

Article

From TOE Readiness to Firm Performance: A Staged Capability Transformation Model of AI Adoption in Mainland China's Tourism SMEs

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Highlights

What are the main findings?

- Organizational readiness is the most consistent readiness-related antecedent of digital self-efficacy and AI adoption.
- Digital self-efficacy, AI adoption, and operational capability form a staged pathway associated with perceived firm performance.

What are the implications of the main findings?

- Tourism SMEs should treat AI adoption as a capability-conversion process rather than a stand-alone technology investment.
- Managers should strengthen organizational support, employee confidence, and operational routines to convert AI readiness into performance-related outcomes.

Abstract

Artificial intelligence (AI) is reshaping tourism service operations, smart tourism ecosystems, and digital customer engagement, yet many tourism SMEs still struggle to convert AI readiness into operational capability and firm performance. This study develops a staged capability-conversion model that integrates the Technology-Organization-Environment (TOE) framework, Social Cognitive Theory, the Resource-Based View, and Dynamic Capabilities Theory. Using a quantitative cross-sectional design, data were collected from employees and managers of tourism SMEs, particularly small and medium-sized travel agencies in mainland China. After data screening, 433 valid responses were analyzed using exploratory factor analysis, confirmatory factor analysis, covariance-based structural equation modeling, and 5000-resample bootstrap mediation testing. The results suggest that organizational readiness is the most consistent readiness-related antecedent, digital self-efficacy is positively associated with AI adoption and operational capability, and operational capability shows the strongest direct association with perceived firm performance. These findings are consistent with the view that AI-enabled value in tourism SMEs is associated less with technology adoption alone than with the conversion of readiness into behavioral and operational capabilities.

Keywords: artificial intelligence adoption; tourism SMEs; TOE framework; digital self-efficacy; operational capability; firm performance; China; structural equation modeling



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1. Introduction

Artificial intelligence (AI), smart tourism technologies, digital platforms, and intelligent automation are rapidly transforming tourism service ecosystems, customer engagement, operational coordination, and adaptive decision-making (Garcia-Madurga & Grillo-Mendez, 2023; Majid et al., 2023; Rather, 2025). Recent tourism and digital innovation studies increasingly treat AI not as an isolated tool but as part of wider digital transformation, smart tourism governance, platform-based service innovation, and intelligent servicescapes (Nambisan et al., 2017; Liu et al., 2024; Yin et al., 2023). In mainland China, smart tourism policies, digital travel ecosystems, mobile-platform competition, and post-pandemic restructuring have intensified pressure on tourism SMEs, particularly small and medium-sized travel agencies, to adopt AI despite limited human, financial, and technological resources (OECD, 2024; Tang, 2024).

Despite growing AI adoption, three gaps remain important. Theoretically, Technology-Organization-Environment (TOE) research has explained adoption and innovation assimilation more often than post-adoption value conversion. Empirically, tourism AI studies have examined smart services, automation, and customer-facing applications, but fewer studies explain how readiness conditions become operational capability and firm performance in resource-constrained tourism SMEs. Contextually, mainland China's small and medium-sized travel agencies operate under platform competition, policy-driven digitalization, and uneven access to specialized AI talent, making AI adoption a capability-building problem rather than only a technology-investment decision.

To address these gaps, this study aims to explain how readiness conditions are converted into perceived firm performance through behavioral, technological, and operational mechanisms. It develops a staged capability-conversion model integrating the TOE framework, Social Cognitive Theory, the Resource-Based View (RBV), and Dynamic Capabilities Theory. The model treats technology, organizational, and environmental readiness as structural antecedents; digital self-efficacy as the behavioral mechanism through which employees enact AI-related work; AI adoption as the technological assimilation stage; and operational capability as the organizational mechanism linking AI use with perceived firm performance.

Accordingly, this study addresses four research questions: (RQ1) How are technology, organizational, and environmental readiness associated with digital self-efficacy and AI adoption? (RQ2) How are digital self-efficacy and AI adoption associated with operational capability? (RQ3) How are AI adoption and operational capability associated with perceived firm performance? (RQ4) How do digital self-efficacy, AI adoption, and operational capability mediate the relationships between readiness conditions and performance outcomes?

The study contributes to the literature in three ways. First, it extends TOE research from adoption prediction to post-adoption capability conversion. Second, it links firm-level readiness conditions with employee-level digital self-efficacy and capability-based operational routines. Third, it provides empirical evidence from mainland China's tourism SMEs, where organizational support, employee confidence, and operational embedding appear more decisive than technology availability alone.

2. Theoretical Background and Hypotheses

2.1. Theoretical Integration and Conceptual Framework

The proposed model is built on four complementary theoretical perspectives. The TOE framework explains how technological, organizational, and environmental conditions shape organizational readiness for innovation. However, TOE alone is less able to explain

how readiness becomes employee confidence, operational routines, and performance outcomes after adoption.

Social Cognitive Theory adds the behavioral mechanism by emphasizing digital self-efficacy. In tourism SMEs, employees need confidence to learn, interpret, and apply AI-supported systems in service work. This micro-level mechanism explains why similar readiness conditions may produce different adoption and capability outcomes across firms.

The Resource-Based View and Dynamic Capabilities Theory explain the organizational value-conversion stage. AI-related infrastructure and adopted systems can be valuable resources, but value is realized only when firms integrate them into adaptive routines, coordination processes, customer-service workflows, co-creation, service innovation, and operational learning (Bhat & Sharma, 2022). Operational capability therefore functions as the conversion mechanism between AI use and perceived firm performance.

This integration supports a staged model in which readiness conditions provide structural support, digital self-efficacy enables behavioral enactment, AI adoption represents technological assimilation, and operational capability converts AI use into performance-related outcomes.

As shown in Figure 1, the proposed framework explains AI-enabled firm performance through a staged capability-conversion mechanism within tourism SMEs, particularly small and medium-sized travel agencies in mainland China. The direct hypotheses (H1–H11) specify the structural relationships among readiness, Digital Self-Efficacy, AI Adoption, Operational Capability, and Firm Performance, whereas H12–H23 examine the indirect mechanisms linking these constructs.

