DOI: https://doi.org/10.63944/sjmx2.JFEMR
Vol.2 No.7

Determinants of Insurance Operational Efficiency Perception under Inclusive Digital Transformation: A Case Study of Digitalization at A Insurance Company Guangxi , China

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Abstract: The objectives of this research were to 1) examine the current level of customer-perceived operational efficiency, and 2) analyze the effects of intelligent underwriting, online claims processing, digital marketing, digital transformation, and data analytics capability on this efficiency at A Insurance Company in Guangxi, China. This quantitative study collected data from 356 customers, selected through a two- stage sampling procedure combining simple random sampling at the company level and stratified random sampling by prefecture-level cities at the customer level. The data were analyzed using descriptive statistics, reliability analysis, content validity analysis (IOC), Pearson correlation analysis, and multiple linear regression analysis. The research findings revealed that 1) despite the complete digital service modules established by Company A, a substantial proportion of respondents rarely utilized digital insurance tools, indicating a gap between digital infrastructure development and actual user adoption. 2) All five digitalization-related factors exerted significant positive effects on customer-perceived operational efficiency, with online claims processing demonstrating the strongest predictive effect while data analytics capability showed relatively weaker though still significant influence. The regression model achieved satisfactory explanatory power, and the measurement scales demonstrated satisfactory reliability and content validity, with all five research hypotheses supported.

Keywords: digital transformation; insurance company; operational efficiency; customer perception; digital marketing; data analytics capability

1. Introduction

1.1 Research Background and Significance

Driven by technological progress, changing customer demands, market competition and regulatory guidance, the global insurance industry is undergoing profound digital transformation[5]. The Asia-Pacific region accounts for a large share of global InsurTech investment, and China's fintech policies continuously push insurance institutions toward digital upgrading[6]. The domestic

insurance sector has gone through channel digitization, process automation and data-driven intelligent transformation phases[2]. Leading insurance groups apply artificial intelligence, big data and cloud computing across underwriting, claim settlement and customer service to boost operational performance[4].

Insurance digital transformation may produce uneven customer adoption even when digital channels are available. Differences in access, familiarity, and service needs can limit customers' use of digital tools. These issues are especially relevant when a study includes both urban and rural respondents, but the present data do not establish a regional digital divide.

This study uses A Insurance Company in Guangxi, China as a bounded case for examining how customers perceive digital insurance services and operational efficiency. The case designation does not imply that the company is representative of all insurers in Guangxi, nor does the study independently verify the company's internal level of digital development.

Theoretical significance: The study applies the Technology-Organization-Environment (TOE) framework and Dynamic Capabilities Theory to a customer-perception model of insurance digitalization. Its contribution is limited to evidence from one regional case and should not be interpreted as a direct assessment of organizational capabilities.

Practical significance: The estimated associations indicate which customer-visible digital service dimensions warrant further managerial investigation. The results may inform service improvement, but resource-allocation decisions should also use objective operational data and internal process evidence.

1.2 Conceptual Framework

The model includes intelligent underwriting, online claims processing, digital marketing, digital transformation, and data analytics capability as independent variables and customer-perceived operational efficiency as the single dependent variable. All six constructs are measured from customer questionnaire responses.

The model proposes that favorable customer perceptions of each digital service dimension are positively associated with customer-perceived operational efficiency. It does not test the company's actual processing costs, staffing productivity, system architecture, or internal analytical performance.

For digital transformation and data analytics capability in particular, respondents evaluated customer-visible manifestations, such as the integration, timeliness, personalization, and consistency of digital services. The scores therefore represent perceived service outcomes that customers may attribute to these capabilities; they are not direct audits of internal systems or organizational routines.

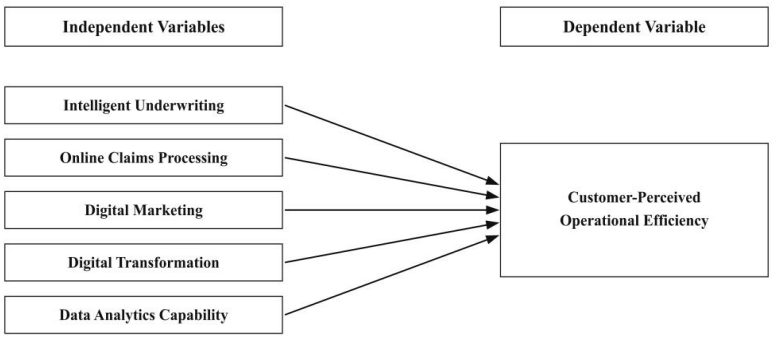


Figure 1. Conceptual Framework

Note. All constructs are measured from the customer perspective. The outcome is Customer-Perceived Operational Efficiency.

