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AN EMPIRICAL STUDY ON MODERATION EFFECT OF PERCEIVED RISK BETWEEN PERCEIVED VALUE AND PURCHASE INTENTION IN JIANGSU'S DIGITAL SERVICE CONSUMPTION, CHINA

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Abstract: This study explores the relationships among consumer benefit, perceived value, perceived risk, and purchase intention in the context of Jiangsu Province's fast-growing digital service in China. Drawing on the Theory of Reasoned Action and The Consumer Decision-Making Process Theory, the research investigates how consumer benefit and perceived value influence consumers' purchase intentions, and how perceived risk moderates the perceived value–purchase intention relationship. Data were analyzed to assess both measurement and structural models. The empirical results reveal that consumer benefit exerts a significant positive effect on perceived value, and perceived value strongly predicts purchase intention. Importantly, perceived risk negatively moderates the relationship between perceived value and purchase intention, indicating that higher levels of perceived risk weaken the influence of perceived value on consumers' intention to purchase. These findings highlight that enhancing consumer benefits and reducing perceived risks are critical strategies for digital service providers seeking to strengthen consumers' purchase intentions. The study offers theoretical contributions by integrating perceived risk as a moderator into the benefit–value–intention framework, and provides practical insights for improving service design and consumer trust in Jiangsu's digital service.
Keywords: Consumer Benefit, Perceived Value, Perceived Risk, Purchase Intention, Digital Service, Jiangsu

1.INTRODUCTION

Based on the data of the National Bureau of Statistics, China's per capita service consumption expenditure will be 10590 yuan in 2022, accounting for 43.2% of residents' per capita consumption expenditure (Li, 2023). Service consumption is the main direction of upgrading the consumption structure of residents and is of great significance to the high-quality development of the national economy, and the development of service consumption is mainly manifested in the following two points (Mao, 2023):The proportion of service consumption is increasing, and the structure of residents' consumption is changing from physical consumption to service consumption, with an obvious trend of consumption upgrading. Jiangsu Province, as one of China's most economically active regions, has seen a surge in digital service consumption, where consumers increasingly rely on online platforms for financial, entertainment, and lifestyle services.
Research has shown that consumers' perceived value of services is influenced by information access channels, social influences and personal psychological factors (Zheng, 2020). Research on the impact of AI services on customer behaviour, including changes in the perceived value of services, has found that the introduction of AI services has changed the way services are delivered and the customer's interactive experience, which in turn affects the customer's perceived value of services. For example, the reliability and responsiveness of AI services may be enhanced, but at the same time it may lead to a decrease in customers' perceptions of service safety and empathy. This suggests that changes in the perceived value of services in an intelligent service environment are influenced not only by technological factors, but also by customers' psychological expectations and social interactions (Du et al., 2022).

2.LITERATURE REVIEW

2.1 Theoretical Justification

The consumer decision-making process theory is a cornerstone of marketing and consumer behavior research. It seeks to unravel the intricate cognitive and affective mechanisms that drive consumers from recognizing a need to making a purchase decision and post-purchase evaluation.

Sudirjo reviewed psychological dynamics in consumer decision-making processes in the digital marketing era. The study emphasized how digital interactions and the availability of information influence consumer preferences and purchase decisions (Sudirjo, 2024). This comprehensive approach is significant as it illustrates the interconnectedness of different theories in explaining consumer behavior.

Additionally, perceived value is crucial in the digital marketplace. In an environment driven by competition, where consumers can easily compare offerings, perceived value becomes an element that can drive purchase decisions. Studies suggest that creating unique value propositions that align closely with consumer expectations can significantly influence both perceived value and purchase intentions (Ma et al., 2024).

Perceived risk encompasses the potential negative outcomes associated with a purchase decision. It is categorized into several dimensions, including financial risk, performance risk, social risk, and psychological risk (Tjahjono et al., 2021). In the context of the consumer decision-making process, perceived risk can heavily influence purchase intentions.