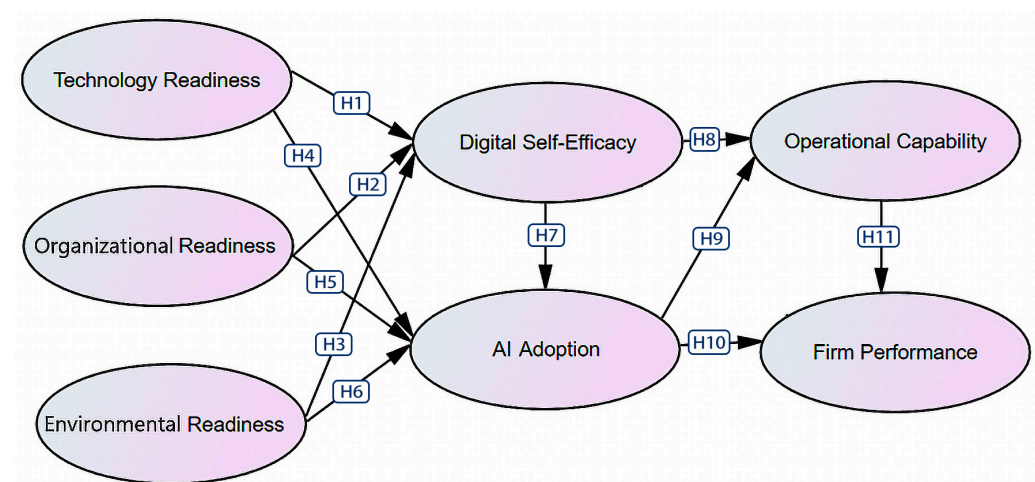


Figure 1. Conceptual research model with direct hypothesis numbers. H1–H11 represent the direct structural relationships. H12–H23 represent simple and sequential mediation hypotheses estimated through the connected direct structural paths rather than additional structural paths.

Technology Readiness, Organizational Readiness, and Environmental Readiness represent the contextual readiness conditions for AI implementation. Digital Self-Efficacy reflects employees' confidence in using AI-related technologies, AI Adoption represents technological assimilation, and Operational Capability captures the organizational routines through which AI use is embedded into daily operations. Collectively, the framework suggests that perceived Firm Performance is associated with the integration of organizational readiness, employee capability, technological assimilation, and operational capability rather than technology availability alone.

Research Hypotheses

The hypotheses are organized around four linked mechanisms. First, TOE readiness conditions are expected to shape digital self-efficacy and AI adoption, because technological, organizational, and environmental conditions influence whether tourism SMEs can prepare employees and systems for AI-enabled work (H1–H7).

Second, digital self-efficacy is expected to support both AI adoption and operational capability, while AI adoption is expected to enhance operational capability and firm performance (H8–H11). These hypotheses reflect the view that employee confidence and technology use must be translated into practical routines before they generate value.

Third, digital self-efficacy, AI adoption, and operational capability are proposed as mediating mechanisms that connect readiness conditions with operational and performance outcomes (H12–H20). Finally, the model tests longer sequential mediation paths linking TOE readiness to firm performance through digital self-efficacy, AI adoption, and operational capability (H21–H23). The full hypothesis numbering is retained in the results tables for traceability.

2.2. TOE Readiness and AI Adoption

The Technology–Organization–Environment (TOE) framework explains organizational technology adoption through technological conditions, organizational capability, and environmental pressure (Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990). Technology Readiness reflects digital infrastructure and system compatibility, Organizational Readiness captures leadership support and internal resources, while Environmental Readiness represents competitive pressure, institutional influence, and industry digitalization dynamics (Zhu et al., 2006). Recent tourism studies increasingly recognize that AI and smart tourism technologies are becoming central to operational adaptation, customer engagement, and digital service coordination within tourism ecosystems (Garcia-Madurga & Grillo-Mendez, 2023; Nannelli et al., 2023).

However, prior TOE research has primarily emphasized adoption intention and technological assimilation while providing limited explanation of how readiness conditions are linked to operational capability and organizational value after adoption occurs (Oliveira & Martins, 2011). Existing digital transformation literature further suggests that firms with similar technological resources may experience different outcomes because organizational support, employee capability, and operational integration shape technology utilization differently across firms (Vial, 2019; Vanpetch & Sattayathamrongthian, 2024). Consequently, TOE readiness should be viewed not merely as a predictor of AI adoption, but as a structural foundation that may help firms operationalize AI within adaptive tourism environments.

The direct readiness hypotheses are therefore developed separately. Technology Readiness is expected to support Digital Self-Efficacy by increasing exposure to compatible systems and technical resources (H1), and to support AI Adoption by reducing implementation barriers (H4). Organizational Readiness is expected to strengthen Digital Self-Efficacy through leadership support, training, and resource commitment (H2), and to facilitate AI Adoption through managerial commitment and internal readiness for change (H5). Environmental Readiness is expected to influence Digital Self-Efficacy through exposure to external digital ecosystems (H3), and to encourage AI Adoption through competitive pressure, institutional support, and industry digitalization (H6).

2.3. Digital Self-Efficacy

Social Cognitive Theory explains how organizational conditions are translated into practical behavior through individuals' capability beliefs (Bandura, 1997). Digital Self-Efficacy refers to employees' confidence in learning, utilizing, and adapting digital and

AI-related technologies within operational environments (Compeau & Higgins, 1995). In AI-enabled tourism systems, employees must interpret AI outputs, coordinate digital workflows, and integrate intelligent technologies into service delivery processes.

Existing digital transformation research increasingly recognizes that organizational adaptability depends not only on technological resources but also on employees' capability to adjust behaviors and operational processes in rapidly changing environments (Vanpetch & Sattayathamrongthian, 2024). Employees with stronger digital self-efficacy are therefore more likely to experiment with AI-supported systems, facilitate technology assimilation, and support operational adaptation within tourism SMEs. In contrast, firms with weak employee digital confidence may adopt technology only superficially. Digital Self-Efficacy therefore functions as an important behavioral mechanism linking organizational readiness to practical AI use.

On this basis, Digital Self-Efficacy is expected to promote AI Adoption because confident employees are more willing to experiment with AI-supported systems and translate perceived usefulness into work practices (H7). It is also expected to strengthen Operational Capability because confident employees can integrate digital tools into routines, coordination, and problem solving (H8). In mediation terms, Digital Self-Efficacy is expected to transmit the effects of Technology Readiness, Organizational Readiness, and Environmental Readiness to AI Adoption (H12–H14).