1.3 Research Questions

1. What is the current level of customer-perceived operational efficiency at A Insurance Company in Guangxi, China?

2. How are the five customer-rated digital service dimensions associated with customer-perceived operational efficiency, and which dimension has the largest standardized regression coefficient?

1.4 Research Objectives

1. To examine the current level of customer-perceived operational efficiency at A Insurance Company in Guangxi, China.

2. To analyze the associations of intelligent underwriting, online claims processing, digital marketing, digital transformation, and data analytics capability with customer-perceived operational efficiency.

1.5 Research Hypotheses

H1: Customer-perceived intelligent underwriting is positively associated with customer-perceived operational efficiency.

H2: Customer-perceived online claims processing is positively associated with customer-perceived operational efficiency.

H3: Customer-perceived digital marketing is positively associated with customer-perceived operational efficiency.

H4: Customer-perceived digital transformation is positively associated with customer-perceived operational efficiency.

H5: Customer-perceived data analytics capability is positively associated with customer-perceived operational efficiency.

1.6 Research Scope

Scope of content: The study examines five customer-rated digital service dimensions and customer-perceived operational efficiency in the case of A Insurance Company in Guangxi, China.

Scope of population and sample: Eligible respondents were customers of the case company who had used at least one of its digital insurance services before participating. The survey link was distributed through Wenjuanxing, WeChat, and customer-service channels. This voluntary, non-probability recruitment approach reached respondents across the 14 prefecture-level cities of Guangxi. A total of 420 questionnaires were distributed, and 356 valid responses were retained.

1.7 Definition of Key Concepts

Intelligent underwriting: Customers' perceptions of automated or digitally supported risk evaluation and underwriting services that are visible through speed, clarity, consistency, or convenience.

Online claims processing: Customers' perceptions of digital claim submission, document handling, status communication, assessment, and settlement.

Digital marketing: Customers' perceptions of the company's use of websites, mobile applications, social media, and other digital channels for product information, communication, and relationship maintenance.

Digital transformation: Customers' perceptions of the integration and coordination of digital technologies across service touchpoints. This measure does not directly assess internal organizational restructuring or system architecture.

Data analytics capability: Customers' perceptions of service personalization, timeliness, relevance, and consistency that may reflect the company's use of data. This measure does not directly assess internal data infrastructure, analytical models, or employee skills.

Customer-perceived operational efficiency: Customers' assessments of the speed, convenience, responsiveness, consistency, and service quality of insurance processes. It is distinct from objective efficiency indicators such as cost, labor productivity, or processing time recorded by the company.

2. Literature Review

2.1 Concept of Operational Efficiency

Operational efficiency generally concerns the relationship between organizational inputs and outputs. In digital insurance, it may also be reflected in process speed, responsiveness, service quality, and the customer-facing effects of digital applications[1,8]. Because this study uses customer questionnaires, it measures customer-perceived operational efficiency rather than objective organizational efficiency. Prior research links digital technologies with insurance processes and customer experience, but evidence from one customer sample cannot establish actual cost or productivity gains.

2.2 Concept of Intelligent Underwriting

Intelligent underwriting is a typical InsurTech application, replacing partial manual underwriting work with AI and big-data analysis[3]. It accelerates risk evaluation, reduces repetitive manual labor and improves the consistency of underwriting decisions. Most existing studies focus on large national insurance groups, while empirical evidence from regional insurance operations is limited.

2.3 Concept of Online Claims Processing

Online claims processing transforms traditional paper-based claim workflows into digital services. It shortens settlement cycles and improves transparency and customer experience[7]. Claim settlement is the most perceptible business scenario for insurance customers. Existing research has verified its value for efficiency improvement, while few quantitative studies discuss its effect differences under urban-rural inclusive contexts.

