The Impact of Artificial Intelligence Development on the Digital Transformation of Catering Food Safety

Fengning Zhang

Xi'an Polytechnic University, Xi'an 710048, Shaanxi, P. R. China

13855582220@163.com

Abstract. Ensuring catering food safety is central to the national public-safety system and livelihood protection. Digital transformation is a necessary approach to address structural weaknesses in traditional governance, and artificial intelligence (AI), as a core technology of the new technological revolution, is a key driver. Building on technology enablement theory and integrating path dependence theory and the resource-based view, this study proposes an integrated framework of "core perception–multidimensional transformation–boundary moderation." Using 517 valid nationwide survey responses from stakeholders related to catering food safety, structural equation modeling (SEM) and hierarchical regression are applied to test the effects and mechanisms of stakeholders' core perception of AI development on digital transformation. Results show that core perception significantly and positively promotes digital transformation across relationship building, system performance, and social recognition. Traditional-mode cognition, perceived policy/regulatory constraints, and perceived opportunity costs significantly and negatively moderate these relationships: stronger path dependence, higher perceived compliance risk and institutional uncertainty, and higher perceived opportunity costs weaken AI's enabling effects. This study clarifies the key dimensions of digital transformation in catering food safety and identifies heterogeneous transmission mechanisms and boundary conditions, providing empirical evidence for policy optimization and implementation.

Keywords: artificial intelligence; catering food safety; digital transformation; technology enablement; moderating effects.

1 Introduction

Catering food safety is a core element of national public safety, directly affecting public health and life, and constitutes a fundamental baseline for livelihood protection and high-quality development of the catering industry. In recent years, China's catering sector has expanded rapidly, yet the mismatch between market growth and the capacity of food-safety governance has become more pronounced. The sector's complex supply chains and highly fragmented operators create persistent governance constraints, including severe information barriers, limited traceability precision, delayed risk warnings, and insufficient multi-actor coordination. These constraints are increasingly

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incompatible with modern food-safety governance, making digital transformation necessary to achieve a systemic improvement in governance capability.

Iterative advances in digital technologies provide critical support for shifting governance paradigms. Digital transformation of catering food safety has become an essential pathway to overcome traditional bottlenecks and establish collaborative governance involving multiple actors. As a key technology of the new technological revolution, AI has advantages in multi-source data mining, intelligent risk warning, end-to-end traceability, and automated remote supervision. AI is penetrating procurement, processing, service, and regulation across the full governance process and has become a key antecedent of digital transformation.

In practice, AI application in China's catering sector has moved from pilot exploration to scaled diffusion, with continued deepening of scenarios such as "transparent kitchens" intelligent supervision, full-chain intelligent ingredient traceability, and AI-based food-safety risk warnings. However, a persistent blockage remains between "technology perception" and "implementation": stakeholders differ in AI value perception and adoption decisions, while path dependence on traditional modes, regulatory-fit constraints, and opportunity-cost considerations constrain the realized enabling effect of AI.

Although prior studies recognize AI's enabling role in food-safety governance, limitations remain: existing research is often descriptive and lacks an integrated framework clarifying the core dimensions and internal mechanisms through which AI development drives digital transformation in catering food safety; research focuses on direct effects but pays insufficient attention to multidimensional transmission paths and boundary conditions, especially the moderating roles of traditional-mode cognition, policy/regulation, and opportunity costs; and large-sample quantitative evidence remains limited, reducing robustness and generalizability.

Accordingly, this study develops an integrated "core perception–multidimensional transformation–boundary moderation" framework based on technology enablement theory, path dependence theory, and the resource-based view. It examines the main effects of core perception on three dimensions of digital transformation (relationship building, system performance, and social recognition), and tests the moderating effects of traditional-mode cognition, policy/regulation, and opportunity costs to identify boundary conditions for AI-driven transformation.

