Risk Perception and behavioral intention (Yuqing, 2024). Kaur and Arora (2020) further revealed that Risk Perception can exert an indirect yet significant influence on technology adoption intention through trust mechanisms (Kaur & Arora, 2020). Gu (2022) emphasized the dynamic, nonlinear coupling relationship between the transparency of risk communication and institutional trust, noting that information opacity may trigger a sharp decline in public trust (Gu et al., 2022). However, existing research still suffers from three main limitations: First, most studies have not sufficiently considered the potential nonlinear moderating effect of Risk Prevention Sensitivity, thereby failing to fully uncover the complex interactive mechanisms between Risk Perception and trust. Second, from a methodological perspective, traditional Structural Equation Modeling (SEM) is still widely used, despite its evident limitations in handling parameter uncertainty and small sample sizes. Third, regional studies often remain confined to single-dimensional analyses, lacking systematic, comprehensive, and regionally differentiated investigations into the transmission pathways of AIGC-related risks.

As a major hub for technological innovation in China, Jiangsu Province has in recent years actively pursued development strategies in artificial intelligence and the digital economy. It has accumulated rich practical experience in the AIGC field, while also revealing typical application risks and governance challenges. Therefore, taking Jiangsu Province as a representative region for studying AIGC risk assessment and governance pathways not only provides a scientific basis for decision-making by local governments and technology enterprises, but also offers valuable paradigmatic insights for risk governance in other regions. Specifically, conducting in-depth quantitative and path analyses of key dimensions—such as public Risk Perception, System Trust, Risk Trust, and Risk Prevention Sensitivity—can help optimize strategies for the social adoption of AIGC technologies, improve risk control systems and governance mechanisms, and provide robust theoretical and practical support for relevant policy formulation.

To effectively address the limitations of existing research, this study aims to achieve breakthroughs in three key areas at both the theoretical and methodological levels. First, at the theoretical level, drawing on the multi-level trust moderation mechanism proposed by Yuqing (2024), System Trust is introduced as a critical buffering variable to more deeply uncover the nonlinear transmission mechanisms among Risk Perception, Risk Trust, and public Behavioral Intention. Second, at the methodological level, the study integrates the analytical strengths of risk–trust balancing theory and Bayesian Structural Equation Modeling (BSEM), thereby overcoming the technical constraints of traditional SEM in dealing with parameter estimation uncertainty and small sample sizes. Third, at the regional governance level, the study innovatively incorporates the risk communication governance framework proposed by Gu et al. (2022), along with the institutional factors of Jiangsu Province's digital economy governance, in order to enhance the policy applicability and practical relevance of the research findings.

In summary, this study takes Jiangsu Province's representative experience as the empirical sample and adopts Bayesian Structural Equation Modeling as the core methodological approach to deeply analyze the complex interactive relationships and dynamic evolutionary mechanisms of Risk Perception, trust management, and risk governance in AIGC technology applications. This research not only responds to the academic demand for deeper exploration into technological risk management but also provides practical decision-making support for policy formulation in technology governance—forming the core logic and fundamental framework of this paper.

Literature Review

2.1 AIGC Technology Risks and Public Perception

Existing research indicates that the formation of AIGC-related risks exhibits distinct characteristics of technological generational shifts and cross-modal features. Unlike traditional AI technologies, which primarily involve algorithmic bias, AIGC risks are manifested in multiple dimensions such as the lack of content credibility and the ethical risks associated with content dissemination. Lin et al. (2024) conducted an empirical study revealing that semantic distortion is prevalent in AIGC-generated content, and that the dissemination speed of misinformation is 3.8 times higher than that of traditional user-generated content (UGC). This significantly heightens public concern regarding content credibility (Lin et al., 2024). Di (2024), in the context of new media, further pointed out that although improved GAN models have raised the accuracy of video tampering detection to 91%, the authenticity issues of deepfake-generated content still severely undermine public trust (Di, 2024). Additionally, Zhu (2022), through a study in the marketing field, demonstrated a nonlinear dissemination effect of ethical risks in AIGC content—where a single misleading promotional message may trigger an amplified "ripple effect," thereby intensifying public Risk Perception (Zhu, 2022).

In terms of public Risk Perception, the application of AIGC technologies has exacerbated cognitive dilemmas. Neyazi (2023) found in an experimental study that more than 50% of users were unable to accurately identify the source of AIGC-generated content, and that there is an inverted U-shaped relationship between public cognitive bias and AIGC usage frequency (Neyazi et al., 2023). Similarly, Chen et al. (2023) noted in the medical field that when diagnostic advice generated by AIGC lacks sufficient interpretability, patients' Risk Perception increases dramatically. This finding confirms that the imbalance between technological complexity and users' cognitive capacity is a key factor in amplifying risk (Chen et al., 2023).

Taken together, these studies suggest that a salient characteristic of AIGC-related risks lies in the "overload effect" of public Risk Perception, wherein the complexity and uncertainty of the technology significantly amplify perceived risk. Therefore, this study identifies Risk Perception as one of the core latent variables, operationalized through three observed dimensions: perceived severity of consequences, likelihood of occurrence, and perceived uncontrollability. Accordingly, we propose Hypothesis H1: Risk Perception positively influences Risk Trust (derived from Qin et al., 2021, regarding the role of risk awareness in driving institutional trust).

2.2 AIGC Trust Crisis and Construction Pathways

The public trust crisis surrounding AIGC technologies stems from a dual dilemma inherent in the technology itself: First, the probabilistic and uncertain nature of AIGC-generated content makes it difficult for the public to establish stable psychological expectations; second, the ambiguity of the content generators leads to unclear accountability. Stein (2022), from a legal perspective, noted that liability determination costs in AIGC-related infringement cases are 43% higher than those in traditional AI systems, significantly weakening the institutional foundation of public trust (Stein, 2022). In response, Lin et al. (2024) proposed a content traceability method integrating blockchain and smart contracts, which significantly improves content credibility and represents an effective "technical anchoring" pathway (Lin et al., 2024). Zhang et al. (2024), in the context of autonomous driving, demonstrated that a cloud–edge–terminal distributed architecture can effectively reduce decision-making uncertainty and facilitate cross-scenario trust mechanisms (Zhang et al., 2024).