2.4. AI Adoption, Operational Capability, and Firm Performance

The Resource-Based View (RBV) and Dynamic Capabilities Theory explain why AI adoption alone may not directly improve firm performance (Barney, 1991; Teece, 2007). Although AI technologies may function as strategic resources, organizational value depends on firms' ability to integrate these technologies into operational routines, adaptive processes, and organizational learning systems. Recent digital transformation research consistently emphasizes that technological value is realized through capability development and operational integration rather than technology acquisition alone (Mikalef et al., 2020; Vial, 2019).

In tourism SMEs, AI adoption can support personalization, customer analytics, intelligent coordination, and service automation, yet performance improvement depends largely on firms' capability to operationally embed these technologies into service processes (Yin et al., 2023; Ku & Chen, 2024). Prior tourism research further suggests that technological readiness and implementation capability often vary across local operational environments, influencing the effectiveness of tourism service delivery (Sattayathamrongthian & Vanpetch, 2025). Consequently, Operational Capability acts as a critical conversion mechanism linking AI utilization to perceived Firm Performance, particularly in SMEs where resource limitations frequently constrain digital transformation processes.

The capability-conversion hypotheses follow from this logic. AI Adoption is expected to strengthen Operational Capability by enabling automation, analytics, service coordination, co-creation, and service innovation (H9), and to be associated with Firm Performance through improved service responsiveness and decision support (H10). This logic is consistent with hospitality research showing that technological innovation contributes to service innovation, co-creation, and firm performance when it is embedded in service processes (Bhat & Sharma, 2022). Operational Capability is expected to show a direct positive association with Firm Performance because routines and adaptive processes are the immediate mechanisms through which AI-enabled work becomes organizational value (H11). The mediation hypotheses then test whether Digital Self-Efficacy, AI Adoption, and Operational Capability transmit readiness effects to operational and performance outcomes through simple and sequential paths (H15–H23).

2.5. Literature Gap and Study Contributions

Several important gaps remain insufficiently addressed in existing literature. Theoretically, TOE studies primarily explain adoption intention and technological assimilation while providing limited explanation of post-adoption capability transformation and organizational value realization (Oliveira & Martins, 2011). Empirically, tourism AI research increasingly examines smart tourism systems and service automation, yet relatively fewer studies investigate how readiness conditions are transformed into operational capability and firm performance within tourism SMEs (Garcia-Madurga & Grillo-Mendez, 2023).

Contextually, tourism SMEs, particularly small and medium-sized travel agencies in mainland China, face digitalization pressure under conditions that differ from many larger or more resource-rich firms. Their operations are often shaped by platform-based distribution, price competition, seasonal demand, post-pandemic recovery pressures, and limited access to specialized digital talent. These conditions make AI adoption a practical operational problem, not only a technology-investment decision. Methodologically, prior studies frequently examine direct relationships independently rather than integrating structural readiness, behavioral mechanisms, operational capability, and organizational performance within a unified framework. More integrated SEM-based evidence is therefore needed to explain how tourism SMEs convert TOE readiness into operational capability and perceived organizational value within AI-enabled tourism ecosystems.

By addressing these gaps, this study contributes a process-oriented explanation of AI value creation in tourism SMEs. It clarifies why organizational readiness may be more important than technology readiness in resource-constrained firms, why employee digital self-efficacy matters for AI-enabled operational change, and why operational capability is central to converting AI adoption into perceived performance.

3. Materials and Methods

This study employed a quantitative cross-sectional research design grounded in the post-positivist paradigm. The quantitative approach is appropriate because the study examines theory-driven relationships among multiple latent constructs related to AI readiness, digital self-efficacy, operational capability, AI adoption, and firm performance using structural equation modeling (SEM) (Kline, 2023). The target population consisted of employees, managers, supervisors, and operational staff working in small and medium-sized travel agencies and tourism SMEs in mainland China.

A non-probability sampling approach combining purposive, convenience, and snow-ball sampling was employed. Respondents were eligible if they were adult employees, managers, supervisors, or operational staff working in tourism SMEs or small and medium-sized travel agencies in mainland China and had sufficient familiarity with tourism operations and AI- or digital-technology-related work practices. This approach was appropriate because the study targeted geographically dispersed tourism SMEs without access to a centralized sampling frame. Although non-probability sampling may reduce statistical generalizability, it remains widely accepted in exploratory organizational and SME research contexts (Etikan et al., 2016).

Data were collected during April 2026 using a structured questionnaire adapted from previously validated measurement scales and contextualized for tourism SME and AI adoption environments. The questionnaire used five-point Likert-scale items ranging from strongly disagree to strongly agree and was distributed through mixed online and offline channels. Before full data collection, a small pilot test was conducted with respondents from the target population to check clarity, item comprehension, and questionnaire flow. Procedural remedies for common method bias included voluntary participation, informed consent, anonymity, neutral wording, and separation of construct sections (Podsakoff et al.,

2003). A total of 480 responses were initially collected. The screening process removed 24 straight-lining or low-quality responses and 23 multivariate outliers identified across two pre-estimation Mahalanobis-distance screening checks before final CFA and SEM estimation, leaving 433 valid responses for analysis.

IBM SPSS Statistics 27.0 and IBM SPSS Amos 24.0 were employed for exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and covariance-based structural equation modeling (CB-SEM). Preliminary EFA was conducted before CFA to assess dimensionality and support theoretically guided item screening. Following the two-step SEM approach (Anderson & Gerbing, 1988), CFA assessed reliability, convergent validity, discriminant validity, and model fit, while SEM examined the proposed structural relationships and mediation effects (Kline, 2023; Hair et al., 2019). The final sample of 433 exceeded common minimum recommendations for CB-SEM and provided more than 20 responses per retained measurement indicator, supporting adequate estimation stability for the proposed model. Indirect and serial mediation effects were tested using a 5000-resample bootstrap procedure because bootstrap estimation is considered statistically robust for mediation and regression-based structural analysis (Hayes, 2022). Recent methodological research further emphasizes that robust estimation procedures improve the accuracy of standard error estimation and statistical inference in regression-based modeling (Gu et al., 2026).

Table 1 presents the measurement constructs and item classifications used in this study. The model includes seven latent constructs related to TOE readiness, digital self-efficacy, AI adoption, operational capability, and perceived firm performance. All constructs were measured using items adapted from established studies and contextualized for tourism SMEs, particularly small and medium-sized travel agency operations in mainland China.