2 Literature Review

2.1 Technology Enablement and Digital Transformation

Technology enablement theory explains how digital technology drives organizational change. Perceived technology value is a prerequisite for converting potential enablement into realized outcomes. Prior studies indicate that digital technology enables innovation mainly through data-driven decision optimization, process automation, and enhanced organizational flexibility. Qi et al. (2020)(Qi Yudong & Xiao Xu)[1] discuss management transformation in the digital economy, emphasizing user-value orientation and substitution-based competition as key drivers of networked and flattened structures and more precise marketing.

In digital innovation management, Liu et al. (2020)(Liu Yang et al., 2020)[2] synthesize international research and propose a framework organized around “innovation support–innovation process–innovation output,” providing a systematic perspective on how digital technology reshapes innovation. He and Liu (2019)(HE Fan & LIU Hongxia, 2019)[3] show that digital transformation improves operational efficiency and market competitiveness. Chen et al. (2020)(Chen Jian et al., 2020)[4] further discuss transformation paths in digital environments through the dual logics of “empowerment” and “enablement.”

2.2 Digital Governance of Food Safety

Digital transformation in food-safety governance has become a major topic. Existing research discusses practical models, mechanisms, and constraints. Yan and Yu (2022)(Yan Haina, & Yu Jing, 2022)[5], using qualitative analysis of 243 cases, show that digital technologies reduce regulatory information barriers and improve responsiveness. Lin and Lu (2025)(Lin Xin, & Lu Qianqian, 2025)[6] argue that traditional regulation is poorly suited to the catering sector’s dispersed and complex formats, making digital transformation a necessary choice.

At the application level, existing studies (Chang et al., 2025(CHANG Kuan et al., 2025)[7]; Guo, 2026(Guo Yu, 2026)[8]; Jin, 2025(Jin Jianchang, 2025)[9]) show that AI covers the full chain from procurement and processing to consumption and regulation, creating value in intelligent detection, risk warning, and full-chain traceability. At the system-building level, Zhao (2024)(Zhao Zhongxue, 2024)[10] proposes a framework for smart food-safety regulation; Peng (2024)(Peng Shaojie, 2024)[11] clarifies policy logic and implementation paths; Zhou et al. (2026)(ZHOU Haonan et al., 2026)[12] explore standardization in digital regulation; Zuo et al. (2024)(ZUO Min et al., 2024)[13] review the development of “smart + food regulation” and future directions. Pan and Huang (2023)(Pan Na & Huang Wanyi, 2023)[14] provide evidence that technology acceptance and public trust shape participation in traceability systems, supporting the “social recognition” dimension. Ding (2025)(Ding Liping, 2025)[15] proposes principles and key points for constructing digital food-safety management systems

2.3 Path Dependence and Organizational Change

Path dependence theory explains resistance in digital transformation. Long-established routines and traditional management modes can generate lock-in effects that obstruct technological change and model transformation. Lin and Li (2012)(LIN Zhi-yang & LI Hai-dong, 2012)[16] show that routines, institutions, and cognitive patterns constrain structural change, which helps explain behavioral inertia among governance actors. Xiong et al. (2025)(Xiong Zhengde et al., 2025)[17] further find that economic policy uncertainty strengthens path dependence and leads to conservative transformation decisions.

2.4 Resource-Based View and Opportunity Costs

The resource-based view provides a baseline framework for digital transformation decisions. Zhang et al. (2023)(Zhang Lu et al., 2023)[18] emphasize that sustainable advantage stems from heterogeneous resources that are valuable, rare, inimitable, and organizationally embedded. Because resources are scarce, actors evaluate opportunity costs when allocating resources; higher opportunity costs result in more cautious investment decisions. This logic helps explain stakeholders' adoption behavior in catering food-safety digital transformation.

2.5 Summary

While the literature offers a solid foundation, gaps remain in integrated theory building for the catering food-safety context and in large-sample empirical testing. This study addresses these gaps by constructing and testing an integrated framework and providing quantitative evidence on both main and moderating effects.