The Theory of Reasoned Action focuses on the psychological mechanism that translates evaluations into behavioral intentions. It offers psychological frameworks for predicting consumer intentions and behaviors. The theory posits that consumers' behaviors are guided by their attitudes, subjective norms, and perceived behavioral control.

The combination of the Theory of Reasoned Action (TRA) and perceived value has shown that attitudes and subjective norms influence not only the intention to purchase but also the perceived value of a product or service (Ajzen, 1991).

Perceived value comprises the assessment of benefits received against the costs incurred during consumption. TRA directly links perceived value to purchase intentions, suggesting that consumers will evaluate a service based on their beliefs (attitudes) and the norms they internalize regarding that service.

Wang et al. explored the implications of social media on perceived value and purchasing behaviors within the context of green products, emphasizing that perceived environmental benefits increased consumer intentions to engage with these products—an effect mediated by positive attitudinal shifts towards sustainable consumption (Wang et al., 2024).

2.2 Empirical review

Purchase intention has been widely used in the literature as a predictor of subsequent purchases. More specifically, Mitchell, Davies, Moutinho and Vassos and Wood and Scheer have successfully demonstrated that purchase intentions are negatively driven by the perceived risk associated with a purchase.

Empirical studies provide evidence for the moderating role of perceived risk. For example, a study by Kukar-Kinney and Close (2010) found that the positive impact of perceived value on purchase intentions was greater for consumers with lower perceived risk. In contrast, when perceived risk is high, the effect of perceived value on purchase intentions is weaker, suggesting that consumers may be more cautious and seek more information or reassurance before making a purchase.When perceived value is high and perceived risk is low, consumers are more likely to purchase. However, when perceived risk is high, the positive effect of perceived value on purchase intention is significantly reduced.

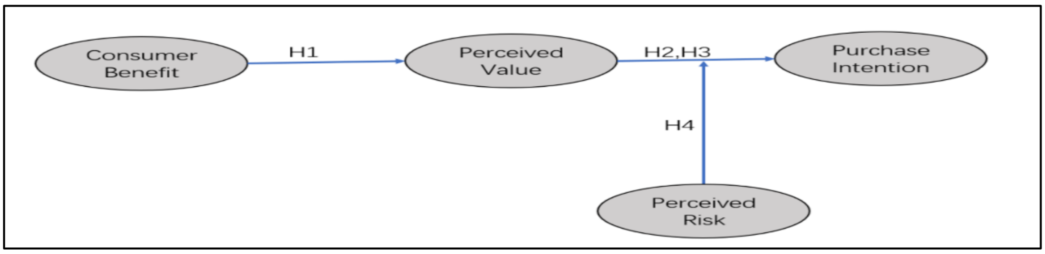
In online and technology-mediated environments, the relationship between benefits and value remains robust. Chiu, Wang, Fang and Huang (2014) examined the relationship between e-service quality and the benefits of online shopping among Taiwanese consumers. They found that utilitarian benefits and hedonic benefits significantly enhanced perceived value. They concluded that perceived value acts as a key mediator between benefits and purchase intention in digital settings.

Similarly, Liang et al. (2024) examined food delivery platforms in China and showed that functional benefits, hedonic benefits, and relational benefits all positively influence perceived value, with hedonic and relational benefits having the greatest impact. Their PLS-SEM results confirm the central role of perceived benefits in explaining value perceptions among digital consumers.

3.Research framework and hypotheses

The overall research framework is illustrated in Figure 1.

Figure1: Research framework



Research Hypotheses
H1: Consumer benefit (CB) has positive effect on perceived value (PV)
H2: Perceived value (PV) has positive effect on purchase intention (PI)
H3: Perceived value mediates the effect between consumer benefit and purchase intention (PI)
H4: Perceived risk moderates the effect between perceived value (PV) and purchase intention (PI)