Table 1. Measurement scales and variables.

Construct	Items	Measurement Focus	Source Basis
Technology Readiness (TR)	TR1–TR8	Digital infrastructure, system compatibility, data availability, IT integration, and technical support for AI implementation.	TOE readiness and e-business assimilation literature (Oliveira & Martins, 2011; Zhu et al., 2006; Tornatzky & Fleischer, 1990).
Organizational Readiness (OR)	OR1–OR8	Leadership support, resource commitment, digital strategy, training, and organizational willingness to support AI use.	Organizational readiness and change readiness literature (Vial, 2019; Weiner, 2009).
Environmental Readiness (ER)	ER1–ER8	Competitive pressure, customer expectations, institutional support, partner ecosystems, and external digital infrastructure.	TOE environmental context and innovation ecosystem literature (Zhu et al., 2006; Tornatzky & Fleischer, 1990).
Digital Self-Efficacy (DSE)	DSE1–DSE8	Employees' confidence in learning, using, troubleshooting, and integrating digital and AI-related tools into work tasks.	Computer self-efficacy and social cognitive theory (Compeau & Higgins, 1995; Bandura, 1997).
AI Adoption (AIA)	AIA1–AIA8	Extent of AI use in customer service, itinerary planning, marketing, analytics, operations, and managerial decision support.	AI adoption, digital transformation, and tourism technology literature (Nannelli et al., 2023; Ku & Chen, 2024; Dwivedi et al., 2021).

Table 1. Cont.

Construct	Items	Measurement Focus	Source Basis
Operational Capability (OC)	OC1–OC8	Ability to execute, coordinate, improve, and reconfigure operational processes through AI-supported routines.	Operational capability, RBV, and dynamic capabilities literature (Mikalef et al., 2020; Barney, 1991; Teece, 2007).
Firm Performance (FP)	FP1–FP8	Perceived improvement in service quality, productivity, responsiveness, competitiveness, customer outcomes, and business performance.	Firm performance and digital capability literature (Mikalef et al., 2020; Venkatesh et al., 2012).

4. Results

4.1. Data Screening and Preliminary Analysis

Data screening and preliminary analysis were conducted prior to hypothesis testing to ensure the accuracy, reliability, and suitability of the dataset for structural equation modeling (SEM). Preliminary screening procedures are essential in SEM research because inaccurate, inconsistent, or non-normal data may distort parameter estimation and reduce model validity (Kline, 2023). The screening process included the assessment of missing values, straight-lining behavior, outliers, normality, multicollinearity, and common method bias.

For the online questionnaire, forced-response settings were used to minimize missing responses. Offline questionnaires were manually checked before data entry, and incomplete or invalid responses were excluded during the screening process. As a result, no missing values were retained in the final dataset. Straight-lining behavior and low-quality responses were examined through response-pattern analysis and subsequently removed prior to statistical analysis. Univariate outliers were assessed using standardized z-scores following the recommended threshold of ± 3.29 , while multivariate outliers were evaluated using Mahalanobis distance (Tabachnick & Fidell, 2019). Normality was assessed using skewness and kurtosis statistics, with results indicating acceptable distributional properties for SEM estimation.

Multicollinearity was examined using correlation coefficients and variance inflation factor (VIF) values. Correlations remained below the 0.90 threshold, construct-level VIF values ranged from 1.725 to 3.831, and full-collinearity VIF values ranged from 1.025 to 1.218, below the conservative 3.3 guideline for serious common-method-related collinearity. In addition, procedural remedies for common method bias included respondent anonymity, neutral wording, and separation of construct sections (Podsakoff et al., 2003). Harman's single-factor assessment showed that the first unrotated factor explained 15.06% of the total variance, below the commonly used 50% guideline. Overall, severe common method bias was not detected, although the cross-sectional and self-reported design is acknowledged as a limitation.

4.2. Descriptive Statistics of Study Variables

Descriptive statistical analysis was conducted to examine respondents' demographic characteristics and the distributional properties of the study variables prior to measurement and structural model evaluation. The analysis included frequency distributions, mean scores, standard deviations, skewness, and kurtosis values for Technology Readiness, Organizational Readiness, Environmental Readiness, Digital Self-Efficacy, AI Adoption, Operational Capability, and Firm Performance. Preliminary descriptive analysis is impor-

tant because it provides insight into respondents' perceptions, response patterns, and the suitability of the dataset for subsequent SEM procedures (Kline, 2023).

The demographic profile indicates that the sample was diverse and appropriate for the study context. Most respondents were female (59.8%), while 40.2% were male. Most respondents were between 20 and 39 years old (86.4%), representing the primary working-age population within tourism SMEs, particularly small and medium-sized travel agencies. In terms of educational background, most respondents possessed high school qualifications (67.0%), followed by diploma holders (14.1%), bachelor's degree holders (10.6%), and master's degree or higher qualifications (8.3%). This distribution reflects the practice-oriented and operational nature of tourism SME environments in mainland China.

Respondents were relatively well distributed across organizational positions, including operational staff (35.3%), middle management (34.9%), and senior management (29.8%). In addition, over 70% reported more than three years of work experience, indicating adequate professional exposure to tourism operations and digital work environments. Nearly half of the respondents reported moderate AI experience (48.5%), suggesting familiarity with AI-related technologies and digital operational systems. Most respondents were employed in small organizations (73.7%), consistent with the SME-dominated structure of China's tourism industry.

Overall, the descriptive statistics indicated moderate to high perceptions across most constructs. Skewness and kurtosis values remained within acceptable thresholds, supporting approximate normality and confirming the suitability of the dataset for EFA, CFA, and SEM analysis (Tabachnick & Fidell, 2019).

4.3. Summary of Exploratory Factor Analysis (EFA)

Preliminary EFA was conducted using the original measurement item pools to examine dimensionality and support theoretically guided item screening before CFA. Item retention was not based solely on statistical criteria. Instead, retained indicators were selected by jointly considering factor loadings, potential cross-loading and communality risk, item redundancy, theoretical relevance, and preservation of the conceptual domain represented by each construct. Items were removed only when their exclusion did not compromise the core conceptual meaning of the construct. The final three-indicator sets were subsequently evaluated through CFA-based reliability, convergent validity, discriminant validity, and overall model-fit evidence. Appendix A summarizes the item-refinement process from the original item pools to the final retained indicators.