3 Mechanism Analysis and Research Hypotheses

This study builds on technology enablement theory and integrates path dependence theory and the resource-based view. The independent variable is core perception of AI development, defined as stakeholders' overall perception and recognition of AI's core value, functional utility, and development prospects in catering food safety. The dependent variable is digital transformation of catering food safety, decomposed into relationship building, system performance, and social recognition. The moderators are traditional-mode comparison, policy and regulation perception, and opportunity cost perception.

3.1 Main Effects of Core Perception

Core Perception and Relationship Building.

Relationship building refers to digitally reducing information barriers among regulators, operators, consumers, and supply-chain actors, thereby reconstructing trust and coordination and forming collaborative governance. AI can enable full-process data capture, tamper-resistant records, and cross-actor sharing; facilitate a shift from "passive regulation" to "active compliance"; and improve transparency to reduce consumer–operator information asymmetry and strengthen public supervision.

H1: Core perception of AI development has a significant positive effect on relationship building in digital transformation of catering food safety.

Core Perception and System Performance.

System performance reflects digital management system capabilities, including response speed, traceability accuracy, risk-warning ability, and end-to-end control. AI can improve real-time processing of heterogeneous data, enhance full-chain precise traceability (e.g., via AI + blockchain), and enable learning-based risk-warning models that support a shift from ex-post disposal to ex-ante warning and in-process intervention.

H2: Core perception of AI development has a significant positive effect on system performance in digital transformation of catering food safety.

Core Perception and Social Recognition.

Social recognition reflects consumer acceptance, approval, and participation in digital governance. AI can increase transparency of governance processes and provide convenient participation channels for public supervision, improving acceptance and participation.

H3: Core perception of AI development has a significant positive effect on social recognition in digital transformation of catering food safety.

3.2 Moderating Effects (Boundary Conditions)

Moderation by Traditional-Mode Comparison.

Traditional-mode comparison captures stakeholders' comparative cognition between traditional and digital modes, reflecting identification with traditional management and path dependence. Stronger path dependence increases cognitive barriers and behavioral inertia and weakens the enabling effect of core perception on transformation.

H4: Traditional-mode comparison negatively moderates the relationship between core perception of AI development and digital transformation of catering food safety.

Moderation by Policy and Regulation Perception.

AI applications evolve rapidly and may not fully fit existing food-safety regulation, data security law, and personal information protection requirements. Higher perceived regulatory constraints increase perceived compliance risk, trial-and-error risk, and institutional uncertainty, thereby weakening transformation enabling effects.

H5: Policy and regulation perception negatively moderates the relationship between core perception of AI development and digital transformation of catering food safety.

Moderation by Opportunity Cost Perception.

Opportunity cost reflects perceived costs of forgoing alternative operational choices when investing limited financial, human, and organizational resources in AI and digital transformation. Higher perceived opportunity costs strengthen short-term cost concerns and reduce transformation speed.

H6: Opportunity cost perception negatively moderates the relationship between core perception of AI development and digital transformation of catering food safety.

4 Research Design

4.1 Data Source and Sample Characteristics

Data were collected through an online survey. Respondents covered catering operators, food-safety regulators, supply-chain practitioners, and consumer representatives. A total of 517 questionnaires were collected; after screening, 517 valid responses remained (valid response rate: 100%), with no missing values. The sample distribution is shown in Table 1.

Table 1. Sample composition.

Category	Option	Frequency	Percentage (%)
Gender	Male	271	52.42
	Female	246	47.58
Age group	0–20	42	8.12
	21–30	176	34.04
	31–40	186	35.98
	41–50	83	16.05
	51–60	19	3.68
	60+	11	2.13
Area of residence	Central urban area	80	15.47
	Urban–rural fringe	178	34.43
	New district/new town	176	34.04
	Rural area	83	16.05
Highest education	Primary school or below	16	3.09
	Junior high school	52	10.06
	Senior high/vocational/technical	39	7.54
	Associate degree	139	26.89
	Bachelor’s degree	249	48.16
	Above bachelor’s	22	4.26
Occupation	Student	21	4.06
	Enterprise employee	362	70.02
	Public institution employee	49	9.48
	Civil servant	51	9.86
	Freelancer	20	3.87
	Unemployed	6	1.16
	Other	8	1.55
Average monthly income (CNY)	Below 3,000	54	10.44
	3,000–5,000	91	17.60
	5,000–10,000	298	57.64
	Above 10,000	74	14.31
Total		517	100.0