4.FINDINGS

4.1 Demographic Characteristics
The demographic profile of the sample is presented in Table 1.

Table 1: Demographic Characteristics

Variables	Group	Frequency	Ratio (%)
Gender	Male	267	46.6
	female	306	53.4
Marital status	Married	207	36.1
	unmarried	237	41.4
	other	129	22.5
Age	under 22	41	7.2
	23–29	164	28.6
	30–39	158	27.6
	40–49	118	20.6
	50–59	49	8.6
	Over 60	43	7.5
Education level	undergraduate degree or higher	155	27.1
	Junior College	194	33.9
	high school	149	26
	junior school or lower than junior school	75	13.1
Monthly income	3000 yuan or less than 3000 yuan	169	29.5
	3000–5000 yuan	137	23.9
	5000–10000 yuan	100	17.5
	10,000–20,000 yuan	110	19.2
	Over 20,000 yuan	57	9.9

According to demographic statistics, the sample size was 573. Among them, 267 were male, accounting for 46.6%, and 306 were female, accounting for 53.4%. Regarding marital status, 207 were married, 237 were unmarried, and 129 were in other circumstances. Unmarried individuals constituted the majority, accounting for approximately 41.4%. The age of respondents was concentrated between 23 and 49 years old, collectively accounting for over 70% of the total. Educational attainment: 155 held bachelor's degrees or higher (27.1%), 194 held associate degrees (33.9%), 149 held secondary school qualifications (26%), and 75 held junior secondary or lower qualifications (13.1%). Monthly income distribution: 169 individuals (29.5%) earned £3,000 or less; 137 (23.9%) earned between £3,000 and £5,000; 100 (17.5%) earned between £5,000 and £10,000; 110 (19.2%) earned between £10,000 and £20,000; and 57 (9.9%) earned over £20,000.

4.2 Descriptive Statistics

Descriptive statistics provide a statistical characterisation of all variables within a survey population, encompassing measures such as central tendency, dispersion, and distribution. This study calculated the mean values for the variables CB, PV, PR, and PI. Specifically, CB comprises five items, PV eight items, PR eight items, and PI four items. Table 2 provides a summary of the descriptive statistics for the sample.

Table 2: Descriptive Statistics

	Minimum	Maximum	Mean	S.D.	Variance	Skewness	Kurtosis
CB	1	5	3.621	0.865	0.748	-0.636	-0.171
PV	1.375	5	3.595	0.865	0.748	-0.394	-0.865
PR	1.125	5	3.455	0.897	0.805	-0.288	-0.916
PI	1	5	3.362	0.941	0.885	-0.352	-0.587

Descriptive statistics reveal that CB has a minimum value of 1, a maximum value of 5, a mean of 3.621, a standard deviation of 0.865, a variance of 0.748, a skewness of -0.636, and a kurtosis of -0.171. For PV, the minimum value is 1.375, the maximum is 5, the mean is 3.595, the standard deviation is 0.865, the variance is 0.784, the skewness is -0.394, and the kurtosis is -0.865. PR has a minimum value of 1.125, a maximum value of 5, a mean of 3.455, a standard deviation of 0.897, a variance of 0.805, a skewness of -0.288, and a kurtosis of -0.916. The minimum value for PI is 1, the maximum is 5, the mean is 3.362, the standard deviation is 0.941, the variance is 0.885, the skewness is -0.352, and the kurtosis is -0.587. No outliers were observed.

4.3 Exploratory Factor Analysis

Reliability analysis is commonly employed to assess the internal consistency of scale data. Table 3 summarizes the reliability coefficients and exploratory factor analysis results.

Table 3: Reliability and Exploratory Factor Analysis

	1	2	3	4	Cronbach's α
CB1	0.134	-0.031	0.830	0.121	0.894
CB2	0.164	0.004	0.816	0.091	
CB3	0.174	0.068	0.842	0.084	
CB4	0.127	-0.012	0.839	0.072	
CB5	0.145	0.050	0.772	0.092	
PV1	0.806	-0.025	0.118	0.089	0.927
PV2	0.817	-0.022	0.090	0.136	
PV3	0.796	-0.064	0.109	0.099	
PV4	0.804	-0.039	0.084	0.060	
PV5	0.757	-0.076	0.143	0.060	
PV6	0.815	-0.016	0.132	0.069	
PV7	0.806	-0.052	0.087	0.146	
PV8	0.797	-0.017	0.156	0.086	
PR1	-0.037	0.824	-0.022	-0.050	0.924
PR2	0.008	0.809	0.017	-0.098	
PR3	-0.055	0.807	-0.022	-0.059	
PR4	-0.021	0.807	0.010	-0.033	
PR5	-0.025	0.792	0.025	-0.057	