Note. Preliminary exploratory factor analysis (EFA) was conducted before CFA to assess dimensionality and support preliminary item screening. All factor loadings exceeded the recommended threshold of 0.70, while communalities remained above 0.50, indicating adequate shared variance and construct reliability (Hair et al., 2019). Bartlett's test of sphericity was significant across all constructs ($p < 0.001$).

As summarized in Table 2, the exploratory factor analysis (EFA) results provide preliminary dimensionality and item-screening evidence across all study variables. KMO values ranged from 0.676 to 0.901, while Bartlett's test of sphericity was significant for all constructs ($p < 0.001$), confirming the suitability of the dataset for factor analysis. All retained constructs showed clear preliminary unidimensional structures with eigenvalues greater than 1 and variance explained exceeding the recommended threshold of 60%. Factor loadings and communalities also exceeded recommended criteria. Overall, the EFA results supported the appropriateness of the retained indicators for subsequent CFA and SEM analysis; final measurement validity was evaluated through the CFA-based reliability, AVE, CR, and HTMT results reported below.

Table 2. Summary of exploratory factor analysis (EFA) results and preliminary item screening.

Construct	Final Retained Items	KMO	Bartlett's Test Sig.	Eigenvalue	Variance Explained (%)	Factor Loading Range	Communality Range
Technology Readiness (TR)	TR2, TR5, TR8	0.689	0.000 ***	2.028	67.596	0.805–0.847	0.648–0.717
Organizational Readiness (OR)	OR2, OR6, OR8	0.676	0.000 ***	2.413	80.450	0.814–0.940	0.663–0.884
Environmental Readiness (ER)	ER2, ER6, ER8	0.715	0.000 ***	2.146	71.528	0.766–0.906	0.586–0.821
Digital Self-Efficacy (DSE)	DSE1, DSE3, DSE5	0.692	0.000 ***	2.079	69.294	0.796–0.870	0.633–0.757
AI Adoption (AIA)	AIA1, AIA2, AIA5	0.901	0.000 ***	2.399	79.967	0.813–0.949	0.661–0.901
Operational Capability (OC)	OC1, OC2, OC8	0.737	0.000 ***	2.173	72.432	0.795–0.897	0.632–0.804
Firm Performance (FP)	FP4, FP6, FP7	0.720	0.000 ***	2.459	81.969	0.876–0.927	0.767–0.859

Note. Preliminary exploratory factor analysis (EFA) was conducted before CFA to assess dimensionality and support preliminary item screening. All factor loadings exceeded the recommended threshold of 0.70, while communalities remained above 0.50, indicating adequate shared variance and construct reliability (Hair et al., 2019). Bartlett's test of sphericity was significant across all constructs (***) indicates $p < 0.001$.

4.4. Standardized Factor Loadings, Reliability, and Convergent Validity

Table 3 presents the final CFA-based measurement results. Most standardized factor loadings exceeded the recommended threshold of 0.70. Although a few loadings were slightly below this preferred value, the corresponding constructs demonstrated acceptable composite reliability (CR), average variance extracted (AVE), and HTMT discriminant validity. These items were therefore retained because they contributed to the conceptual coverage of the constructs. Cronbach's alpha and CR values exceeded 0.70, while all AVE values were above 0.50, supporting satisfactory reliability and convergent validity (Fornell & Larcker, 1981).

Table 3. Summary of measurement model results.

Construct	Item	Std. Loading	Cronbach's Alpha	CR	AVE
TR	TR2	0.675	0.760	0.762	0.517
	TR5	0.787			
	TR8	0.690			
OR	OR2	0.654	0.876	0.887	0.728
	OR6	0.962			
	OR8	0.913			
ER	ER2	0.798	0.764	0.772	0.534
	ER6	0.783			
	ER8	0.593			
DSE	DSE1	0.715	0.763	0.764	0.519
	DSE3	0.737			
	DSE5	0.709			
AIA	AIA1	0.883	0.809	0.817	0.601
	AIA2	0.720			
	AIA5	0.710			
OC	OC1	0.792	0.770	0.773	0.533
	OC2	0.720			
	OC8	0.673			
FP	FP4	0.861	0.895	0.897	0.744
	FP6	0.924			
	FP7	0.798			

The use of three retained indicators per construct is acknowledged as a measurement limitation because substantial item reduction may narrow construct coverage. However, item retention was evaluated by integrating theoretical considerations with EFA dimensionality, CFA loadings, CR, AVE, and HTMT evidence rather than relying on a single statistical criterion. Consequently, the retained indicators adequately represent the core conceptual meaning of each construct within the tourism SME and AI adoption context.

Table 4 presents the HTMT ratios used to assess discriminant validity among the latent constructs. All values were below the conservative threshold of 0.85, supporting discriminant validity (Henseler et al., 2015). In addition, convergent validity was supported by AVE values exceeding 0.50.

Table 4. HTMT discriminant validity assessment.

Construct	TR	OR	ER	DSE	AIA	OC	FP
TR	—						
OR	0.553	—					
ER	0.581	0.602	—				
DSE	0.521	0.574	0.543	—			
AIA	0.493	0.612	0.594	0.632	—		
OC	0.468	0.556	0.571	0.603	0.664	—	
FP	0.502	0.584	0.601	0.623	0.689	0.712	—

4.5. Structural Model and Hypothesis Testing

As shown in Figure 2, the structural model illustrates the relationships among Technology Readiness, Organizational Readiness, Environmental Readiness, Digital Self-Efficacy, AI Adoption, Operational Capability, and Firm Performance within tourism SMEs, particularly small and medium-sized travel agencies in mainland China. The model shows acceptable factor loadings and meaningful structural relationships, which are consistent with the proposed staged capability-conversion framework.

