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Article

The Influence Mechanism of Logistics Information Technology on Consumer Purchase Decisions in Digital Supply Chains

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Abstract: Studying how logistics information technology affects consumers' purchasing decisions holds significant positive implications and functions for the further development of e-commerce and the logistics industry. Based on the SOR theory, this paper examines the driving effect and mechanism of logistics information technology on consumers' purchasing decisions. Starting from the data attributes of logistics information technology, it uses the ordinary least squares method to construct a multiple linear regression model of the impact of logistics information technology on consumers' purchasing decisions. And by using relevant software, it conducts an empirical study on the data collected from the questionnaire through correlation analysis and regression analysis. The results show that in the digital supply chain, logistics information technology (transparency, real-time interaction, and service predictability) and consumers' state perception both have a significant positive effect on consumers' purchasing decisions; consumers' state perception plays a partial mediating role in the relationship between logistics information technology and consumers' purchasing decisions. The maturity of the digital supply chain can positively regulate the relationship between logistics information transparency, logistics information service predictability and consumers' purchasing decisions, but there is no regulatory effect on the relationship between logistics information interaction real-timeity and purchasing decisions. Finally, based on the empirical results, policy recommendations are proposed.

Keywords: SOR theory; multiple regression model; least squares method; digital supply chain; logistics information technology; consumers' purchasing decisions

1. Introduction

With the development of Internet technology, digital supply chain management has gradually become an important part of enterprises, bringing higher efficiency and better management experience to them [1-2]. Under the application of logistics information technology, the information interaction among trading partners, consumers and suppliers has become more efficient and convenient. It influences consumers' purchasing decisions through multiple dimensions such as perception reliability, perception controllability and time value perception [3-5].

Firstly, with the development of the logistics industry, digital transformation has become an inevitable trend in the industry. The wide application of new technologies has promoted the logistics industry to move from traditional manual operations towards informatization, digitalization and intelligence [6-7]. For example, logistics enterprises have begun to utilize new technologies such as cloud computing, big data analysis and artificial intelligence to achieve optimized management of the logistics network, improve the efficiency and accuracy of goods delivery, and promote consumers' purchasing decisions [8-9]. Secondly, the application of logistics information technology has improved the information flow in logistics supply chain management, achieving comprehensive real-time logistics information [10-11]. Logistics enterprises establish logistics management systems, allowing consumers to obtain real-time information on the transportation status, cargo location, handover time and other aspects of each node in the logistics process. This information sharing and transparency have greatly improved the efficiency of the logistics industry, reduced errors and traffic congestion problems, and enhanced consumers' purchasing decisions [12-13]. Moreover, the application of logistics information technology has also made the logistics process in logistics supply chain management more intelligent and efficient [14-15]. For example, logistics enterprises can use Internet of Things technology to achieve real-time monitoring and tracking of goods, thereby better managing the delivery vehicles and drivers during the transportation process. Intelligent scheduling systems can arrange routes and delivery plans based on real-time traffic conditions and cargo demands, reducing transportation time and costs, and further influencing consumers' purchasing decisions [16-18].

In view of this, this paper intends to construct a conceptual model from the perspective of logistics information technology in the digital supply chain, based on the SOR theoretical framework. It will review the theories and empirical research results related to logistics information technology and consumer decision-making in the digital supply chain, and then build a conceptual model. The conceptual model will be tested based on the survey data, and the driving effect of logistics information technology in the digital supply chain on consumer purchase decisions will be studied. The consumer state perception variable will be introduced to explore its mediating effect between logistics information technology and consumer purchase decisions. At the same time, the moderating role of digital supply chain maturity will be investigated.