4.2 Measurement of Variables

To ensure reliability and validity, measurement items were adapted from established scales and adjusted to the Chinese context of AI development and catering food-safety digital transformation. The “AI development” scale referenced Su (2023)(Xiaoyang Su, 2023)[19] on AI’s impact on food-safety regulation, and the “digital transformation of catering food safety” scale referenced Dai (2020)(Dai Chan, 2020)[20]. All variables were measured using a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

- Independent variable: Core perception of AI development (5 items; A1–A5).
- Dependent variable: Digital transformation (three dimensions): relationship building (5 items; B1–B5), system performance (5 items; C1–C5), social recognition (3 items; D1–D3).
- Moderators: Traditional-mode comparison (5 items; E1–E5), policy and regulation (4 items; F1–F4), opportunity cost (4 items; G1–G4).

4.3 Analytical Methods

SPSSAU 26.0 was used. Descriptive statistics and frequency analyses summarized the sample and variables. Cronbach’s alpha tested reliability. Exploratory factor analysis (EFA) assessed construct validity using KMO, Bartlett’s test, factor loadings, and explained variance. Pearson correlations examined associations among variables. Hierarchical regression tested moderating effects (with mean-centering and simple slope analysis). SEM tested main-effect paths and overall model fit using multiple fit indices.

5 Empirical Findings

5.1 Common Method Bias

Given self-reported survey data, procedural controls (e.g., randomized item order and reverse-coded items) were used. Harman’s single-factor test was conducted: the first unrotated factor explained 56.105% of variance (below the 70% threshold), and multiple factors with eigenvalues > 1 emerged, indicating no severe common method bias.

5.2 Descriptive Statistics and Correlation Analysis

Table 2 reports descriptive statistics and Pearson correlations. All variables had N = 517, min = 1.000, max = 5.000, with no anomalies. Means were above 3.4 and medians were 4, indicating relatively high agreement with AI development and digital transformation items. Standard deviations were within a reasonable range.

Table 2. Pearson correlation matrix of key variables.

Variable	Mean	SD	1	2	3	4	5	6	7
1. Core perception	3.615	1.219	1						

Variable	Mean	SD	1	2	3	4	5	6	7
2. Relationship building	3.501	1.235	0.757**	1					
3. System performance	3.528	1.227	0.789**	0.609**	1				
4. Social recognition	3.514	1.247	0.739**	0.632**	0.623**	1			
5. Traditional-mode comparison	3.517	1.229	0.893**	0.715**	0.791**	0.817**	1		
6. Policy and regulation	3.489	1.266	0.864**	0.715**	0.791**	0.817**	0.749**	1	
7. Opportunity cost	3.500	1.263	0.834**	0.715**	0.791**	0.817**	0.749**	0.735**	1

Note: $p < 0.01$ (two-tailed).

Correlations indicate that core perception is significantly and positively related to the three transformation dimensions (supporting H1–H3 preliminarily). The three transformation dimensions are also significantly positively correlated. Correlations are below 0.9, suggesting no severe multicollinearity.

5.3 Reliability and Validity Tests

Reliability.

This study used Cronbach's alpha (α) coefficient to assess the reliability of the scale, and the test results are shown in Table 3. Cronbach's alpha values for all variables exceed 0.8; CITC values exceed 0.4; and deleting any item does not substantially increase alpha, indicating strong internal consistency.

Table 3. Reliability test results.