Regarding the mediating mechanisms of trust, two mainstream perspectives have emerged in academic discourse: technological transparency and institutional assurance. Howard et al. (2024) emphasized the importance of transparency in user interface design, confirming that transparency significantly enhances public trust levels (Howard & Schulte, 2024). Aleshkovski (2022) argued that a robust institutional compliance framework can significantly increase public tolerance of technological risks (Aleshkovski, 2022).

It is thus evident that the construction of AIGC trust mechanisms hinges on the co-evolution of "technological transparency" and "institutional assurance." That is, enhancing technological maturity can improve the controllability of generated content, while strengthening the institutional framework can improve the public's societal coping capacity. Accordingly, this study defines System Trust as a multidimensional latent variable encompassing technological transparency, technological maturity, and social coping capacity. We therefore propose Hypothesis H2: System Trust positively influences Risk Trust (in line with the technology attribute–trust transmission mechanism proposed by Kaur & Arora, 2020).

2.3 Evolution and Limitations of AIGC Risk Governance Models

Current research on AIGC technology risk governance models is undergoing a transformation across three dimensions: methodology, technical pathways, and governance perspectives. At the methodological level, there is a shift from traditional discrete risk assessment toward embedded governance during the content generation process. For example, Best et al. (2024) proposed a real-time monitoring model featuring government–enterprise collaboration, which effectively reduces the risk of content violations (Best et al., 2024). In terms of technical pathways, governance strategies have evolved from single-algorithm optimization to the coordinated governance of heterogeneous systems. Chen et al. (2023), for instance, used digital twin technology to maintain AI error rates at extremely low levels (Chen et al., 2023). From the governance perspective, research has gradually expanded from a focus on single-content regulation to the holistic governance of the AIGC ecosystem. Zhou et al. (2024) introduced a resource allocation algorithm to enable rapid risk response (Zhou et al., 2023).

However, these studies still exhibit several notable limitations. First, traditional analytical approaches struggle to capture relational risks across multimodal data. Second, static risk assessment frameworks fail to reflect the dynamic evolution of technological risks. Third, linear regression methods often overlook the nonlinear characteristics and moderating effects of the public's Risk Prevention Sensitivity (Neyazi et al., 2023; Schaeffer et al., 2024). To address these challenges, this study introduces Bayesian Structural Equation Modeling (BSEM) to tackle issues related to parameter uncertainty and small-sample estimation. Simultaneously, it incorporates Risk Prevention Sensitivity as a latent variable, operationalized through three observed dimensions: risk assessment capability, self-protection ability, and alertness to new technologies. Accordingly, we propose the following hypotheses: H3: Risk Trust positively influences Behavioral Intention (extending the trust–behavior linear model proposed by Liu et al., 2023); H4: Risk Prevention Sensitivity negatively moderates Behavioral Intention (in line with the empirical conclusions on risk avoidance tendencies from Gu et al., 2022).

In conclusion, while existing academic research has systematically revealed the cross-modal nature of AIGC-related risks, as well as the internal mechanisms of public Risk Perception, trust crises, and governance pathways, limitations remain in understanding the nonlinear interactive effects between Risk Perception and trust, the moderating role of Risk Prevention Sensitivity, and regionally differentiated governance strategies. This study integrates prior findings by incorporating key latent variables—Risk Perception, System Trust, Risk Trust, Risk Prevention Sensitivity, and Behavioral Intention—and employs Bayesian Structural Equation Modeling (BSEM) to explore the internal logic and governance pathways of AIGC risk transmission. In doing so, it aims to offer new research perspectives for both theoretical innovation and policy practice.

Methodology

3.1 Sampling Design and Data Collection

Data collection was conducted using a three-stage unequal probability sampling method. Compared to traditional equal probability sampling, unequal probability sampling better accounts for urban–rural differences, levels of economic development, and population structure characteristics, thereby enhancing the representativeness and heterogeneity of the sample. This approach ensures that the survey results more accurately reflect the socioeconomic diversity within Jiangsu Province. The survey was carried out simultaneously from July to August 2024 across northern, central, and southern regions of Jiangsu Province, targeting 12 selected neighborhoods in 6 prefecture-level cities. Respondents were local permanent residents.

The sample size was determined based on the finite population correction principle and calculated scientifically under a 95% confidence level ($Z = 1.96$). Taking into account the number of surveyed neighborhoods (12) and the population proportions of each city, the final effective sample size was set at 575 respondents. This sampling design not only meets the representativeness and data accuracy requirements of Bayesian Structural Equation Modeling (BSEM) but also provides a robust data foundation for addressing parameter uncertainty and conducting small-sample analysis in subsequent model estimation.

3.2 Construction of the Indicator System

Although the traditional Technology Acceptance Model (TAM) has been widely applied in early research on technology adoption, it has gradually revealed significant limitations in describing and explaining the interaction among risk perception, trust mechanisms, and behavioral intention in complex systems. To address this shortcoming, this study introduces the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Social Amplification of Risk Framework (SARF), and integrates the risk stratification theory, trust transmission model, and the risk-behavior interaction framework to construct a theoretical analytical path more suitable for the risk communication context of AIGC technologies (Stein, 2022; Seth, 2024; Wei et al., 2023).

UTAUT2 approaches technology adoption from the perspective of individual users, emphasizing how factors such as performance expectancy, social influence, and facilitating conditions affect usage intention and behavioral tendencies, with particular attention to the moderating role of situational and social contextual variables. In contrast, SARF adopts a macro-level societal perspective, revealing how risk information is amplified or attenuated through interactions among media, organizations, and the public, thereby influencing individual risk perception and group trust structures. The synergy between the two lies in UTAUT2 offering a micro-level cognitive–behavioral logic, while SARF elucidates the mechanisms through which risk information and trust are transmitted within broader societal contexts. Through this theoretical complementarity, the study captures both the cognitive response mechanisms of individual users facing AIGC technologies and how societal risk information is constructed and disseminated via media and trust networks to influence behavioral intention. Based on this integrative perspective, a risk management index system comprising five core latent variables and fifteen observed indicators is established (see Table 1), enabling a more systematic exploration of the dynamic relationships among public perception, trust, and behavioral intention.