PR6	-0.040	0.801	0.002	-0.020	
PR7	-0.065	0.799	0.014	-0.043	
PR8	-0.063	0.801	0.055	-0.075	
PI1	0.143	-0.056	0.096	0.853	0.878
PI2	0.155	-0.077	0.082	0.883	
PI3	0.159	-0.118	0.118	0.853	
PI4	0.104	-0.097	0.134	0.737	
Total	5.327	5.240	3.528	2.926	
% of Variance	21.308	20.960	14.110	11.705	
Cumulative %	21.308	42.268	56.378	68.083	
KMO=0.919, Bartlett=8884.407, df=300, Sig.=0.000					

This study utilised the α reliability coefficient method for testing, revealing CB reliability at 0.894, PV reliability at 0.927, PR reliability at 0.924, and PI reliability at 0.878. The reliability coefficients for all four variables exceeded 0.8, indicating excellent reliability of the sample data.

Factor analysis employs dimensionality reduction techniques to examine the internal structure of observed variables. Principal component analysis was employed, with factor rotation conducted using Kaiser's normalised variance maximisation method. Factors with eigenvalues exceeding 1 were extracted. After five iterations achieving convergence, the component matrix yielded a KMO value of 0.919, a Bartlett's value of 8884.407, degrees of freedom of 300, and a significance level of 0.000. The 25 items yielded four components: CB, PV, PI, and PR. All factor loadings exceeded 0.5 in absolute value, with total variance explained at 68.083%—exceeding the 60% threshold. Collectively, this indicates sound construct validity for this study.

4.4 Confirmatory factor analysis

Figure 2 illustrates the measurement model used in this study.

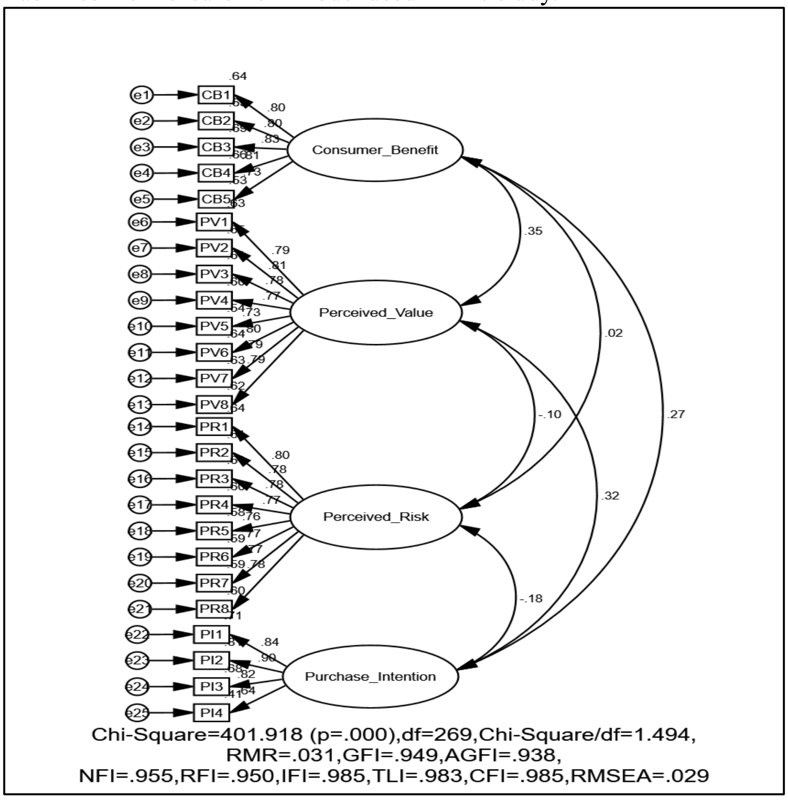


Figure2: Measurement Mode 1

Table 4: Confirmatory factor analysis

	Estimate	S.E.	C.R.	P	AVE	CR
CB1	0.800	0.351			0.631	0.895
CB2	0.796	0.372	20.598	***		
CB3	0.829	0.318	21.674	***		