Variable	No. of items	Cronbach's α	CITC range	α if item deleted (range)
Core perception	5	0.923	0.742–0.922	0.882–0.917
Relationship building	5	0.918	0.758–0.815	0.894–0.906
System performance	5	0.919	0.760–0.814	0.897–0.908
Social recognition	3	0.871	0.752–0.756	0.816–0.820
Traditional-mode comparison	5	0.908	0.741–0.814	0.878–0.893
Policy and regulation	4	0.893	0.737–0.816	0.843–0.872
Opportunity cost	4	0.891	0.733–0.782	0.850–0.869

Validity.

EFA results show KMO = 0.979 and Bartlett's test $p < 0.001$, supporting factorability. Seven factors with eigenvalues > 1 were extracted, matching the seven constructs, with cumulative explained variance of 76.305%. Loadings exceed 0.6 with no serious cross-loadings; communalities exceed 0.4. Overall, convergent and discriminant validity are acceptable.

5.4 Main-Effect Test (SEM)

SEM was used to test main effects and model fit. Fit indices meet conventional thresholds (Table 4), indicating good overall fit.

Table 4. Overall SEM fit indices.

Fit index	χ^2	df	p	χ^2/df	GFI	AGFI	RMR	RMSEA	CFI	NFI	NNFI	TLI	IFI	SRMR
Value	432.264	419	0.317	1.032	0.950	0.941	0.030	0.008	0.999	0.969	0.999	0.999	0.999	0.020
Criterion	–	–	>0.05	<3	>0.9	>0.9	<0.05	<0.10	>0.9	>0.9	>0.9	>0.9	>0.9	<0.1
Assessment	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable	Acceptable

Path estimates (Table 5) show significant positive effects of core perception on all three dimensions, supporting H1–H3.

Table 5. Main-effect path coefficients.

Independent variable	→ Dependent variable	Unstandardized	SE	z	p	Standardized β	Result
Core perception	→ Relationship building	0.638	0.111	5.727	0.000**	0.715	H1 supported
Core perception	→ System performance	0.687	0.103	6.700	0.000**	0.791	H2 supported
Core perception	→ Social recognition	0.741	0.121	6.143	0.000**	0.817	H3 supported

Note: $p < 0.01$.

5.5 Moderation Tests (Hierarchical Regression)

All predictors and moderators were mean-centered. Three-step hierarchical regression was used: Model 1 included core perception; Model 2 added the moderator; Model 3 added the interaction term. Significant interactions indicate moderation; simple slope analyses (figures referenced) further illustrate patterns.

Moderation by Traditional-Mode Comparison.

Results in Table 6 show a significant negative interaction ($B = -0.049$, $p = 0.008$), supporting H4. As traditional-mode comparison increases, the positive effect of core perception on digital transformation weakens.

Table 6. Moderation test: Traditional-mode comparison.

Variable	Model 1		Model 2		Model 3	
	B	t	B	t	B	t
Constant	3.515***	181.576	3.515***	185.453	3.559***	140.477
Core perception	0.775***	42.640	0.651***	20.821	0.624***	19.127
Traditional-mode comparison			0.153***	4.819	0.146***	4.630
Core perception × Traditional-mode comparison					-0.049**	-2.642
R^2	0.779		0.789		0.792	
Adjusted R^2	0.779		0.788		0.790	

Variable	Model 1	Model 2	Model 3
F	1818.197***	959.948***	649.741***
$\triangle R^2$	0.779	0.010	0.003
$\triangle F$	1818.197***	23.227***	6.982**

Note: p < 0.01, *p < 0.001

The results of the simple slope analysis further confirm that, as the perceived level of policy and regulatory frameworks increases, the positive driving effect of core perception on digital transformation gradually weakens.

Moderation by Policy and Regulation.

Table 7 shows a significant negative interaction (B = −0.059, p < 0.001), supporting H5. Higher perceived regulatory constraints weaken the positive effect of core perception.

Table 7. Moderation test: Policy and regulation.