2.4 Concept of Digital Marketing

Insurance digital marketing applies websites, mobile applications and social-media tools for product promotion and customer communication[9]. It optimizes customer-acquisition workflows. Domestic and foreign studies have proven its contributions to organizational agility and customer engagement, but few papers explore its influence on operational efficiency from the perspective of regional customer perception.

2.5 Concept of Digital Transformation

Digital transformation involves organizational change in business processes, structures, and value creation rather than the adoption of isolated technologies[10,12]. Dynamic Capabilities Theory explains how firms may integrate and reconfigure resources to respond to changing conditions[15,17]. In this study, however, customers report only the service-facing manifestations of transformation, not the underlying internal capability.

2.6 Concept of Data Analytics Capability

Data analytics capability refers to an organization's capacity to deploy data and analytical resources for decision-making and process improvement[13]. Prior research links big-data analytics capability with firm performance and process-oriented dynamic capabilities[14]. In the present questionnaire, this construct is limited to customer perceptions of observable service outcomes and does not directly measure internal data resources.

2.7 Empirical Research on Insurance Digital Transformation

International InsurTech research indicates digital technologies optimize underwriting, claim settlement and risk-control processes. Relevant studies pay attention to operational-efficiency promotion, customer-service upgrading and business-model innovation[7]. Domestic literature points out that the Chinese insurance industry is shifting from channel digitization toward intelligent operations[3]. Most empirical studies concentrate on large national insurance groups, with insufficient attention paid to western regional insurance operations and urban-rural digital inclusion issues.

2.8 Theoretical Foundations

2.8.1 TOE (Technology- Organization- Environment) Framework

The Technology-Organization-Environment (TOE) framework explains technology adoption through technological, organizational, and environmental contexts[16]. In this study, intelligent underwriting and online claims processing represent technological applications; digital transformation and data analytics capability represent organizational capacity as perceived through services; and digital marketing represents the company's outward-facing response to customers and market conditions.

2.8.2 Dynamic Capabilities Theory

Dynamic Capabilities Theory defines competitive adaptation in terms of a firm's ability to integrate, build, and reconfigure internal and external competences in changing environments[17]. Later digital-transformation research describes related sensing, seizing, and transforming processes[15]. The theory provides an organizational explanation, while the empirical measures in this study remain customer perceptions.

2.8.3 Integration of Variables and Theories

The five-variable classification is an analytical mapping rather than a claim that each construct belongs exclusively to one TOE context. Intelligent underwriting and online claims processing are placed in the technological context because they are specific digital applications. Digital transformation and data analytics capability are placed in the organizational context because they concern integration and resource use. Digital marketing could also be treated as an internal technological or organizational activity; it is placed in the environmental context here because the questionnaire emphasizes outward-facing communication and responses to customer demand and competition. Dynamic Capabilities Theory then explains how organizational reconfiguration may connect these activities with performance, although the study observes only customers' perceptions of that connection.

2.9 Research Gaps and Positioning

The literature suggests three gaps relevant to this study. First, relatively few customer-level

studies combine the TOE framework and Dynamic Capabilities Theory in a single insurance-service model. Second, prior research often examines individual technologies rather than several customer-visible digital dimensions together. Third, customer adoption and service accessibility may condition the perceived value of digital insurance services. These gaps justify a bounded case study but do not establish that the case represents all insurers in western China.

Accordingly, this study examines the five digital service dimensions in one customer sample from A Insurance Company in Guangxi. The analysis is positioned as evidence about customer perceptions and statistical associations, not as a direct test of the company's internal capabilities or the broader Guangxi insurance market.

3. Research Methodology

3.1 Research Design

Primary data were collected through a structured customer questionnaire. The five independent variables are customer-rated intelligent underwriting, online claims processing, digital marketing, digital transformation, and data analytics capability. The dependent variable is customer-perceived operational efficiency. SPSS was used for descriptive statistics, Cronbach's alpha, expert IOC assessment, Pearson correlation, and multiple linear regression. The cross-sectional design supports association and prediction statements, not causal conclusions.

3.2 Population and Sample

Target population and eligibility: Customers of A Insurance Company in Guangxi, China who had used at least one digital insurance service or channel before completing the questionnaire. A response of 'seldom' indicates infrequent use and does not mean that the respondent had never used a digital service.