CB4	0.813	0.400	21.132	***		
CB5	0.730	0.527	18.499	***		
PV1	0.792	0.416			0.616	0.928
PV2	0.808	0.392	21.440	***		
PV3	0.782	0.442	20.565	***		
PV4	0.774	0.455	20.306	***		
PV5	0.734	0.471	18.983	***		
PV6	0.802	0.418	21.232	***		
PV7	0.794	0.408	20.962	***		
PV8	0.788	0.451	20.750	***		
PR1	0.799	0.438			0.603	0.924
PR2	0.783	0.450	20.730	***		
PR3	0.782	0.504	20.686	***		
PR4	0.775	0.508	20.450	***		
PR5	0.762	0.510	20.000	***		
PR6	0.767	0.547	20.179	***		
PR7	0.768	0.470	20.197	***		
PR8	0.776	0.490	20.490	***		
PI1	0.841	0.360			0.653	0.881
PI2	0.902	0.239	25.876	***		
PI3	0.825	0.373	23.302	***		
PI4	0.639	0.678	16.433	***		
χ=401.918, DF=269, χ^2/DF=1.494, GFI=0.976, AGFI=0.964, NFI=0.97, RFI=0.962, IFI=0.997, TLI=0.996, CFI=0.997, RMSEA=0.017						

Confirmatory factor analysis was employed to examine the degree of data convergence. Generally, to achieve high convergent validity, the Average Variance Extracted (AVE) should exceed 0.5, whilst the Composite Reliability (CR) should surpass 0.7. The confirmatory factor analysis results for this study indicate a goodness-of-fit X^2 = 401.918, DF = 269, X^2 / DF = 1.49; GFI = 0.976, AGFI = 0.964, NFI = 0.97, RFI = 0.962, IFI = 0.997, TLI = 0.996, CFI = 0.997, RMSEA = 0.017. /DF=1.494, GFI=0.976, AGFI=0.964, NFI=0.970, RFI=0.962, IFI=0.997, TLI=0.996, CFI=0.997, PMSEA=0.017. Overall, the fit is satisfactory. The AVE values are 0.631 for CB, 0.616 for PV, 0.603 for PR, and 0.653 for PI. All four variables exceed the 0.6 threshold, thus meeting the criterion of AVE > 0.5. The composite reliability (CR) values were 0.895 for CB, 0.928 for PV, 0.924 for PR, and 0.881 for PI, all exceeding 0.8. In summary, the data exhibit sound discriminant validity.

4.5 Correlation Analysis

Correlation analysis is employed to examine the relationship between two variables, thereby measuring the degree of association between them. As shown in Table 5, the key variables exhibit correlations.

Table 5: Correlations

	Mean	Std. Deviation	CB	PV	PR	PI
CB	3.621	0.865	1			
PV	3.595	0.865	.323**	1		
PR	3.455	0.897	0.015	-.098*	1	
PI	3.362	0.941	.255**	.295**	-.172**	1
**P<0.01, *P<0.05						

This study utilised Pearson's correlation analysis. Results indicate a significant positive correlation between CB and PV ($P < 0.01$), with a correlation coefficient of 0.323. The correlation between CB and PR was non-significant ($P > 0.05$). CB and PI exhibited a significant positive correlation ($P < 0.01$) with a correlation coefficient of 0.255, indicating that higher CB values correlate with higher PI values. PV and PR showed a significant negative correlation ($P < 0.05$) with a coefficient of -0.098, meaning that higher PV values correlate with lower PR values. The correlation between PV and PI was significant (P

< 0.01), with a correlation coefficient of 0.295 indicating a positive relationship: higher PV values corresponded with higher PI values. The correlation between PR and PI was significant (P < 0.01), with a correlation coefficient of -0.172 indicating a negative relationship: higher PR values corresponded with lower PI values.