2. Model Construction and Assumptions

2.1. SOR Model

The Stimulus-Organism-Response (SOR) model is a classic model used to explain the complexity of human behavior and emotional responses. Its model structure is shown in Figure 1 [19]. The core concept is that the organism (O) is influenced by external stimuli (S) to generate cognitive responses, which then lead to psychological or behavioral responses (R). Here, the stimulus (S) refers to the influence of the external environment on the individual, the organism (O) refers to the individual's cognitive system, and the response (R) refers to the behavior or emotional response made by the individual to the stimulus. This internal processing of the stimulus may be conscious or unconscious. Eventually, this internal processing will trigger emotional responses, which in turn will produce external or internal behavioral responses. The SOR model has been widely applied in consumer behavior research. Some studies have shown that environmental stimuli can cause consumers to exhibit two behavioral responses, namely approaching or avoiding. These behavioral responses are caused by the individual's internal assessment of the environmental stimuli. The SOR model helps to analyze people's decision-making methods and the impact of different types of internal assessments on decision-making ability. This article uses this theory as the logical basis and attempts to explore the driving mechanism of the influence of the external stimulus factor, namely logistics information technology in the digital supply chain, on consumers' purchase decisions.

Figure 1. SOR model

2.2. Research Hypotheses

The consumer purchase decision refers to the psychological change process that occurs before a consumer makes a purchase. This process is a systematic and complex decision-making process, mainly consisting of three elements: clear goals - making choices - taking action and evaluating. Consumers generate purchase motivation based on their own needs, make choices based on personal preferences, product prices, packaging and other information, determine their choices, then take action to complete the purchase, and then evaluate the product or service after using it. Consumers make purchase decisions mainly following principles such as maximum satisfaction, relative satisfaction, minimum regret, and expected satisfaction. According to different dimensions, consumer purchase decisions can also be divided into different types, such as complex purchase decisions, coordinated purchase decisions, variable purchase decisions and habitual purchase decisions. Based on the SOR model, this study investigates the mechanism of the impact of logistics information technology in the digital supply chain on consumer purchase decisions.

The characteristics of logistics information technology in the digital supply chain include transparency, real-time interaction and predictability. Therefore, the following hypotheses are proposed:

H1: Logistics information technology (transparency, real-time interaction and predictability) in the digital supply chain is conducive to promoting consumer purchase decisions.

The involved entity is the consumer's perception state, so the following hypothesis is proposed:

H2: Logistics information technology (transparency, real-time interaction and predictability) is conducive to improving the consumer's perception state.

H3: Consumer state perception plays a direct mediating role between logistics information technology (transparency, real-time interaction and predictability) and consumer purchase decisions.

In addition, the study believes that the maturity of the digital supply chain may affect consumers' purchases, so the following hypothesis is proposed:

H4: The maturity of the digital supply chain positively moderates the relationship between logistics information technology and consumer purchase decisions.

3. Empirical Research Design

3.1. Data Source

To collect the data, this article first invited the faculty and staff of various universities in Jiangsu Province to fill out the questionnaires on-site, and a total of 520 paper questionnaires were collected; subsequently, questionnaires were distributed on the online platform, and a total of 300 questionnaires were collected; colleagues and classmates around were invited to help share the questionnaire links, and a total of 180 questionnaires were collected. In total, 960 questionnaires were collected. Then, the collected questionnaires were screened to eliminate those with inconsistent answers before and after and those with excessively high consistency in choices. Finally, 54 invalid questionnaires were eliminated, and 906 valid questionnaires were obtained, with an effective recovery rate of 90.6%. This survey was conducted from November 2024 to February 2025.

3.2. Variable Measurement

This study collected data through questionnaire surveys. All measurement scales were adapted to the context based on existing mature scales. The logistics information transparency (denoted as TMD) was mainly divided into three dimensions. Sample items included "The logistics information on this platform enables me to clearly understand every transfer stage of the package" and "The explanation of various status information on the logistics detail page is clear and understandable". The logistics information interactivity (marked as JHX) was divided into three items, with sample items including "When the logistics status changes, the platform will promptly send me notifications" and "I can always query the latest delivery progress". The logistics information service predictability (denoted as KYC) had three items, with sample items including "The estimated delivery time provided by the platform is very accurate" and "The platform can extract warnings of possible delivery delays". Consumer perception status (denoted as GZ) was measured through perception of functional value (denoted as GN), perception of emotional value (denoted as JZ), and perception of social value (denoted as SH). Perception of functional value was measured through three items such as "The product you purchased has a relatively high cost-performance ratio". Perception of emotional value was measured through four items such as "You feel that purchasing this product can make you feel happy". Perception of social value was measured through four items such as "You feel that purchasing this product can make you more confident". Consumer purchase decision (denoted as GM) was measured through four items such as "You are willing to frequently purchase this product". The digital supply chain maturity (CSD) was measured from three dimensions: the degree of automation in data collection, the level of information system integration, and the ability of intelligent decision support. The control variables in this study include the consumer's gender, age, income and years of education; at the same time, this study adopts the Likert 7-point scale for analysis, where "extremely opposed" is scored as 1 point and "very supportive" is scored as 7 points.