Sampling method: The study used the selected company as a case and recruited eligible customers through a non-probability, voluntary-response procedure. The Wenjuanxing questionnaire link was circulated through WeChat and customer-service channels. Because respondents chose whether to participate and no complete customer list was used to draw individuals randomly, the customer sample should not be described as stratified random sampling.

Sample size and response record: A total of 420 questionnaires were distributed, comprising 300 online and 120 offline questionnaires. After screening, 356 valid responses were retained, giving a valid-response rate of 84.8%.

Geographic coverage: Recruitment sought responses from the 14 prefecture-level cities of Guangxi: Nanning, Liuzhou, Guilin, Wuzhou, Beihai, Fangchenggang, Qinzhou, Guigang, Yulin, Baise, Hezhou, Hechi, Laibin, and Chongzuo. City coverage does not convert the voluntary-response sample into a probability sample.

Case selection: A Insurance Company in Guangxi was the focal case. The manuscript does not claim that the company was selected by a reproducible random draw from 34 insurers.

Respondent selection: Customer-service and WeChat channels provided access to potential respondents who met the prior-use criterion. Participation depended on voluntary completion of the questionnaire.

Data screening: Questionnaires with substantial missing data, duplicate submissions, or internally contradictory responses were excluded before the final sample of 356 was analyzed.

3.3 Research Instrument

The questionnaire consisted of two parts. Part I recorded gender, age, residential area, insurance type, and frequency of digital-insurance-tool use. Part II contained multi-item measures

adapted to the insurance-service context and used a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The items asked respondents to evaluate customer-visible service experiences. Digital transformation and data analytics capability therefore represent perceived manifestations of those capabilities, not direct observations of internal systems. Cronbach's alpha was used to assess internal consistency, and expert IOC ratings were used to assess content relevance. These procedures do not by themselves establish convergent, discriminant, or criterion validity.

3.4 Data Collection Process

The opening page of the questionnaire explained the study purpose, voluntary participation, the academic use of responses, and the participants' right to stop before submission. Respondents proceeded only after indicating consent. The questionnaire did not request respondents' names, and results were analyzed and reported in aggregate. No formal institutional review board approval or formal company authorization is claimed. Data collection lasted approximately three weeks. Submissions with substantial missing values, duplicates, or obvious internal contradictions were excluded.

3.5 Data Analysis Methods

Descriptive statistics: Frequencies and percentages summarize respondent characteristics, while means, standard deviations, skewness, and kurtosis describe the observed distributions of the composite variables. Skewness and kurtosis of individual variables are not treated as proof that regression residuals are normally distributed.

Reliability and content review: Cronbach's alpha was used to assess internal-consistency reliability, with values above 0.70 treated as acceptable. Three experts evaluated item-objective congruence using ratings of +1 (appropriate), 0 (uncertain), or -1 (inappropriate). Items were revised in response to expert comments, and the IOC values reported in Table 4 are the final post-revision ratings. IOC addresses content relevance; it does not establish construct validity. No exploratory or confirmatory factor analysis, convergent-validity test, discriminant-validity test, or dedicated common-method-bias test was conducted.

Pearson correlation analysis: Correlations were used to describe the direction and strength of bivariate associations between the five independent variables and customer-perceived operational efficiency.

Multiple linear regression analysis: The five customer-rated digital dimensions were entered as predictors of customer-perceived operational efficiency. The model F statistic, standardized and unstandardized coefficients, p values, R-squared, adjusted R-squared, Durbin-Watson statistic, variance inflation factors, and tolerance values were reported. Hypotheses H1-H5 were evaluated as association hypotheses.

4. Research Results

4.1 Demographic Descriptive Statistics

Table 1 presents the respondent profile. Respondents aged 26-45 accounted for 69.66% of the sample. Men accounted for 54.78% and women 45.22%; 56.46% lived in urban areas and 43.54% in rural areas. For digital insurance tool use, 39.32% reported 'seldom' and 33.43% reported 'sometimes,' a combined 72.75%. Respondents classified as 'seldom' remained eligible because the criterion required at least one previous use, not frequent use. The study did not conduct an inferential test of urban-rural differences, so the data do not support a statistically confirmed digital divide.