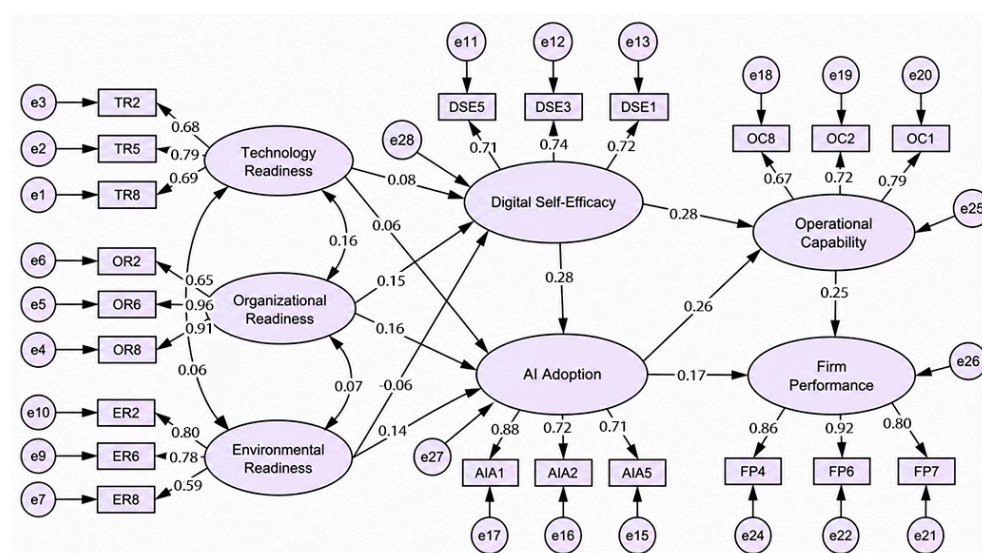


Figure 2. Structural equation model (SEM).

Among the readiness constructs, Organizational Readiness shows the strongest positive association with Digital Self-Efficacy ($\beta = 0.15$) and AI Adoption ($\beta = 0.16$), suggesting that managerial support, internal resources, and organizational preparedness matter for

AI-related capability development. Environmental Readiness is also positively associated with AI Adoption ($\beta = 0.14$), indicating that external competitive pressure and digital tourism ecosystems encourage AI use. Technology Readiness demonstrates weaker direct effects, implying that infrastructure alone may be insufficient to support operational capability conversion.

Digital Self-Efficacy is positively associated with both AI Adoption ($\beta = 0.28$) and Operational Capability ($\beta = 0.28$), supporting the argument that employee confidence in using digital technologies may facilitate technology assimilation and operational adaptation. AI Adoption is also positively associated with Operational Capability ($\beta = 0.26$) and Firm Performance ($\beta = 0.17$). Operational Capability demonstrates the strongest direct association with Firm Performance ($\beta = 0.25$), suggesting that organizational capability is an important conversion mechanism linking AI use with perceived performance outcomes.

Table 5 reports the structural model fit indices. The structural model demonstrated satisfactory goodness-of-fit across all recommended indices.

Table 5. Structural model fit indices.

Fit Index	Recommended Threshold	Result	Decision
χ^2/df	<3.00	2.041	Accepted
GFI	≥ 0.90	0.928	Accepted
AGFI	≥ 0.90	0.907	Accepted
CFI	≥ 0.90	0.969	Accepted
TLI	≥ 0.90	0.965	Accepted
RMSEA	<0.08	0.049	Accepted
SRMR	<0.08	0.044	Accepted

The χ^2/df value was below the recommended threshold of 3.00, while GFI, AGFI, CFI, and TLI exceeded the recommended value of 0.90. In addition, RMSEA and SRMR values remained below the recommended cutoff values, indicating that the proposed structural model adequately represented the observed data and was suitable for hypothesis testing (Kline, 2023; Hair et al., 2019).

Table 6 reports the standardized and unstandardized SEM path coefficients. The SEM results show that Organizational Readiness is significantly associated with both Digital Self-Efficacy ($\beta = 0.154$, $p = 0.007$) and AI Adoption ($\beta = 0.158$, $p = 0.003$), while Environmental Readiness is positively associated with AI Adoption ($\beta = 0.138$, $p = 0.016$). In contrast, Technology Readiness does not demonstrate significant effects. Digital Self-Efficacy is significantly and positively associated with AI Adoption and Operational Capability, indicating the importance of employee confidence in technology use. AI Adoption is positively associated with Operational Capability and Firm Performance, whereas Operational Capability shows the strongest direct association with Firm Performance ($\beta = 0.253$, $p < 0.001$).

The unsupported direct paths are theoretically meaningful rather than merely negative findings. The non-significant Technology Readiness paths (H1 and H4) suggest that infrastructure, compatibility, and technical support may be baseline conditions but are insufficient to increase employee confidence or adoption behavior unless accompanied by managerial support, training, and routinized organizational commitment. The non-significant Environmental Readiness to Digital Self-Efficacy path (H3) further suggests that external pressure and ecosystem readiness may encourage adoption decisions, but they do not automatically increase employees' confidence in using AI-related tools.

Table 6. Structural path coefficients: standardized and unstandardized SEM results.

Hypothesis	Structural Path	Std. Beta	Unstd. B	S.E.	C.R.	p-Value	Result
H1	TR → DSE	0.081	0.085	0.066	1.288	0.198	Not Supported
H2	OR → DSE	0.154	0.142	0.053	2.681	0.007	Supported
H3	ER → DSE	−0.060	−0.101	0.103	−0.984	0.325	Not Supported
H4	TR → AIA	0.059	0.050	0.049	1.021	0.307	Not Supported
H5	OR → AIA	0.158	0.117	0.040	2.953	0.003	Supported
H6	ER → AIA	0.138	0.186	0.078	2.401	0.016	Supported
H7	DSE → AIA	0.276	0.223	0.050	4.458	<0.001	Supported
H8	DSE → OC	0.280	0.270	0.064	4.242	<0.001	Supported
H9	AIA → OC	0.265	0.316	0.075	4.241	<0.001	Supported
H10	AIA → FP	0.171	0.174	0.059	2.953	0.003	Supported
H11	OC → FP	0.253	0.215	0.053	4.092	<0.001	Supported

Table 7 reports the mediation and serial mediation results. Bias-corrected bootstrap procedures with 5000 resamples were employed to assess indirect and sequential mediation effects. Mediation effects were considered statistically significant when the 95% bootstrap confidence interval did not include zero. The findings indicate that Organizational Readiness demonstrates significant indirect and sequential effects through Digital Self-Efficacy, AI Adoption, and Operational Capability, whereas Technology Readiness and Environmental Readiness do not exhibit significant indirect mechanisms through the full staged process. Digital Self-Efficacy and AI Adoption also play mediating roles in linking organizational readiness with operational capability and perceived firm performance. Although several sequential mediation effects were statistically significant, the effect sizes remained relatively small, which suggests that the proposed capability-conversion process should be interpreted cautiously.