3.3. Construction of Data Analysis Model

By carefully reading the relevant scholars' studies on the influence of certain factors on the purchasing decisions of online consumers, the author combined the factors studied by previous scholars and started from the characteristics of digital supply chain logistics information technology. The transparency, real-time interaction, and predictability of digital supply chain logistics information technology were taken as the independent variables of this study, while the purchasing decisions of consumers were regarded as the dependent variable.

In multivariate statistical analysis, regression analysis is the most widely used method among all methods and is also the most commonly used method in mathematical statistics. Regression analysis is a theory for exploring the dependent relationship between independent variables. However, in the classical single-equation econometric model, since the dependent variable is affected by multiple independent variables in actual economic problems, and the purchasing decisions of consumers in this study are also influenced by multiple factors, the regression model established in this paper is a multiple linear regression model [20].

In this article, the dependent variable is named Y, and the five independent variables are respectively named X_1, X_2, X_3, X_4, and X_5. Thus, the regression model of the dependent variable Y with the independent variables X_1, X_2, X_3, X_4, and X_5 can be obtained:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \mu \tag{1}$$

The estimators of the ordinary least squares method possess excellent properties such as linearity, unbiasedness and efficiency. It is the best linear unbiased estimator, so using the least squares method to estimate parameters is the optimal choice [21]. The ordinary least squares method utilizes the SPSS13.0 software to find $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\beta}_4$, and $\hat{\beta}_5$, aiming to minimize the sum of squared residuals. The formula is as follows:

$$\begin{aligned} Q\left(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2 \cdots \hat{\beta}_p\right) &= \sum_{i=1}^{n}\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \cdots - \hat{\beta}_p x_{ip}\right)^2 \\ &= \min_{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2 \cdots \hat{\beta}_p} \sum_{i=1}^{n}\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \cdots - \hat{\beta}_p x_{ip}\right)^2 \end{aligned} \tag{2}$$

In order to minimize the parameter estimation values, the normal equation set for the parameter estimations can be obtained through matrix operations and differentiation:

$$\begin{aligned} &\sum\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \cdots - \hat{\beta}_p x_{ip}\right) \\ &= \sum y_i \sum\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \cdots - \hat{\beta}_p x_{ip}\right) x_{i1} \\ &= \sum y_i x_{i1} \sum\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \ldots - \hat{\beta}_p x_{ip}\right) x_{i2} \\ &= \sum y_i x_{i2} \\ &\cdots \\ &\sum\left(Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \ldots - \hat{\beta}_p x_{ip}\right) x_{ip} = \sum y_i x_{ip} \end{aligned} \tag{3}$$

By using formulas (2) and (3), the parameters $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\beta}_4$, and $\hat{\beta}_5$ can be derived. Thus, the multiple linear regression model of this paper is:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \hat{\beta}_3 x_{i3} + \hat{\beta}_4 x_{i4} + \hat{\beta}_5 x_{i5} \tag{4}$$

4. Empirical Results and Analysis

Homologous bias is widely present in studies using the questionnaire method. It is an artificial covariation between predictor variables and criterion variables in the process of behavioral research. This artificially generated covariation phenomenon is essentially a systematic error, which not only seriously confuses the research results but also potentially misleads the research conclusions. Therefore, before the formal analysis, this paper uses AMOS 29.0 to establish a single-factor structural equation model and calculates the fitting situation of the single-factor model as follows: $\chi^2 / df = 5.111$, which is greater than the critical value 5; GFI = 0.789, NFI = 0.762, CFI = 0.798, RFI = 0.735, which are all less than the critical value 0.9; RMSEA = 0.114, which is greater than the critical value 0.08. The model fitting does not meet the requirements, indicating that there is no serious homologous bias in this study.