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Table 1. Measurement Framework for Risk Perception and Trust-Building in AIGC Applications

Latent Variable	Indicator Code	Observed Indicator
Risk Perception (A)	A1	Severity of risk consequences
	A2	Likelihood of risk occurrence
	A3	Perceived uncontrollability of risks
System Trust (B)	B1	Technological transparency
	B2	Technological maturity
	B3	Social coping capacity
Risk Trust (C)	C1	Trust in government regulation
	C2	Trust in technology enterprises
	C3	Trust in public participation mechanisms
Behavioral Intention (D)	D1	Willingness to try the technology
	D2	Willingness to support technology promotion
	D3	Willingness to engage in risk prevention
Risk Prevention Sensitivity (E)	E1	Risk assessment capability
	E2	Self-protection ability
	E3	Alertness to new technologies

Specifically, Risk Perception (A) draws on the Social Amplification of Risk Framework (SARF), which emphasizes how risks are amplified through societal processes. It begins with the public's subjective evaluation of technological threats and incorporates three dimensions—severity of consequences, likelihood of occurrence, and perceived uncontrollability—to comprehensively capture the amplification effects and subjective characteristics of risks in public cognition.

System Trust (B), informed by the UTAUT2 framework's focus on contextual factors and social expectancy effects, integrates three indicators—technological transparency, technological maturity, and social coping capacity—to reflect the public's overall trust in the AIGC application environment.

From the perspective of social governance, Risk Trust (C) is assessed through three dimensions: trust in government regulation, trust in technology enterprises, and trust in public participation mechanisms. These indicators evaluate the credibility of risk governance actors within social interaction and communication processes, embodying SARF's emphasis on the moderating role of institutional factors in shaping Risk Perception.

Behavioral Intention (D) is grounded in UTAUT2's assertion of the relationship between individual technology adoption and social influence. It is further specified into three dimensions: willingness to adopt the technology, willingness to support its promotion, and willingness to participate in collaborative risk governance—thus reflecting the public's practical inclination to engage in risk governance activities.

Finally, Risk Prevention Sensitivity (E) is conceptualized based on SARF's recognition of individual differences in risk response behavior. It captures the public's sensitivity to risk and its moderating effect on Behavioral Intention through three components: risk assessment capability, self-protection ability, and alertness to new technologies.

3.3 Construction of the Bayesian Structural Equation Model

Given the limitations of traditional Structural Equation Modeling (SEM) regarding assumptions of data distribution and sample size requirements, this study adopts Bayesian Structural Equation Modeling (BSEM) as a methodological alternative. Classical SEM typically relies on maximum likelihood estimation (MLE), which assumes that the data follow a multivariate normal distribution and requires a relatively large sample size to ensure stable parameter estimation. However, in practical survey research, these assumptions are often difficult to meet—especially when the sample size is limited or the data deviate from normality—leading to biased parameter estimates and underestimated standard errors (Song & Lee, 2012). In addition, traditional SEM does not effectively incorporate researchers' prior knowledge or theoretical expectations into the model, which constrains its flexibility and explanatory power.

In contrast, BSEM treats parameters as random variables and incorporates prior distributions, enabling more robust estimation by integrating both observed data and theoretical information, while imposing less stringent assumptions on data distribution (Zhou et al., 2023). This approach not only enhances the model's adaptability in small-sample contexts but also quantifies estimation uncertainty through posterior distributions, thereby reducing the risk of overfitting. As such, BSEM is better aligned with the practical needs of this study, which involves path analysis under conditions of non-normality and limited sample size (Chen et al., 2024).

Specifically, the BSEM method employed in this study involves two core steps: First, the standardized path coefficients from classical SEM are converted into weakly informative prior distributions, thereby reasonably constraining the parameter estimation range. Second, Markov Chain Monte Carlo (MCMC) sampling is used to obtain the posterior distributions of parameters. The fit between the theoretical model and the empirical data is assessed through posterior predictive checks, forming an iterative optimization framework that combines prior specification, parameter estimation, and model validation, thus improving the accuracy and robustness of hypothesis testing.

3.3.1 Measurement Model and Structural Model Construction

The measurement and structural models provide the foundation for SEM by defining the relationships among latent variables. In this study, five latent variables are each associated with three observed variables. Let the vector of observed variables be defined as $y = [y_1, y_2 \quad , \ldots, y_{15}]^\top$, and the vector of latent variables be denoted as ω, which includes exogenous latent variables $\xi = [\xi_A, \xi_B, \xi_E]^\top$ and endogenous latent variables $\eta = [\eta_C, \eta_D]^\top$. The measurement model is expressed as:

$$y = \Lambda\omega + \epsilon, \tag{1}$$

where Λ is a 15×5 factor loading matrix and ϵ is a 15×1 measurement error vector, assumed to follow a normal distribution with mean 0 and variance Ψ_ϵ.

The structural model describes the causal relationships among latent variables. The relationships between the endogenous and exogenous latent variables are expressed as:

$$\eta = \Pi\eta + \Gamma\xi + \delta, \tag{2}$$

where Π and Γ are parameter matrices to be estimated, and δ is a normally distributed error vector with mean 0 and variance Ψ_δ. The error terms ϵ and δ are assumed to be independent. The exogenous latent variables ξ follow a normal distribution with mean 0 and variance Φ (Jie-Ling & Yuan-Chang, 2021). The specific structural relationships among the latent variables in this study are represented as:

$$\begin{cases} \eta_C = \gamma_1\xi_A + \gamma_2\xi_B + \delta_1 \\ \eta_D = \beta\eta_C + \gamma_5\xi_D + \delta_2 \end{cases}, \tag{3}$$

where ξ_A, ξ_B, and ξ_E follow normal distributions $N[0, \Phi]$, and the error terms δ follow $N[0, \Psi_\epsilon]$ accordingly.