4.6 Path Analysis

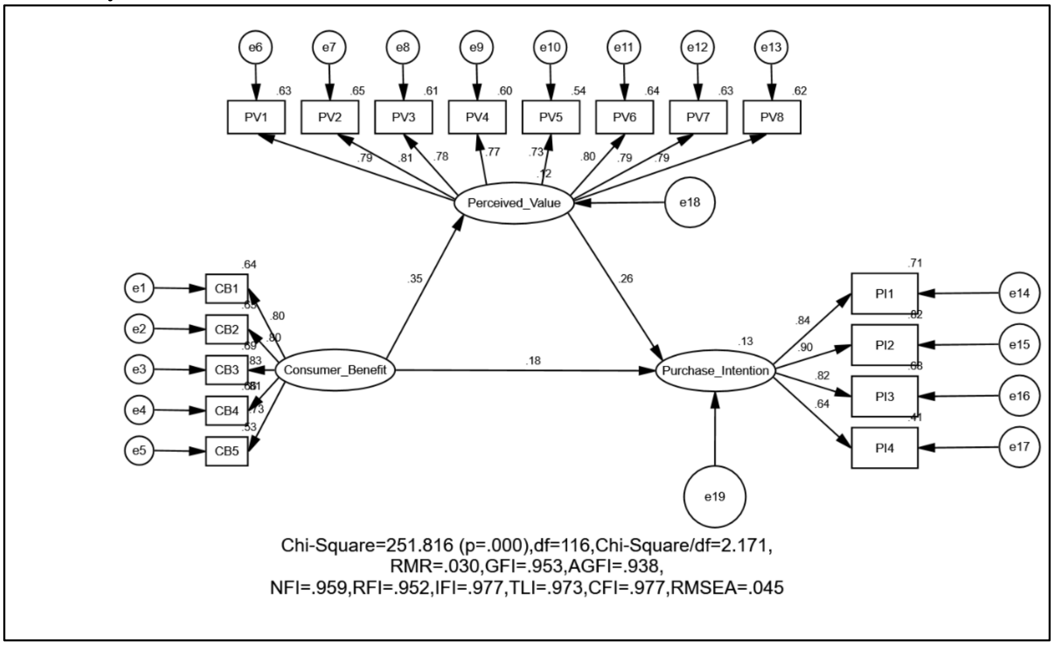


Figure3: Measurement Mode 2

Table 6: Path Analysis Results

Hypothesis	Path			Standardised Estimate	S.E.	C.R.	P	Results
H1	PV	<---	CB	0.353	0.049	7.651	***	Supported
H2	PI	<---	PV	0.259	0.053	5.420	***	Supported
	PI	<---	CB	0.177	0.056	3.690	***	Supported
X =251.816,DF=116,X /DF=2.171,RMR=0.030,GFI=0.953,AGFI=0.938,NFI=0.959,RFI=0.952,IFI=0.977,TLI=0.973,CFI =0.977,PMSEA=0.045 ***p<0.005								

Path analysis reveals the influence pathways between variables. As shown in Figure 3 and Table 6. This study first validated the theoretical model using structural equation modelling (SEM), with all fit indices meeting ideal standards: X = 251.816, DF=116, /DF=2.171, RMR=0.030, GFI=0.953, AGFI=0.938, NFI=0.959, RFI=0.952, IFI=0.977, TLI=0.973, CFI=0.977, PMSEA=0.045. The model demonstrated good fit with the data.

CB significantly influences PV, with a standardised path coefficient of 0.353 ($p < 0.005$). Hypothesis H1 is supported. This finding aligns with prior research demonstrating that benefit enhances consumers' perceived value. Putra & Sobari (2024) highlight that perceived value is a comparative measure where higher benefits accompanied by lower costs result in increased value perception.