4.1. Reliability and Validity Testing

In order to assess the stability and reliability of the variable measurements, the Cronbach's α coefficient was used to examine the reliability of each variable. The results of the variable reliability test are shown in Table 1 [22]. The critical value of Cronbach's α is related to the number of items of the variable. When the number of items is greater than 5, a Cronbach's α coefficient higher than 0.7 indicates that the variable has a high internal consistency. When the number of items is less than 5, a Cronbach's α coefficient greater than 0.6 indicates that the test has passed the reliability check. The calculation of the Cronbach's α coefficient is achieved through the SPSS software. As can be seen from the table, the Cronbach's α coefficient of each variable is greater than the critical value, indicating that the consistency and stability of each variable meet the requirements.

Table 1. Test results of variable reliability test

Variable	Item	Cronbach's α
Transparency	3	0.689
Interactivity	3	0.692
Service predictability	3	0.677
Consumer perception	11	0.753
Maturity	3	0.696
Consumer decision	4	0.705

The validity of the questionnaire was determined by using KMO and Bartlett's sphericity test. The results of the variable validity analysis are shown in Table 2. The KMO values of logistics information technology transparency, real-time interaction, and predictability in the digital supply chain are 0.831, 0.889, and 0.872 respectively, all greater than 0.7. Therefore, the validity of the three explanatory variables is good. Similarly, the KMO values of purchase decision, supply chain maturity, and consumer perception status are also greater than 0.7, indicating good validity. The significance of the Bartlett's sphericity test for each variable is 0.000, which rejects the null hypothesis that the original variables are not related, indicating good reliability.

Table 2. Variable validity analysis

Variable	KMO-value	Cronbach's α	
		Approximate card	Sig.
Transparency	0.831	1268.88	0.000
Interactivity	0.889	1268.95	0.000
Service predictability	0.872	880.55	0.000
Consumer perception	0.845	1011.32	0.000
Maturity	0.886	1025.37	0.000
Consumer decision	0.862	1108.42	0.000

4.2. Descriptive Statistics and Correlation Analysis

The descriptive statistics of each variable are shown in Table 3. As can be seen from Table 3, the ages of the respondents range from 19 to 45 years old, with an average age of 25.72, which is in line with the survey target of mainly young people. The mean value of the gender variable is 0.455, close to 0.5, indicating a relatively balanced ratio of males and females. The maximum value of the educational attainment is 5, which is a doctoral degree, and the minimum value is 1, which is below junior high school. It can be seen that the respondents have well-covered young people with different educational backgrounds. The minimum value of income is 0.178, the maximum value is 0.425, and the standard deviation is 1.4407, indicating a large income gap among the respondents.

Table 3. Variable descriptive statistics

Variable	Mean	SD	Minimum	Maximum
TMD	0.181	0.9311	0.135	0.282
JHX	0.622	0.5605	0.551	0.731
KYC	0.421	0.3881	0.397	0.522
GZ	0.288	0.7552	0.219	0.371
GM	0.112	0.8991	0.015	0.258
CSD	0.235	0.7882	0.022	0.357
Age	25.72	0.7256	19	45
Edu	2.335	0.7113	1	5
Income	0.238	1.4407	0.178	0.425
Gender	0.455	1.1468	0	1

The correlation test analysis method is designed to examine the potential correlations among multiple variables, in order to measure the close connection between various factors. If the correlation coefficient passes the significance test, it indicates that there is a correlation between the variables. To ensure the fairness and academic nature of the research, this study uses the Pearson correlation coefficient to test the degree of correlation among logistics information technology transparency, real-time interaction, predictability, consumer state perception, supply chain maturity, and consumer purchase decisions in the digital supply chain. The results of the correlation analysis of each variable are shown in Table 4. As can be seen from Table 4, the correlation coefficients of logistics information technology transparency, real-time interaction, predictability, consumer state perception, supply chain maturity, and consumer purchase decisions in the digital supply chain are between 0.3 and 0.8, indicating a significant positive correlation and a moderate degree of correlation between them. The absolute values of the Pearson correlation coefficients between the remaining variables are between 0.2 and 0.4, indicating a significant positive correlation and a weak correlation between them. Overall, the correlations among all variables have met the standard requirements and can proceed to the next analysis.