Table 1. Demographic and Consumption Behavior Profile of Respondents (N=356)

Variable	Option	Frequency	Percent(%)
Age	18-25 years old	18	5.06
	26-35 years old	111	31.18
	36-45 years old	137	38.48
	46-55 years old	80	22.47
	56 years old and above	10	2.81
Gender	Male	195	54.78
	Female	161	45.22
Residential area	Urban (city center or town center)	201	56.46
	Rural (village or suburb)	155	43.54
Main type of insurance purchased	Life insurance	160	44.94
	Property and casualty insurance	143	40.17
	Health insurance	50	14.04
	Others	3	0.84
Frequency of using digital insurance tools	Seldom	140	39.32
	Sometimes	119	33.43
	Frequently	84	23.6
	Very frequently	13	3.65
Total		356	100

4.2 Descriptive Statistics of Key Variables

Table 2 summarizes the observed distributions for the six composite variables (N = 356). Customer-perceived operational efficiency had the highest mean (M = 3.370, SD = 0.9164). Absolute skewness values were below 1 and absolute kurtosis values were below 2, indicating no severe univariate distributional asymmetry in these composite scores. These statistics do not test the normality of regression residuals; residual diagnostics are addressed separately in Section 4.6.

Table 2. Descriptive statistics

	N	Min	Max	Mean	Std.dev	Skewness	Kurtosis
Intelligent Underwriting	356	1	5	3.344	0.9396	-0.130	-0.753
Online Claims Processing	356	1	5	3.291	0.9618	-0.034	-0.845
Digital Marketing	356	1	5	3.262	0.9213	-0.035	-0.899
Digital Transformation	356	1	5	3.293	0.9473	0.022	-0.981
Data Analytics Capability	356	1	5	3.346	0.9422	-0.194	-0.737
Customer-Perceived Operational Efficiency	356	1	5	3.370	0.9164	-0.001	-1.046

4.3 Reliability Analysis

Table 3 reports internal-consistency reliability. Cronbach's alpha exceeded 0.70 for all six constructs: intelligent underwriting, 0.842; online claims processing, 0.837; digital marketing, 0.900; digital transformation, 0.908; data analytics capability, 0.855; and customer-perceived operational efficiency, 0.892. These results support internal consistency but do not, by themselves, establish construct validity.

Table 3. Reliability Analysis

Variable	Number of terms	N	Cronbach's alpha
Intelligent Underwriting	3	356	0.842
Online Claims Processing	3	356	0.837
Digital Marketing	4	356	0.900
Digital Transformation	4	356	0.908
Data Analytics Capability	3	356	0.855
Customer-Perceived Operational Efficiency	5	356	0.892

4.4 Content Validity and Common Method Considerations

Table 4. Content Validity Analysis

Variable	Number of terms	Final Average IOC	Interpretation
Intelligent Underwriting	3	1.00	Acceptable (final version)
Online Claims Processing	3	1.00	Acceptable (final version)
Digital Marketing	4	1.00	Acceptable (final version)
Digital Transformation	4	1.00	Acceptable (final version)
Data Analytics Capability	3	1.00	Acceptable (final version)
Customer-Perceived Operational Efficiency	5	1.00	Acceptable (final version)

Table 4 reports the final IOC scores after expert comments had been incorporated into the questionnaire. All six constructs received a final average IOC of 1.00; the interpretation is therefore reported consistently as acceptable for the final version. IOC provides evidence of expert-assessed content relevance only. Because the study did not conduct factor analysis or tests of convergent and discriminant validity, the measures should not be described as fully validated. In addition, all predictor and outcome measures came from the same self-report questionnaire. No dedicated statistical assessment of common method bias was conducted, so possible common method variance remains a limitation.

4.5 Pearson Correlation Analysis

Table 5 presents the correlations. Intelligent underwriting, online claims processing, digital marketing, digital transformation, and data analytics capability were each positively correlated with customer-perceived operational efficiency ($p < 0.01$). The correlations with the outcome ranged from 0.242 to 0.325. The lowest correlation in the full matrix was 0.116. These results describe bivariate associations and do not establish causality or construct validity.