Table 7. Mediation and serial mediation effects of the structural model.

Hypothesis	Mediation Type	Structural Path	Std. Indirect Effect	Boot SE	95% BC Bootstrap CI	Result
H12	Simple Mediation	TR → DSE → AIA	0.022	0.024	−0.010 to 0.085	Not Supported
H13	Simple Mediation	OR → DSE → AIA	0.043	0.028	0.018 to 0.130	Supported
H14	Simple Mediation	ER → DSE → AIA	−0.017	0.028	−0.091 to 0.021	Not Supported
H15	Simple Mediation	DSE → AIA → OC	0.073	0.025	0.044 to 0.143	Supported
H16	Simple Mediation	AIA → OC → FP	0.067	0.02	0.020 to 0.101	Supported
H17	Sequential Mediation	TR → DSE → AIA → OC	0.006	0.007	−0.002 to 0.026	Not Supported
H18	Sequential Mediation	OR → DSE → AIA → OC	0.011	0.008	0.005 to 0.039	Supported
H19	Sequential Mediation	ER → DSE → AIA → OC	−0.004	0.008	−0.030 to 0.005	Not Supported
H20	Sequential Mediation	DSE → AIA → OC → FP	0.018	0.007	0.006 to 0.035	Supported
H21	Sequential Mediation	TR → DSE → AIA → OC → FP	0.002	0.001	−0.000 to 0.006	Not Supported
H22	Sequential Mediation	OR → DSE → AIA → OC → FP	0.003	0.002	0.001 to 0.010	Supported
H23	Sequential Mediation	ER → DSE → AIA → OC → FP	−0.001	0.002	−0.007 to 0.001	Not Supported

The unsupported mediation paths (H12, H14, H17, H19, H21, and H23) indicate that readiness dimensions do not contribute equally to capability conversion. Technology Readiness did not generate significant indirect effects because its direct associations with Digital Self-Efficacy and AI Adoption were weak. Environmental Readiness contributed to AI Adoption directly but did not operate through Digital Self-Efficacy, which limited

its sequential mediation effects. These findings support the interpretation that external pressure and technical infrastructure become valuable only when they are converted through organizational support, employee confidence, and operational routines.

Table 8 presents the R^2 values for the endogenous constructs. R^2 values represent the proportion of variance explained by the predictor variables within the structural model. The results indicate that the model explains 8.3% of the variance in Digital Self-Efficacy, 28.7% in AI Adoption, 31.4% in Operational Capability, and 22.7% in Firm Performance. These values suggest moderate explanatory power for AI Adoption and Operational Capability and more modest explanatory power for Digital Self-Efficacy and Firm Performance, which is consistent with the complexity of organizational and behavioral research contexts (Hair et al., 2019).

Table 8. Explained variance (R^2) of endogenous constructs.

Endogenous Construct	R^2	Interpretation
Digital Self-Efficacy (DSE)	0.083	Weak
AI Adoption (AIA)	0.287	Moderate
Operational Capability (OC)	0.314	Moderate
Firm Performance (FP)	0.227	Weak to Moderate

Taken together, the structural and mediation results indicate that Organizational Readiness and Digital Self-Efficacy play comparatively important roles in the staged capability-conversion process, while Operational Capability shows the strongest direct association with perceived Firm Performance.

This pattern explains why Organizational Readiness emerged as the most consistent readiness condition. In tourism SMEs, managerial commitment, resource allocation, training, and workflow support are closer to employees' daily technology use than abstract technological availability. Organizational readiness therefore appears to function as the practical bridge between AI investment and capability conversion.

5. Discussion

The findings show that Organizational Readiness is associated with both Digital Self-Efficacy and AI Adoption, indicating that managerial commitment, internal support, training, and organizational preparedness matter more than technological availability alone. This result is important because tourism SMEs may have access to digital infrastructure or AI tools, yet still struggle to translate these resources into employee confidence or operational use. Technology Readiness did not significantly influence either Digital Self-Efficacy or AI Adoption, suggesting that technology availability functions as a necessary but insufficient condition for AI-enabled transformation.

Environmental Readiness is positively associated with AI Adoption, implying that external digitalization pressure, smart tourism ecosystems, and platform-based competition encourage tourism SMEs to adopt AI technologies. However, Environmental Readiness does not significantly strengthen Digital Self-Efficacy. This distinction suggests that external pressure may accelerate adoption decisions without necessarily improving employees' confidence, skills, or practical ability to use AI tools. For tourism SMEs, environmental pressure therefore needs to be translated into internal training, guidance, and work-process support.

Digital Self-Efficacy is significantly associated with both AI Adoption and Operational Capability, supporting Social Cognitive Theory (Bandura, 1997). Employees with stronger digital confidence are more likely to adapt workflows, integrate AI-supported systems, and support operational improvement. AI Adoption is also positively associated with Operational Capability and perceived Firm Performance, while Operational Capability shows

the strongest direct association with Firm Performance. This finding matters theoretically because it suggests that organizational value is associated with operational embedding and capability conversion rather than technology acquisition itself. The result is also consistent with RBV and Dynamic Capabilities Theory, which emphasize that technological resources become valuable when they are integrated into adaptive routines and operational processes (Barney, 1991; Teece, 2007).

The mediation findings further suggest that Organizational Readiness contributes indirectly to Operational Capability and Firm Performance through Digital Self-Efficacy and AI Adoption. In contrast, the unsupported mediation paths linked to Technology Readiness and Environmental Readiness show that readiness dimensions are not interchangeable. Technical resources and external pressure may create enabling conditions, but they do not necessarily produce capability conversion unless organizational support and employee confidence are present. This helps explain why the significant model pathways are concentrated around Organizational Readiness, Digital Self-Efficacy, AI Adoption, and Operational Capability.

Taken together, these findings suggest that the three readiness dimensions perform complementary rather than interchangeable roles in AI-enabled transformation. Technology Readiness provides the technical foundation for AI implementation, Environmental Readiness creates external incentives and competitive pressure for digitalization, whereas Organizational Readiness serves as the practical mechanism through which these conditions are translated into employee capability, AI utilization, and operational improvement. This distinction helps explain why Organizational Readiness emerged as the most consistent predictor across the proposed capability-conversion framework. Overall, the findings indicate that organizational value is associated not with technology availability alone, but with the organization's ability to transform readiness into employee competence, operational capability, and ultimately perceived firm performance.