Table 4. Correlation test analysis of variables

Variable	TMD	JHX	KYC	GZ	CSD	GM
TMD	1					
JHX	0.372**	1				
KYC	0.411**	0.305**	1			
GZ	0.322**	0.215**	0.228**	1		
CSD	0.375**	0.261**	0.247**	0.303**	1	
GM	0.333**	0.268**	0.381**	0.252**	0.202**	1

4.3. Regression Results of the Baseline Model

Regression analysis of logistics information technology in digital supply chain and consumer state perception, purchase decision. This paper uses SPSS 25.0 software to respectively test the relationship between logistics information technology in the digital supply chain and consumer state perception, as well as the relationship between logistics information technology in the digital supply chain and consumer purchase decision. The specific analysis results are shown in Table 5.

Based on setting gender, age and education level as control variables, using the distribution test method, the relationship between logistics information technology in the digital supply chain and consumer state perception and purchase decision is tested. Firstly, the influence of logistics information technology in the digital supply chain on consumer state perception was tested. The results showed that information transparency (M2, $\beta = 0.35$, $p < 0.01$), interactive real-time performance (M3, $\beta = 0.33$, $p < 0.01$), and service predictability (M4, $\beta = 0.45$, $p < 0.01$) had significant positive correlations with consumer state perception, and hypothesis H2 was verified. Secondly, the influence of logistics information technology in the digital supply chain on consumer purchase decision was tested. The results showed that information clarity (M6, $\beta = 0.28$, $p < 0.01$), interactive real-time performance (M7, $\beta = 0.35$, $p < 0.01$), and service predictability (M8, $\beta = 0.42$, $p < 0.05$) had significant positive correlations with consumer purchase decision, and hypothesis H1 was verified.

Table 5. Main effect test results

Variable	GZ				GM			
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
Gender	0.01	0.05	0.02	0.08	0.05	0.02	0.05	0.12
Age	0.05	0.07	0.03	0.03	0.09	0.07	0.09	0.07
Edu	0.03	0.05*	0.03	0.05*	0.04	0.05	0.02	0.03*
TMD		0.35**				0.28***		
JHX			0.33**				0.35**	
KYC				0.45**				0.42**
R^2	0.03	0.06	0.11	0.19	0.02	0.15	0.14	0.26
$\triangle R^2$	0.03	0.03	0.08	0.16	0.02	0.13	0.12	0.24
F	0.12	2.35**	5.68**	10.95**	0.49**	7.71**	6.42**	15.65**
$\triangle F$	0.12	8.99**	22.31**	45.22**	0.49**	29.15**	24.21**	60.66**

4.4. Mediation Effect Analysis

The consumer state perception and purchase decisions were simultaneously included in the regression model for analysis. The results are shown in Table 6. The results indicated a significant positive correlation between consumer state perception and purchase decisions (M9, $\beta = 0.38$, $p < 0.01$). Then, information transparency (M10), real-time interaction (M11), and service predictability (M12) were respectively placed in the regression model along with consumer state perception and purchase decisions. The study found that consumer state perception played a partial mediating role between information transparency and consumer purchase decisions (β = 0.39, $p < 0.05$), real-time interaction and consumer purchase decisions (β = 0.38, $p < 0.1$), and service predictability and consumer purchase decisions (β = 0.29, $p < 0.1$). Hypothesis H3 was verified.

Table 6. The mediation effect tests the results

Variable	GM			
	M9	**M10**	**M11**	**M12**
Gender	0.02	0.02	0.05	0.09
Age	0.07	0.06	0.05	0.05
Edu	0.06	0.05*	0.02*	0.02*
TMD		0.30***		
JHX			0.22**	
KYC				0.38**
GZ	0.38***	0.39***	0.38*	0.29*
R^2	0.15	0.29	0.26	0.32
$\triangle R^2$	0.14	0.15	0.12	0.11
F	7.52**	14.65**	12.21**	17.31**
△F	30.05**	37.02**	31.41**	18.45**