Table 5. Correlations

	M	SD	1	2	3	4	5	6
Intelligent Underwriting (1)	3.344	0.940	1					
Online Claims Processing (2)	3.291	0.962	0.171**	1				
Digital Marketing (3)	3.262	0.921	0.140**	0.116*	1			
Digital Transformation (4)	3.293	0.947	0.183**	0.165**	0.148**	1		
Data Analytics Capability (5)	3.346	0.942	0.196**	0.248**	0.176**	0.194**	1	
Customer-Perceived Operational Efficiency (6)	3.370	0.916	0.258**	0.325**	0.242**	0.255**	0.253**	1

* $p < 0.05$; ** $p < 0.01$

4.6 Multiple Linear Regression Analysis

Multiple linear regression was conducted with customer-perceived operational efficiency as the dependent variable and the five customer-rated digital dimensions as predictors (Table 6). The model was statistically significant, $F(5, 350) = 19.237$, $p < 0.001$, with R-squared = 0.216 and adjusted R-squared = 0.204. The small difference obtained when F is recalculated from the displayed R-squared reflects rounding of R-squared to three decimals; the F statistic is reported directly from the regression results. The Durbin-Watson statistic was 2.061. VIF values ranged from 1.059 to 1.132 and tolerance values from 0.884 to 0.945, providing no indication of problematic multicollinearity. Residual P-P plots, residual scatterplots, and outlier diagnostics were not retained with the materials available for this manuscript. Therefore, the paper does not claim that residual normality, linearity, homoscedasticity, and outlier assumptions were fully verified, and the regression results should be interpreted with this limitation in mind.

Hypothesis results: H1, intelligent underwriting (beta = 0.149, p = 0.003), supported; H2, online claims processing (beta = 0.230, p < 0.001), supported; H3, digital marketing (beta = 0.153, p = 0.002), supported; H4, digital transformation (beta = 0.146, p = 0.003), supported; and H5, data analytics capability (beta = 0.112, p = 0.027), supported.

All five predictors had positive statistically significant coefficients. Online claims processing had the largest standardized coefficient (beta = 0.230, p < 0.001), but no formal test compared the coefficients with one another. It is therefore described as the largest coefficient in this sample, not as definitively stronger than every other predictor.

Table 6. Multiple Linear Regression Results (N = 356)

	Unstandardized Coefficients		Standardized Coefficients	t	p	Collinearity	
	B	SE	Beta			VIF	TOL
Constant	0.839	0.266	-	3.160	0.002**	-	-
Intelligent Underwriting	0.145	0.048	0.149	3.014	0.003**	1.086	0.921
Online Claims Processing	0.219	0.047	0.230	4.632	< 0.001**	1.099	0.910
Digital Marketing	0.152	0.048	0.153	3.142	0.002**	1.059	0.945
Digital Transformation	0.141	0.048	0.146	2.956	0.003**	1.086	0.921
Data Analytics Capability	0.109	0.049	0.112	2.221	0.027*	1.132	0.884
R-squared				0.216			
Adjusted R-squared				0.204			
F				F(5, 350) = 19.237, p < 0.001			
D-W				2.061			

Dependent Variable: Customer-Perceived Operational Efficiency

* p < 0.05; ** p < 0.01. R-squared values are rounded to three decimals; F is reported from the regression output.

5 Discussion Conclusions Recommendations Limitations and Future Research

5.1 Summary of Major Findings

First, respondents reported moderate mean levels across the five digital service dimensions and customer-perceived operational efficiency. Most respondents used digital insurance tools seldom or sometimes. This pattern describes the sample's frequency of use but does not independently

establish the company's digital maturity or an urban-rural digital divide.

Second, Cronbach's alpha supported internal consistency and the final expert IOC ratings supported content relevance. The study did not establish convergent or discriminant validity and did not test common method bias.

Third, all five customer-rated digital service dimensions were positively correlated with customer-perceived operational efficiency.

Fourth, all five regression coefficients were positive and statistically significant. Online claims processing had the largest standardized coefficient in this sample (beta = 0.230, $p < 0.001$), although coefficients were not formally compared. The model R-squared of 0.216 indicates that the five predictors explained 21.6% of the observed variance in customer-perceived operational efficiency; adjusted R-squared was 0.204. Most of the variance therefore remained outside the model.

5.2 Discussion

The findings are interpreted as associations among customer perceptions. They are compared below with earlier research, while explanations that were not directly measured are presented as possibilities rather than established mechanisms.