PV exerted a significant positive influence on PI, with a standardised path coefficient of 0.259 ($p < 0.005$). Hypothesis H2 was supported. Although this effect was of moderate strength, it corroborated the theoretical framework that perceived value is the core driver of purchase decisions. Hoang & Quang (2020) found that when consumers recognize the value associated with a product—encompassing both functional and emotional benefits—their intent to purchase increases.

4.7 Mediation Analysis

Table 7: Mediation Effect

Variables	Estimate	Bootstrapping Bias-corrected CI = 95%			Decision
Indirect effect		low	high	p-value	
CB→PV→PI	0.091	0.054	0.124	0.001	Accept
Note: CI = confidence interval, the process repeated 2000 times.					

Mediation effect analysis elucidates how CB influences PI by affecting PV. It is shown in Table 7. A significant indirect effect indicates the mediation effect holds. This study employed Bootstrap sampling (repeated 2000 times) to test PV's mediating effect between CB and PI, with a 95% confidence interval. The results are presented in the table above. The indirect effect value of CB on PI via PV is 0.091 (Bias-corrected 95% CI = [0.054, 0.124], $p = 0.001$). The confidence interval does not contain zero, indicating statistical significance. This indicates a significant mediating effect of PV between CB and PI. Combined with path analysis results showing CB's direct effect on PI is significant ($p < 0.05$) with a path coefficient of 0.177, the comprehensive analysis concludes that PV partially mediates the relationship between CB and PI.

4.8 Moderation Analysis

Moderating Effect Test

Table 8: Moderating Effect of PR on the PV→PI Relationship

Variable	coeff	se	t	p	95% BootCI LLCI	95% BootCI ULCI	PR Level	Effect	p
PV*PR	-0.262	0.047	-5.564	0.000	-0.354	-0.169	Low PR (2.558)	0.477	<0.001
							Mean PR (3.455)	0.242	<0.001
							High PR (4.353)	0.007	0.913

Note: Bootstrap resamples = 5000; PR levels calculated as mean ±1SD.

This study employed Hayes (2018) PROCESS Model 14 to conduct a moderated mediation analysis, examining the moderating role of perceived risk (PR) in the mediating pathway from consumer benefits (CB) → perceived value (PV) → purchase intention (PI).

The study employed Bootstrap sampling (5000 iterations) to compute 95% bias-corrected confidence intervals (Bias-corrected CI), ensuring statistical robustness.

Results shown in Table 8 indicate that the interaction coefficient between PV and PR is -0.262 ($p < 0.001$, 95% BootCI [-0.354, -0.169]), demonstrating that PR significantly negatively moderates the effect of PV on PI. That is, as PR increases, the promotional effect of PV on PI progressively diminishes.

Specifically, the effect size of PV on PI varied significantly across different PR levels. At low PR (mean -1SD, PR = 2.558), the effect size was 0.477 ($p < 0.001$), indicating the strongest promotion of PI by PV in low-risk perception contexts. At moderate PR levels (mean, PR = 3.455), the effect size of PV on PI decreased to 0.242 ($p < 0.001$), remaining significant but weakened; When PR was high (mean +1SD, PR = 4.353), the effect size of PV on PI further decreased to 0.007 ($p = 0.913$), becoming non-significant. This indicates that high PR nearly completely suppressed the positive influence of PV on PI.

Overall, these findings support the theoretical proposition that consumers' purchase intentions remain suppressed when perceived risk is elevated, even if the product possesses high perceived value. For instance, Janssens & Semeijn (2023) emphasize that perceived risk, particularly in online purchasing scenarios, significantly disrupts consumer confidence and thereby affects purchase intentions. As consumers weigh potential negative outcomes against perceived benefits, their purchase intentions are likely to decline when those risks loom large.