4.5. Test Results of Adjustment Effect

To test whether the maturity of the digital supply chain plays a mediating role between logistics information technology and purchase decisions, the hypothesis H4 was tested. The regression results of the moderating effect are shown in Table 7. In this table, the explanatory variables in the (1) and (2) columns are information transparency (TMD), in the (3) and (4) columns are interactive real-time performance, and in the (5) and (6) columns are service predictability. According to Table 7, the coefficient of the impact of digital supply chain maturity (CXD) on purchase decisions (GM) is always positive and is significant at the 1% significance level, indicating that digital supply chain maturity has a significant positive impact on consumers' purchase decisions. When the digital supply chain maturity is high, the continuity of aspects such as consumer experience is stronger, which can continuously strengthen consumers' understanding of the brand and thereby promote purchase decisions.

From the coefficients of the interaction terms between the explanatory variables and the moderating variables, the coefficient of the interaction term between information transparency (TMD) and digital supply chain maturity (CSD) is 0.651 (in the case of adding control variables), which is significant at the 1% significance level, indicating that digital supply chain maturity can positively moderate the relationship between information transparency and purchase decisions. The coefficient of the interaction term between interactive real-time performance (JHX) and digital supply chain maturity (CSD) is 0.701, but it is not significant, indicating that the moderating effect of digital supply chain maturity is not significant. The coefficient of the interaction term between service predictability (KYC) and digital supply chain maturity (CSD) is 0.728, which is significant at the 1% significance level. This indicates that the moderating effect of digital supply chain maturity on the relationship between different dimensions of logistics information technology and purchase decisions varies. When the digital supply chain maturity is high, the promoting effects of information transparency and service predictability on purchase decisions are stronger. However, for the interactive real-time performance dimension, the moderating effect of digital supply chain maturity is not significant. This partially proves the validity of hypothesis H4.

Table 7. The adjustment effect returns

Variable	Explained variable GM					
	TMD		JHX		KYC	
	(1)	(2)	(3)	(4)	(5)	(6)
constants	1.531***	1.566***	1.587***	1.304***	1.922***	1.909***
	(3.371)	(3.245)	(4.011)	(4.422)	(3.883)	(4.492)
WLXX	0.025***	0.029***	0.026***	0.025***	0.026***	0.028***
	(9.771)	(12.707)	(13.135)	(7.505)	(14.371)	(13.722)
CSD	1.755***	1.972***	1.774***	1.511***	2.111***	1.521***
	(2.521)	(1.995)	(2.112)	(3.722)	(2.556)	(2.242)
WLXX×CSD	0.722***	0.651***	0.845	0.701	0.849***	0.728***
	(5.105)	(6.666)	(3.701)	(7.225)	(4.665)	(5.501)
Age		0.111**		0.135*		0.131**
		(4.001)		(3.332)		(2.572)
Edu		0.095**		0.125*		0.151**
		(4.841)		(5.531)		(8.785)
Gender		0.512***		0.624***		0.585***
		(6.728)		(1.071)		(1.687)

5. Conclusion

Firstly, through empirical research, it was found that the three dimensions of logistics information technology in the digital supply chain (transparency, real-time interaction, and predictability) have a significant positive impact on consumers' state perception. Secondly, the three dimensions of logistics information technology in the digital supply chain are positively correlated with consumers' purchase decisions, which is consistent with the research conclusions of some existing experts. Thus, enhancing logistics information technology is conducive to enhancing consumers' state perception, thereby further strengthening consumers' purchase decisions. Thirdly, from the above research, it can be found that among the influences of the three dimensions of logistics information technology on consumers' state perception and their purchase decisions, from high to low, they are service predictability, information transparency, and real-time interaction. This indicates that when consumers make purchases, service predictability has the most critical impact on consumers, followed by information transparency and real-time interaction. Moreover, consumer state perception has a partial mediating effect between logistics information technology and consumers' purchase decisions, indicating that in the process of using logistics information technology, logistics information technology cannot directly make consumers have the intention to repurchase, but needs to be perceived and evaluated. Finally, the maturity of the digital supply chain can positively regulate the relationship between information transparency, service predictability, and consumers' purchase decisions, but there is no regulatory effect on the relationship between interaction real-timeity and purchase decisions.

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