3.3.2 Bayesian Inference Foundations and Specification

BSEM estimates SEM models using the Bayesian approach. Let the observed data be denoted as $Y = (y_1, \ldots, y_n)$, where each observation vector $y_i \in R^{15}$ corresponds to a latent variable vector $\omega_i \in R^5$. The model parameters are represented as $\theta = (\Lambda, \Phi, \Psi_\epsilon)$, which include:

(1) The factor loading matrix Λ (from the measurement model);

(2) The covariance matrix of exogenous latent variables Φ (from the structural model);

(3) The measurement error covariance matrix Ψ_ϵ , typically assumed to be diagonal.

The joint posterior distribution is derived from Bayes' Theorem and decomposed as follows:

$$p(\theta, \Omega|Y) \propto \underbrace{p(Y|\Omega, \theta)}_{Likelihood} \cdot \underbrace{p(\Omega|\theta) \cdot p(\theta)}_{Prior}, \quad (4)$$

Where $\Omega = (\omega_1, \ldots, \omega_n)$ is the matrix of latent variables, and θ is the vector of structural parameters. In BSEM, the latent variable matrix is treated as missing data via data augmentation, and is estimated jointly with the model parameters. This approach increases the flexibility of the model and enhances estimation efficiency (Bollen, 1989).

3.3.3 Theory-Driven Hierarchical Prior Structure

The model construction follows the principles of Bayesian hierarchical modeling (Cohen, 1992), using multi-level prior constraints to ensure both model identifiability and parameter stability. Traditional SEM standardized path coefficients are employed to guide the specification of Bayesian priors, enabling an organic integration of prior knowledge with observed data. This approach offers several advantages: it accelerates convergence, reduces uncertainty in the parameter space, constrains parameter ranges to prevent overfitting, incorporates findings from existing studies to improve model reliability, and limits the occurrence of extreme or implausible values, thus enhancing model stability and validity under small-sample conditions.

1.Latent Variable Centering Priors:

Exogenous latent variables $\xi \in \{\xi_A, \xi_B, \xi_E\}$ are assigned a normal prior $\xi \sim N\ (0\ ,\ 0.5^2)$. Endogenous latent variables $\eta \in \{\eta_C, \eta_D\}$ are similarly assumed to follow $\eta \sim N\ (0\ ,\ 0.5^2)$. These priors reflect the standardization assumption for latent variables (Stein, 2022), and the variance parameter is determined through preliminary simulation experiments to balance prior informativeness with estimation flexibility.

2.Regularized Priors for Factor Loadings:

In the measurement model $y_{ij} = \lambda_j \xi_i + \epsilon_{ij}$, each latent variable is measured by three observed variables. The prior distribution for each factor loading λ_j is defined as:

$$\lambda_j \sim N\left([1,1,1],\ 0.1^2\mathbf{I}_3\right)\ ,\ j = 1,2,3,4,5 \quad (5)$$

where $\mathbf{I}_3$ is the 3×3 identity matrix. Setting the mean of the factor loadings to 1 reflects a "unit variance identification" strategy, while allowing a standard deviation of ±0.2 accommodates imperfections in the measurement instruments.

3.Random Effects in the Structural Equations:

A Gaussian process is introduced to model uncertainty in the structural layer of latent variable relationships:

$$\eta_C \sim N\ (\mu = \gamma_1\xi_A + \gamma_2\xi_B, \sigma = 0.2)\ , \quad (6)$$

$$\eta_D \sim N(\mu = \beta\eta_C + \gamma_5\xi_D, \sigma = 0.2)\ . \quad (7)$$

The additive structure implies path coefficients $\gamma_{A\to C} = \gamma_{B\to C} = 1$, and the standard deviation parameter σ characterizes the uncertainty in the structural equations. The choice of $\sigma = 0.2$ is informed by typical effect sizes in psychological research (Zhou et al., 2023).

4.Hierarchical Error Structure for Enhanced Measurement Precision: A layered error specification is adopted: the measurement error follows $\epsilon_{\text{measure}} \sim \text{N}(0\ , 0.5^2)$, representing standardized residuals of observed variables; the structural equation error follows $\epsilon_{struct} \sim N(0\ , 0.2^2)$, capturing unexplained variance among latent variables.

3.3.4 Posterior Inference and Model Diagnostics Framework

In the BSEM framework, the joint posterior distribution of model parameters and latent variables, $p(\theta, \Omega \mid Y)$, generally has no closed-form solution. Markov Chain Monte Carlo (MCMC) is a numerical method designed to draw samples from complex high-dimensional distributions by constructing a Markov chain whose stationary distribution equals the target posterior. The core idea is to construct a Markov chain by designing a transition kernel $K(\theta^{(t+1)}|\theta^{(t)})$, such that the chain's stationary distribution $\pi(\theta)$ equals the posterior distribution $p(\theta|Y)$.

This study adopts a Bayesian inference framework, using the No-U-Turn Sampler (NUTS) algorithm to implement MCMC sampling. The model initiates four independent Markov chains, each running for 4,000 iterations (including the first 1,000 as an adaptive tuning phase), yielding a total of 12,000 posterior samples. Sampling efficiency is ensured through a dual mechanism:

1.During the tuning phase, the step size is dynamically optimized to maintain an average acceptance rate within the recommended range of 65%–80%;

2.The number of iterations is extended to reduce autocorrelation between samples and ensure that the effective sample size (ESS) of key parameters exceeds 400, thus satisfying the Monte Carlo standard error (MCSE) precision threshold of less than 5% of the standard deviation.