Moderated mediating effect

Table 9: Conditional Indirect Effects (CB→PV→PI) by PR Levels

PR Level	Indirect Effect	Boot SE	95% Bootstrap Confidence Interval	Significance
Low (2.558)	0.154	0.026	[0.108, 0.207]	Significant

Mean (3.455)	0.078	0.017	[0.047, 0.113]	Significant
High (4.353)	0.002	0.023	[-0.042, 0.046]	Non-significant
Index of Moderated Mediation	-0.085	0.019	[-0.126, -0.051]	Significant

Based on the results in the table 9 above, the conditional indirect effects are analysed as follows: At low PR levels, the indirect effect of CB on PI via the mediating variable PV is 0.154 (95% BootCI [0.108, 0.207]), which is significantly present; At moderate PR levels, the indirect effect decreased to 0.078 (95% BootCI [0.047, 0.113]), yet remained significant; At high PR levels, the indirect effect further diminished to 0.002 (95% BootCI [-0.042, 0.046]), becoming non-significant.
The Index of Moderated Mediation was -0.085 (95% BootCI [-0.126, -0.051]), significantly negative, further confirming that PR negatively moderates the mediating pathway through which CB influences PI via PV.
This study reveals the pivotal moderating role of perceived risk in consumer decision-making, providing empirical support for moderated mediation models within the field of consumer behaviour. Enterprises operating in low-risk markets may prioritise enhancing perceived value (illustrating the concretisation of perceived value) to maximise consumer purchase intent; whereas those in high-risk markets should focus on reducing perceived risk to counteract the diminishing effect of perceived value.

5. CONCLUSION AND IMPLICATIONS

I. Research Conclusions
Based on consumer behavior theory, this study constructed a theoretical model encompassing Consumer Benefits (CB), Perceived Value (PV), Perceived Risk (PR), and Purchase Intention (PI). The model was empirically tested using data from 573 valid questionnaires. The main conclusions are as follows:
Consumer Benefits (CB) significantly positively influence Perceived Value (PV) and Purchase Intention (PI). Path analysis results show that the standardized path coefficient from CB to PV is 0.353, and the direct effect of CB on PI is 0.177. This indicates that consumers' recognition of product or service benefits is an important antecedent that stimulates their value perception and purchase intention.
Perceived Value (PV) plays a partial mediating role between CB and PI. Mediation effect analysis reveals that the indirect effect of CB on PI through PV is 0.091, and the Bootstrap confidence interval does not include zero. This confirms that PV is an important mechanism transmitting the influence of CB.
Perceived Risk (PR) significantly negatively moderates the effect of PV on PI. Moderating effect analysis indicates that the interaction coefficient between PV and PR is -0.262. Furthermore, the effect of PV on PI varies significantly across different PR levels: it is strongest (0.477) when PR is low and becomes non-significant (0.007) when PR is high. This demonstrates that high perceived risk can weaken or even negate the positive impact of perceived value on purchase intention.
PR moderates the mediating path of CB → PV → PI. The index of moderated mediation is -0.085, further confirming that PR negatively moderates the strength of this indirect mechanism.
2.Theoretical Implications
This study deepens our understanding of the “benefit-value-intention” mechanism in consumer behaviour. Firstly, the findings validate the mediating role of perceived value, whereby consumer benefits indirectly promote purchase intention by enhancing perceived value. This aligns with recent conclusions from digital consumption and service research (Wang et al., 2023)
Secondly, the moderating effect of perceived risk reveals boundary conditions for the value-intention relationship: when risk perception is elevated, the positive influence of perceived value on purchase intention diminishes (Cuong, 2024).
Finally, the study supports the application of a **moderated mediation model**, indicating that consumer decision-making should simultaneously consider both value gain and risk loss assessment mechanisms (Ma et al., 2024). These findings provide theoretical reference for future exploration of conditional indirect effects across diverse consumption contexts.
3.Managerial Implications
From a managerial perspective, enterprises should simultaneously strengthen value delivery and risk control. Firstly, enhance perceived value by communicating consumer benefits across multiple dimensions, such as product functionality, emotional experiences, and social value (Liang et al., 2024).
Secondly, proactively reduce risk perception through measures like return guarantees, payment security certifications, and trust badges to maintain stable value effects.
Finally, enterprises may implement differentiated marketing based on consumers' risk preferences and value orientations, precisely delivering value propositions aligned with their psychological characteristics

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