5.1. Theoretical Implications

This study extends the Technology–Organization–Environment (TOE) framework beyond technology adoption by suggesting that organizational readiness alone is insufficient to explain perceived firm performance. Instead, organizational value is associated with Digital Self-Efficacy, AI Adoption, and Operational Capability, thereby broadening the application of TOE from adoption prediction to post-adoption capability development in tourism SMEs (Oliveira & Martins, 2011; Vial, 2019).

The study also integrates the TOE framework, Social Cognitive Theory, the Resource-Based View (RBV), and Dynamic Capabilities Theory into a unified explanatory framework. TOE explains organizational readiness, Social Cognitive Theory explains the behavioral mechanism through Digital Self-Efficacy (Bandura, 1997), RBV highlights AI-related resources as strategic assets (Barney, 1991), and Dynamic Capabilities Theory explains how these resources are translated into operational capability and organizational value (Teece, 2007). Together, these complementary perspectives provide a more comprehensive explanation of AI-enabled capability development than any single theory alone.

Finally, the findings identify Operational Capability as the principal organizational mechanism associated with the relationship between AI Adoption and perceived Firm Performance. Consistent with RBV and Dynamic Capabilities Theory, the findings suggest that AI creates organizational value primarily through operational embedding and adaptive routines rather than technology acquisition alone (Mikalef et al., 2020; Ku & Chen, 2024). Overall, the study contributes a metatheoretical explanation of how organizational readiness, employee capability, and operational capability are collectively associated with AI-enabled organizational performance in tourism SMEs.

5.2. Practical Implications

The findings suggest that tourism SMEs should approach AI adoption as a capability-building process rather than a simple technology purchase. Managers should prioritize leadership commitment, resource support, employee training, workflow redesign, and operational coordination alongside AI investment. These actions are especially important because Technology Readiness alone did not significantly explain Digital Self-Efficacy or AI Adoption in the final model.

The significant effects of Digital Self-Efficacy on AI Adoption and Operational Capability indicate that employees should be encouraged to experiment with AI-supported systems in customer service, itinerary planning, digital marketing, and operational coordination. The strong association between Operational Capability and Firm Performance further suggests that AI tools generate value when they are embedded into routines, co-created service processes, service innovation, and adaptive decision-making rather than treated as stand-alone technologies (Bhat & Sharma, 2022).

For policymakers and technology providers, the findings imply that smart tourism initiatives should combine infrastructure support with capability-development programs, implementation guidance, staff training, and operational consulting for tourism SMEs. Support programs that focus only on technology access may be less effective than programs that also strengthen organizational readiness and practical capability conversion.

5.3. Limitations and Future Research

Several limitations should be acknowledged. First, this study employed a cross-sectional research design; therefore, causal interpretations should be made cautiously. Although SEM supports theory-driven relationship testing, future studies could adopt longitudinal designs to examine how AI readiness, operational capability, and firm performance evolve over time (Kline, 2023).

Second, the study relied primarily on respondents' perceptions of organizational readiness, AI adoption, operational capability, and firm performance rather than objective organizational indicators. Future research could integrate survey data with financial performance, operational efficiency, customer analytics, platform data, or service-quality indicators to strengthen empirical robustness and reduce perceptual bias.

Third, the sample focused specifically on tourism SMEs, particularly small and medium-sized travel agencies in mainland China, using non-probability sampling procedures, which may limit the generalizability of the findings. Future studies could compare different regions, tourism subsectors, organizational sizes, or cross-country tourism ecosystems to examine contextual differences in AI-enabled transformation processes.

Fourth, although the retained three-item constructs satisfied reliability, convergent validity, and discriminant validity criteria, the substantial item reduction during measurement refinement may limit the breadth of construct coverage. Future research should further validate the refined measurement scales using independent samples and broader item pools. Finally, additional contextual and organizational factors such as leadership style, digital maturity, AI task complexity, organizational culture, employee training quality, and data governance capability may further explain why AI transformation becomes more effective in some tourism SMEs than others.

6. Conclusions

This study examined the relationships among AI readiness conditions, operational capability, and perceived firm performance in tourism SMEs, particularly small and medium-sized travel agencies in mainland China. The results suggest that organizational readiness is

the most consistent readiness antecedent, while technology readiness alone is not sufficient to explain AI adoption or perceived performance outcomes.

The findings further indicate that digital self-efficacy is positively associated with both AI adoption and operational capability, and that operational capability shows the strongest direct association with perceived firm performance. These results suggest that perceived AI-enabled value creation in tourism SMEs is associated with behavioral confidence, technological assimilation, and operational embedding rather than technology possession alone.

For tourism SME managers, the study highlights the importance of building internal support systems, employee digital confidence, and operational routines that may help translate AI use into service responsiveness and perceived business performance. For policymakers and technology providers, the findings suggest that smart tourism initiatives should combine infrastructure support with practical capability-building assistance for resource-constrained SMEs.

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Appendix A

Table A1. Item screening and final retention summary.

Construct	Original Items	Retained Items	Removed Items
TR	TR1-TR8	TR2, TR5, TR8	TR1, TR3, TR4, TR6, TR7
OR	OR1-OR8	OR2, OR6, OR8	OR1, OR3, OR4, OR5, OR7
ER	ER1-ER8	ER2, ER6, ER8	ER1, ER3, ER4, ER5, ER7
DSE	DSE1-DSE8	DSE1, DSE3, DSE5	DSE2, DSE4, DSE6, DSE7, DSE8
AIA	AIA1-AIA8	AIA1, AIA2, AIA5	AIA3, AIA4, AIA6, AIA7, AIA8
OC	OC1-OC8	OC1, OC2, OC8	OC3, OC4, OC5, OC6, OC7
FP	FP1-FP8	FP4, FP6, FP7	FP1, FP2, FP3, FP5, FP8

Note. Item screening and final retention were based on statistical performance, possible cross-loading or communality risk, and theoretical coverage of each construct. The retained indicators were subsequently evaluated through CFA, CR, AVE, and HTMT evidence.

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