Model convergence is verified through a three-stage diagnostic procedure:

1.Joint Distribution Testing of Variable Relationships: This test is based on the logic of Bayesian posterior distributions. Through kernel density estimation and scatterplot matrix analysis, the statistical associations and co-variation trends between latent and observed variables are evaluated. Under multivariate model structures, this method helps identify potential nonlinear relationships and multicollinearity issues, validating the construct validity of the measurement model. By examining the shape and structure of joint distributions, the rationality of model specification can be assessed, providing theoretical support for subsequent path coefficient estimation.

2.Bayesian Model Diagnostics: To ensure the effectiveness of the MCMC sampling process and the reliability of model convergence, diagnostics such as trace plots, autocorrelation coefficients, and the Gelman–Rubin convergence statistic are employed. These tools help determine whether the sampling chains have reached a stationary state and whether parameter estimates are sufficiently precise. This prevents estimation bias due to non-convergent chains or inefficient sampling and enhances the credibility of the model's inferential results.

3.Posterior Distribution and Highest Density Interval (HDI) Testing: Posterior uncertainty is quantified using the shape of the posterior distribution and Highest Density Interval (HDI) analysis. Unlike traditional point estimates, HDIs provide probabilistic interval estimates that more comprehensively reflect the central tendency and variability of parameters. This approach addresses the limitations of frequentist point estimates and improves the interpretability of results under uncertainty.

Together, these three diagnostics ensure the scientific rigor and explanatory power of the model estimation process.

Results

4.1 Data Cleaning and Preliminary Testing

A total of 759 questionnaires were collected during the formal survey. After screening for logical consistency and removing responses with completion times below 60 seconds or above 300 seconds, a final valid sample of 696 responses was obtained, yielding an effective response rate of 91.70%. The sample showed a slightly higher proportion of female participants and was predominantly composed of younger respondents (see Table 2). After excluding demographic variables such as age, education, and gender, reliability and validity tests were conducted on the remaining 19 scale items. The Cronbach's alpha coefficient was calculated to be 0.912, and the Kaiser-Meyer-Olkin (KMO) value was 0.946, indicating high reliability and suitability for factor analysis.

Table 2. Demographic Characteristics of the Sample

Item	Category	Sample Size	Proportion
Gender	Male	318	45.7%
	Female	378	54.3%
Age	Under 18	43	6.2%
	18–30	407	58.5%
	31–40	154	22.1%
	41–50	63	9.1%
	Over 50	29	4.2%
Education	Junior high or below	25	3.6%
	High school/vocational	92	13.2%
	Associate degree	74	10.6%
	Bachelor's degree	471	67.7%
	Master's and above	34	4.9%

A two-stage Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and validity of the measurement model. First, results from the convergent validity analysis (see Table 3) showed that all standardized factor loadings for observed variables ranged from 0.775 to 0.865 (CR > 2.58, p < 0.001), meeting standard thresholds of significance. The Composite Reliability (CR) of each latent construct ranged from 0.831 to 0.871, and the Average Variance Extracted (AVE) ranged from 0.606 to 0.692 (see Table 4), all exceeding the benchmarks recommended by the Fornell–Larcker criterion, indicating excellent internal consistency and discriminant validity of the measurement scales.

Table 3. Convergent Validity Results

Latent Construct	Indicator	Std. Estimate	z (CR)	p-value
Risk Perception (A)	A1	0.833	-	-
	A2	0.806	24.460	0.000
	A3	0.848	26.233	0.000
System Trust (B)	B1	0.781	-	-
	B2	0.780	20.959	0.000
	B3	0.775	20.813	0.000
Risk Trust (C)	C1	0.767	-	-
	C2	0.785	21.936	0.000
	C3	0.811	22.807	0.000
Behavioral Intention (D)	D1	0.807	-	-
	D2	0.811	20.825	0.000
	D3	0.764	19.906	0.000
Risk Prevention Sensitivity (E)	E1	0.836	-	-
	E2	0.794	24.519	0.000
	E3	0.865	27.860	0.000

Table 4. Confirmatory Factor Analysis Results

Dimension	AVE	CR	Reliability Evaluation
Risk Perception	0.688	0.869	Very High
System Trust	0.606	0.822	Very High
Risk Trust	0.621	0.831	Very High
Behavioral Intention	0.631	0.837	Very High
Risk Prevention Sensitivity	0.692	0.871	Very High

4.2 Traditional SEM Path Coefficient Estimation

To enhance the stability and convergence of path coefficient estimation in the Bayesian Structural Equation Model (BSEM), the standardized path coefficients derived from the traditional Structural Equation Model (SEM) were used as informative priors for the Bayesian framework. Initially, a conventional SEM was used to estimate path coefficients and evaluate model fit. As shown in Table 5, the model's chi-square to degrees-of-freedom ratio is 2.932, meeting the recommended threshold of <3. Other goodness-of-fit indices (NFI, IFI, CFI, GFI) all exceed the critical value of 0.9, indicating a good model fit.

As presented in Table 6, the estimated standardized path coefficient from risk perception to risk trust is 0.429 ($p < 0.001$), and from system trust to risk trust is 0.598 ($p < 0.001$). The influence of risk trust on behavioral intention is 0.966 ($p < 0.001$), while risk prevention sensitivity shows a significant negative effect on behavioral intention, with a coefficient of -0.386 ($p < 0.001$). All path coefficients are statistically significant and align with theoretical expectations.

Table 5. Model Fit Indices

Fit Index	Acceptable Range		Observed Value	Fit Evaluation
	Acceptable	Good		
X^2/df	2-3	<2	2.932	Acceptable
NFI	0.7-0.9	≥0.9	0.961	Good
IFI	0.7-0.9	≥0.9	0.973	Good
CFI	0.7-0.9	≥0.9	0.973	Good
GFI	0.7-0.9	≥0.9	0.950	Good

Table 6. Path Coefficients and Significance Testing

Predictor	Outcome	Std. Coefficient	SE	z (CR)	p-value
Risk Perception	Risk Trust	0.429	0.043	8.751	***
System Trust	Risk Trust	0.598	0.054	11.178	***
Risk Trust	Behavioral Intention	0.966	0.149	6.617	***
Risk Prevention Sensitivity	Behavioral Intention	-0.386	0.137	-2.731	***

4.3 Bayesian Structural Equation Model (BSEM): Posterior Distribution Diagnostics

This study employed the PyMC library to construct a Bayesian Structural Equation Model (BSEM) and estimate posterior distributions using the Markov Chain Monte Carlo (MCMC) algorithm. The model was built in three key stages:

1.Model specification: Based on the theoretical framework, structural paths between latent and observed variables were defined.