Variable	Model 1		Model 2		Model 3	
	B	t	B	t	B	t
Constant	3.515***	181.576	3.515***	186.675	3.569***	146.873
Core perception	0.775***	42.640	0.648***	22.310	0.610***	19.929
Policy and regulation			0.155***	5.507	0.152***	5.457
Core perception × Policy and regulation					-0.059***	-3.503
R^2	0.779		0.792		0.796	
Adjusted R^2	0.779		0.791		0.795	
F	1818.197***		976.031***		669.051***	
$\triangle R^2$	0.779		0.012		0.005	
$\triangle F$	1818.197***		30.327***		12.274***	

Note: *p < 0.001.

The results of the simple slope analysis further confirm that, as the perceived level of policy and regulatory frameworks increases, the positive driving effect of core perception on digital transformation gradually weakens.

Moderation by Opportunity Cost.

Table 8 shows a significant negative interaction (B = −0.071, p < 0.001), supporting H6. Higher perceived opportunity costs weaken the positive effect of core perception.

Table 8. Moderation test: Opportunity cost.

Variable	Model 1		Model 2		Model 3	
	B	t	B	t	B	t
Constant	3.515***	181.576	3.515***	183.378	3.577***	148.128
Core perception	0.775***	42.640	0.704***	25.536	0.663***	22.946
Opportunity cost			0.091**	3.357	0.089**	3.347

Variable	Model 1	Model 2	Model 3
Core perception × Opportunity cost			-0.071*** 4.146
R^2	0.779	0.784	0.791
Adjusted R^2	0.779	0.783	0.790
F	1818.197***	932.860***	647.230***
$\triangle R^2$	0.779	0.005	0.007
$\triangle F$	1818.197***	11.269**	17.193***

Note: p < 0.01, *p < 0.001.

The results of the simple slope analysis further confirm that, as the per-ceived level of opportunity costs increases, the positive driving effect of core perception on digital transformation gradually weakens.

5.6 Robustness Test

As a robustness check, the three digital-transformation dimensions were averaged to form a composite score and the hierarchical regressions were re-estimated. Main and moderating effects remained consistent. Re-estimated SEM results also showed unchanged signs and significance, with fit indices remaining within acceptable ranges, indicating robust findings.

6 Conclusions and Policy Implications

6.1 Conclusions

1. Core perception of AI development significantly and positively promotes digital transformation of catering food safety, including relationship building, system performance, and social recognition.
2. Traditional-mode cognition (path dependence) negatively moderates the core perception–transformation relationship; stronger path dependence weakens the enabling effect.
3. Perceived policy/regulatory constraints negatively moderate the relation-ship; higher perceived rigidity, compliance risk, and institutional uncertainty reduce the enabling effect.
4. Perceived opportunity costs negatively moderate the relationship; stronger opportunity-cost concerns weaken the translation of perceived technology value into transformation behavior.

6.2 Policy Recommendations

1. Strengthen the full-chain communication of AI value through standardized demonstrations and targeted capability-building programs to raise stakeholders' core perception and reduce cognitive biases.

2. Reduce path dependence by digitally re-engineering processes across procurement, processing, service, and supervision, and by establishing incentive and accountability mechanisms that incorporate transformation performance into evaluations.
3. Develop adaptive policy and regulatory systems that clarify compliance boundaries, data-security standards, responsibilities, and risk controls, while reserving appropriate space for scenario innovation under a strict food-safety baseline.
4. Optimize resource-allocation mechanisms to reduce opportunity-cost constraints by increasing public investment in digital infrastructure and providing low-cost, lightweight (e.g., SaaS-based) solutions for SMEs and grassroots regulators, complemented by subsidies, tax incentives, and financing support.
5. Improve multi-actor collaborative governance by enabling cross-actor data sharing (e.g., AI + blockchain), shifting regulator–operator relations toward active compliance and constructive interaction, and enhancing digital public-participation channels for information access, complaints, and oversight.

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