The positive coefficient for intelligent underwriting is consistent with research describing how artificial intelligence can support value creation and process consistency in insurance[3,4]. The positive coefficient for online claims processing also accords with studies that identify claims and other service processes as visible points of digital insurance value creation[7,8]. Its comparatively large coefficient may reflect the direct visibility of claim submission, status communication, and settlement to customers, but this mechanism was not measured separately.

The positive digital-marketing coefficient is consistent with research linking digital channels with customer interaction and engagement[9]. The positive digital-transformation coefficient also accords with literature that treats transformation as coordinated organizational and process change rather than isolated technology adoption[10,11]. The data-analytics result is directionally consistent with studies linking analytics capability to performance through complementary organizational processes[13,14]. Its smaller coefficient may arise because customers cannot directly observe internal data systems, because service-facing benefits are indirect, or because the questionnaire captures perceptions imperfectly. Data silos, customer digital literacy, rural infrastructure, and algorithm quality were not measured and therefore remain possible explanations for future research, not findings of this study.

The model explained 21.6% of the observed variance, with an adjusted R-squared of 0.204. This represents limited-to-moderate explanatory power for this sample and leaves substantial variance unexplained. The manuscript does not claim that this value is typical of insurance questionnaire research because no directly comparable benchmark was established. Other relevant factors may include service complexity, staff assistance, customer experience, management practices, regulation, and market conditions.

The study contributes a bounded customer-perception case that connects the TOE framework and Dynamic Capabilities Theory with five digital service dimensions. Its conclusions are limited to perceived operational efficiency and should not be extended to objective cost, productivity, or internal capability without additional data.

5.3 Practical Recommendations

For A Insurance Company in Guangxi, China:

Give priority to investigating online claims processing because it had the largest standardized coefficient in this sample. Process data and customer interviews should be used to identify whether claim-submission steps, status communication, or offline assistance require improvement, especially for customers who use digital tools infrequently.

Review intelligent underwriting, digital marketing, and digital service integration using both customer feedback and internal operational evidence. Algorithm changes should be considered only after accuracy, fairness, manual-review requirements, and customer outcomes have been evaluated; the present questionnaire did not measure algorithm performance.

Assess data analytics capability with internal evidence before drawing operational conclusions. Possible priorities include data quality, integration, governance, and the translation of analytical insights into service improvements. The survey cannot determine whether data silos exist.

Improve accessibility by testing simplified interfaces, clear guidance, and assisted offline options with older, rural, and infrequent digital-service users. These actions should be evaluated in subsequent studies rather than assumed to close an unmeasured digital divide.

For industry bodies and regulators, customer adoption and accessibility may complement system-deployment indicators when digital inclusion is assessed. Broader evidence from multiple companies and regions is needed before policy conclusions are drawn.

5.4 Research Limitations

The cross-sectional design identifies associations and predictive relationships but cannot establish causality.

All variables were measured through the same customer questionnaire, creating a risk of common method variance. No dedicated common-method-bias test was conducted. Customer ratings of digital transformation and data analytics capability capture service-facing perceptions and may not represent the company's internal systems or capabilities accurately.

Cronbach's alpha and IOC support internal consistency and expert-assessed content relevance, respectively, but the study did not conduct exploratory or confirmatory factor analysis or tests of convergent and discriminant validity. Residual plots and outlier diagnostics were not retained, so the full set of regression assumptions could not be documented.

The non-probability, voluntary-response sample came from one company in Guangxi. Self-selection may affect the sample, and conclusions should not be generalized to other companies, provinces, or the Guangxi insurance market as a whole.

5.5 Future Research Directions

Future research should collect longitudinal data and combine customer perceptions with objective indicators such as processing time, error rates, staffing inputs, and service costs.

Future studies should include customer digital literacy, service complexity, staff assistance, infrastructure access, and other contextual variables, with clearly specified control variables.

Larger studies may use validated multi-item scales, exploratory and confirmatory factor analysis, convergent and discriminant validity tests, and procedural or statistical approaches to common method bias.

Probability-based or carefully quota-controlled samples across several insurers and provinces would improve external validity and allow regional comparisons.

Mixed-method research combining customer surveys, internal operational data, and interviews with customers and managers could distinguish customer-visible service effects from internal organizational capabilities.

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