2.Prior setting: Standardized path coefficients obtained from traditional SEM were incorporated as weakly informative priors to accelerate convergence.

3.Posterior estimation: MCMC sampling was conducted to estimate the posterior distributions of model parameters.

After model construction, a three-stage diagnostic framework was employed to assess robustness, reliability, and validity of parameter estimates.

4.3.1 Joint Distribution Diagnostics of Variable Relationships

The first diagnostic step involved assessing the joint distribution between latent variables and observed indicators using kernel density estimation and scatterplot matrix analysis (see Figure 1). The results indicate that the marginal distributions (diagonal) and joint distributions (off-diagonal) of all latent constructs and factor loading parameters form elliptical or approximately circular high-

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density regions. No evidence of multimodality, severe skewness, extreme collinearity, or outliers was detected. These findings suggest that the posterior distributions are well-behaved, with strong convergence and stability.

In sum, the posterior and joint distributions demonstrate no abnormalities, indicating that the model produces robust estimates of latent variables and their loadings.

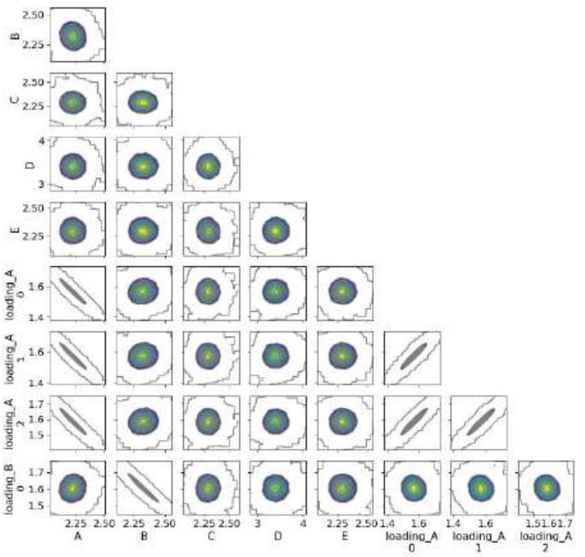

Figure 1. Joint Distribution Plot of Variable Relationships

4.3.2 Bayesian Model Diagnostics

The second stage focused on assessing the stability of parameter estimation through MCMC convergence diagnostics. Specifically, the Gelman-Rubin diagnostic criterion (i.e., Potential Scale Reduction Factor, PSRF) was employed to evaluate the mixing behavior and within-chain autocorrelation across four independent MCMC sampling chains.

The diagnostic plots comprise the marginal posterior distributions (left panel) and MCMC sampling traces (right panel) for each parameter. The marginal distribution plots display smooth, symmetric posterior curves without visible anomalies. In the trace plots, most sampling chains stabilize after a short burn-in period, with high overlap and interweaving among chains—indicating minimal differences between chains. All PSRF values were below the conventional threshold of 1.05, confirming that the model had reached a satisfactory level of convergence.

Although minor fluctuations appeared in the trace plots of a few path loadings, the amplitude of these variations remained within acceptable bounds and did not compromise overall convergence. These results validate the reliability and robustness of parameter estimation, ensuring the effectiveness of the subsequent Bayesian structural model analysis.

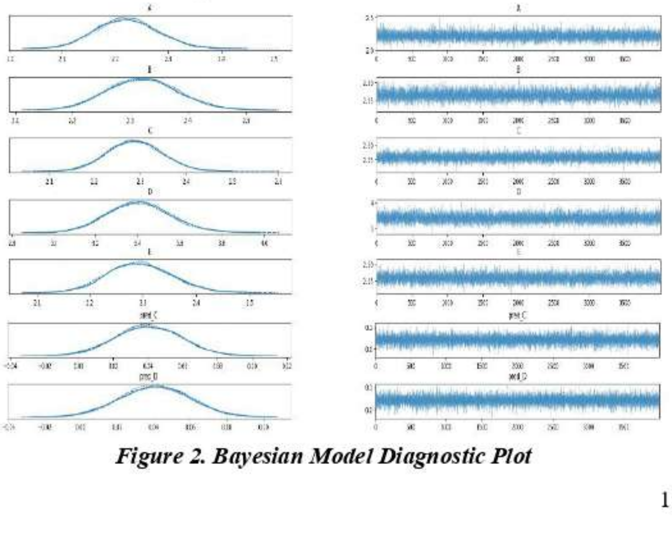

Figure 2. Bayesian Model Diagnostic Plot

4.3.3 Posterior Distribution and Highest Density Interval (HDI) Analysis

The third stage involved a detailed examination of the posterior distributions and the Highest Density Intervals (HDIs) of the model parameters, aimed at evaluating estimation accuracy and parameter uncertainty.

The posterior plots revealed that all model parameters exhibited unimodal and symmetric posterior distributions with well-defined peaks and density concentrated around the parameter means. This pattern indicates that the parameter estimates derived from Bayesian inference are highly credible and stable.

Moreover, analysis of the 94% HDI intervals—which represent the range containing the most credible 94% of the posterior probability mass—demonstrated that all HDIs were narrow and did not include zero, further supporting the low uncertainty in parameter estimates and the model's strong explanatory power for the observed data.

Taken together, the diagnostic results from this stage provide compelling evidence that the BSEM constructed in this study offers precise and robust parameter estimates, lending strong theoretical reliability and practical value to the conclusions drawn from the model.

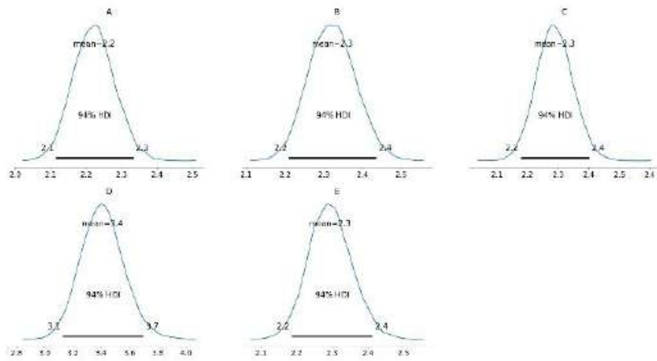

Figure 3. Posterior Distribution and Highest Density Interval Plot

4.4 Bayesian Structural Equation Path Analysis

The results confirm that the BSEM demonstrates good model fit and stability, and that its parameter estimates are reliable, providing a robust statistical foundation for inferring and interpreting path coefficients. On this basis, the path coefficients derived through Bayesian inference further uncover the causal relationships and influence pathways among latent variables, offering in-depth empirical insights into the model's theoretical significance and practical implications.

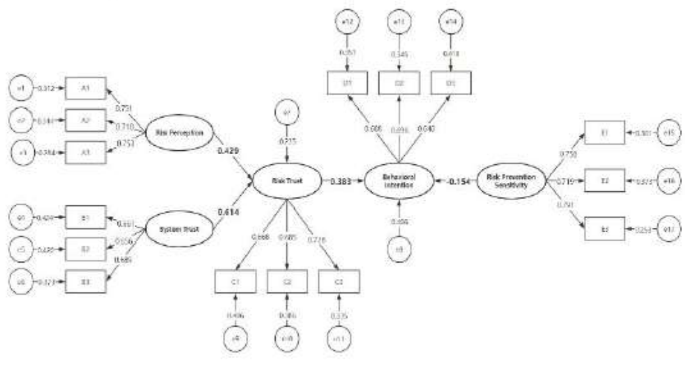

Figure 4. Path Diagram of Standardized Parameter Estimates in Bayesian SEM

The path analysis results based on the BSEM (see Figure 4) reveal the underlying causal relationships and mechanisms of influence among key constructs. First, the path coefficient from Risk Perception (A) to Risk Trust (C) is 0.429, indicating a significant positive effect and supporting Hypothesis H1. This

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suggests that as individuals' risk perception increases, their level of risk trust also tends to rise. Second, the path coefficient from System Trust (B) to Risk Trust (C) is 0.614, thereby supporting Hypothesis H2. This indicates that system trust is a stronger determinant of risk trust—higher system trust levels can substantially enhance individuals' willingness to trust in risky situations. In addition, the path coefficient from Risk Trust (C) to Behavioral Intention (D) is 0.383, validating Hypothesis H3, which implies that higher levels of risk trust are associated with more proactive behavioral intentions. Notably, the path coefficient from Risk Prevention Sensitivity (E) to Behavioral Intention (D) is -0.154, indicating a negative relationship. This suggests that heightened sensitivity to risk prevention may suppress behavioral intention, possibly due to excessive risk vigilance, thus confirming Hypothesis H4.

These path coefficients provide empirical support for the proposed research hypotheses, reflecting the core relational structure of the model and the interaction mechanisms among variables. The findings offer valuable theoretical guidance for optimizing risk management strategies and building effective trust mechanisms.

Conclusion

5.1 Core Pathway Analysis

1. Risk Perception (A) → Risk Trust (C) (β = 0.429)

The results of the Bayesian Structural Equation Modeling (BSEM) indicate that risk perception exerts a significant positive effect on the public's risk trust. At first glance, this finding appears to contradict conventional assumptions, but it can be reasonably interpreted from the perspectives of technological black-box characteristics and risk communication.

In the context of Artificial Intelligence Generated Content (AIGC) technologies, the opaque and algorithmically complex nature of such systems makes it difficult for the public to directly assess risk levels. As a result, individuals are compelled to construct trust through systematic cognitive processing. According to dual-process theory, people typically rely on both rational cognition and emotional intuition when processing risk-related information (Selvarajan et al., 2024). A high level of risk perception regarding AIGC technology often indicates that individuals have cognitively evaluated the potential risks and corresponding mitigation mechanisms, thereby forming a kind of "calibrated" rational trust.

This finding aligns with risk society theory, which emphasizes the paradoxical relationship between the public and expert systems in modern society: due to limitations in lay knowledge, individuals often seek institutional support and informational transparency—paradoxically reinforcing their trust in risk governance mechanisms. Moreover, the Social Amplification of Risk Framework (SARF) suggests that when risk information is sufficiently transparent, even heightened risk perception may coexist with strong risk trust, as individuals perceive existing governance measures to be effective (Li et al., 2024).

Existing research in the AIGC domain also supports this view, showing that functional risk perception tends to positively influence technology trust, whereas emotional risk perception often diminishes it. This indicates that a clear and comprehensive understanding of technological risks can facilitate the formation of rational trust among the public (Niculae, 2023). Therefore, enhancing the transparency and explanatory power of risk communication is crucial for promoting rational public engagement with risk and achieving effective AIGC governance.

2. System Trust (B) → Risk Trust (C) (β = 0.614)

The findings further show that system trust has a particularly significant impact on risk trust, with a path coefficient of 0.614. This suggests that public trust in the broader technological environment—including technology providers, regulatory institutions, and institutional frameworks—serves as a key antecedent of risk trust.

This conclusion echoes the UTAUT2 model's emphasis on contextual and environmental factors in technology acceptance: when evaluating technological risks, individuals often rely on their trust in external institutions as a cognitive shortcut. This heuristic processing is consistent with risk communication theory, which posits that public trust in authoritative entities such as governments and scientific organizations helps mitigate uncertainty associated with emerging technologies (Peng et al., 2024).

Moreover, the finding aligns with the "abstract system trust" perspective in risk society theory, which contends that modern societies heavily depend on institutionalized expertise and systemic trust to alleviate anxiety arising from technological complexity. In the case of AIGC, the high degree of algorithmic complexity often renders the technology incomprehensible to lay users, who end up placing blind trust in its outputs. Consequently, institutional trust guarantees become critically important for shaping public perceptions and behaviors (Sands et al., 2022).

In sum, enhancing institutional credibility and promoting multi-stakeholder collaborative governance are essential strategies for effectively increasing public risk trust in the context of AIGC technologies.

3. Risk Trust (C) → Behavioral Intention (D) (β = 0.383)

The positive effect of risk trust on behavioral intention indicates that when the public has sufficient trust in the risk management capabilities of AIGC technologies, they are more likely to exhibit a favorable intention to adopt such technologies. This finding is highly consistent with both UTAUT2 and the extended Technology Acceptance Model (TAM), which emphasize trust as a critical mediating factor in technology adoption decisions.

Although AIGC technologies may offer substantial performance benefits and convenience, a lack of trust can significantly reduce users' willingness to adopt them (Wong & Jensen, 2020). Empirical studies in the field of artificial intelligence have reached similar conclusions, showing that trust effectively reduces risk perception and enhances positive evaluations of the technology, thereby promoting its adoption (Aleshkovski, 2022).

In the present context, when individuals believe that AIGC systems can effectively mitigate their inherent risks, they are more inclined to focus on the tangible benefits these technologies can bring, which in turn enhances their intention to use. Therefore, strengthening public trust in AIGC risk governance emerges as a key pathway to facilitating technology adoption, and this study provides empirical support for such a mechanism.

4. Risk Prevention Sensitivity (E) → Behavioral Intention (D) (β = –0.154)

The study also finds that risk prevention sensitivity has a significant negative impact on behavioral intention, suggesting that individuals who are overly sensitive to risk prevention tend to exhibit lower levels of willingness to adopt new technologies. This phenomenon reflects the inhibitory effect of risk aversion tendencies on the acceptance of emerging technologies, which aligns with the diffusion of innovation theory, where higher perceived risk is associated with lower technology adoption (Salles & Farisco, 2020).

According to the Social Amplification of Risk Framework (SARF), individuals with high risk prevention sensitivity are more susceptible to negative risk information disseminated through media and social channels, and thus are more likely to avoid potential uncertainties associated with technology use. Dual-process theory further explains this behavior by indicating that highly risk-sensitive individuals are prone to rely on emotion-driven heuristic processing, rather than engaging in deep cognitive analysis of the actual risks and benefits of a given technology (Li et al., 2024). This cognitive pattern increases the likelihood of technology avoidance.

Additionally, risk society theory posits that under high uncertainty, some individuals adopt a "better safe than sorry" attitude, leading to conservative or even resistant stances toward new technologies. However, the relatively small effect size of this path ($\beta = -0.154$) in the current study suggests that most members of the public are not dominated by excessive fear or avoidance.

Therefore, targeted risk education and strategic communication can play a crucial role in alleviating public over-sensitivity to risk, thereby promoting more rational and balanced technology adoption.

5.2 Policy Recommendations

Based on the findings from the path analysis, this study proposes three key policy recommendations:

First, enhance technological transparency and explainability. Enterprises should be encouraged to develop explainable artificial intelligence (XAI) systems, disclosing the basic principles, decision-making logic, and risk control mechanisms of algorithms without compromising commercial confidentiality. A government-led framework for algorithmic transparency standards should be established, incorporating third-party certification mechanisms to reduce uncertainty stemming from the "black-box" nature of AIGC technologies.

Second, strengthen institutional trust through multi-stakeholder collaborative governance. Governments should clarify the legal accountability boundaries of AIGC technologies, implement stringent safety and management standards, and foster governance platforms that involve enterprises, research institutions, industry associations, and public representatives. Such inclusive and authoritative institutional frameworks are essential to consolidating public trust.

Third, advance public education and cognitive-ecological interventions. Proactive monitoring of risk-related information and timely disinformation correction should be prioritized to prevent the amplification of negative perceptions. Additionally, platform algorithms should be optimized to reduce cognitive biases and mitigate the "information cocoon" effect. Nationwide public engagement initiatives such as AI literacy campaigns and interactive technology exhibitions should be implemented to guide the public toward a more rational understanding of technological risks. This would help cultivate a moderate level of risk sensitivity and a resilient trust attitude, ultimately promoting the responsible and rational adoption of AIGC technologies.

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Institutional Review Board Statement

This study received an exemption for ethical review from the Ethics Review Committee of the School of Economics, Jiangsu Normal University Kewen College (Approval Code: KW-E-2408A, dated November 25, 2023). The study strictly adhered to the principles of the Declaration of Helsinki, and the authors ensured the following: • Informed consent was obtained from all participants. • The purpose of the study was explained to participants. • Participants were fully informed about the study's goals. • All participant data were anonymized to ensure privacy and non-traceability. • Participants understood how their data would be used and voluntarily agreed to participate.

Informed Consent Statement

This study obtained written informed consent from all participants. The investigators explained the purpose and scope of the data collection. Data for this empirical study were generated through a questionnaire survey, which all respondents were required to complete. Participation was entirely voluntary. The research background, objectives, planned activities, potential benefits and outcomes of the study, as well as any foreseeable risks, discomfort, or inconveniences, and the confidentiality of recorded information, were clearly explained to the participants.

Participants were informed that they could withdraw from the survey at any time. Before participating, all individuals were fully briefed on the purpose of the study and assured that their data would remain anonymous. Participation was voluntary, and no compensation was provided to participants for their involvement in the study.

Data Availability Statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Statements and Declarations

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Author Contributions

Both authors have contributed equally to the development of this manuscript.

About the Authors

Manman Wei
School of Economics / Jiangsu Normal University Kewen College, Xuzhou, China
Zhiming Song
School of Economics / Jiangsu Normal University Kewen College, Xuzhou, China

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