

THE IMPACT OF VALUE INNOVATION IN FRESH E-COMMERCE ON CONSUMER PURCHASE INTENTION UNDER THE BACKGROUND OF DIGITAL ECONOMY

Bing Wu

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy
Program in Management
Rattanakosin International College of Creative Entrepreneurship
Rajamangala University of Technology Rattanakosin
Academic Year 2026
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2026

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ABSTRACT

The objectives of this research were (1) to examine the relationship between value innovation in fresh e-commerce and consumers' purchase intention, (2) to investigate the mediating effect of consumers' perceived value on the relationship between value innovation in fresh e-commerce and purchase intention, and (3) to examine the moderating effects of consumer innovativeness and digital transformation attitudes on the relationship between consumers' perceived value and purchase intention.

This quantitative research employed a survey research design. The sample consisted of 838 fresh food consumers in Shanghai, China. Data were collected through both online and offline questionnaires and analyzed using structural equation modeling to examine the relationships among value innovation, perceived value, purchase intention, consumer innovativeness, and attitudes toward digital transformation.

Major findings: (1) On the issue of the study findings, the four dimensions of value innovation in fresh e-commerce¬¬—interestingness, interactivity, integration, and individualization—were found to have significant positive effects on consumers' purchase intention; (2) On the issue of the study findings, perceived value, comprising perceived benefits, perceived risks, and perceived costs, partially mediated the relationship between value innovation and purchase intention, with heterogeneous effects across the mediating paths; and (3) On the issue of the study findings, consumer innovativeness significantly moderated only the relationship between perceived risks and purchase intention, whereas attitudes toward digital transformation significantly moderated the relationships between perceived benefits, perceived risks, perceived costs, and purchase intention.

Keywords: Consumer innovativeness, Perceived value, Purchase intention, Value innovation, Digital transformation attitudes

Advisor's Signature .....

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List of Abbreviation and Glossary

Abbreviation / Glossary	Explanation
PB	Perceived Benefits
PC	Perceived costs
PR	Perceived risks
PI	Purchase Intention
CI	Consumer innovativeness
DTA	Digital transformation attitude

CHAPTER 1
INTRODUCTION

This chapter outlines the background and rationale of the study. It begins by explaining the research background by discussing the rise of the digital economy and the growing importance of fresh food e-commerce in China. It then discusses the significance of the study from both theoretical and practical perspectives and identifies the main research gaps in the existing literature. Based on these gaps, the chapter presents the research questions and research objectives. It also outlines the methodology, defines the core conceptions used in the study, and provides an overview of the thesis structure. Overall, this chapter establishes the foundation for examining how value innovation influences consumers' purchase intention in the context of fresh food e-commerce.

1.1 Background of the Study

As digital transformation advances, the digital economy has become a key driver of high-quality development in china and an important force for industrial upgrading and sustained growth. Since the 2016 G20 Hangzhou Summit proposed that the digital economy is a new engine and a new way for China innovation and growth, the overall scale of China data economy and its GDP share have been rising. The Research Report on the Development of China Digital Economy (2022) released by the China Academy of Information and Communication Research shows that as Digital China goes deeper and deeper, the overall scale of the digital economy has been on the upswing, jumping all the way from 27.2 trillion yuan in 2017 to 45.5 trillion yuan in 2021, and exceeding the 50 trillion yuan mark for the first time to reach 50.2 trillion yuan in 2022 (China Information and Communication Research Institute, 2023). Meanwhile, the share of the digital economy in GDP expanded from 32.9% in 2017 to 41.5% in 2022. The Statistical Report on the Development Status of the Internet in China released by the China Internet Network Information Center (2023) showed that as of June 2023, the number of Internet users in China had reached 1,079 million, an increase of 11.09 million compared with December

2022, and the Internet penetration rate had reached 76.4%. The Digital China Development Report (2022) report released by China showed that China's online retail sales reached 13.79 trillion yuan, of which online retail sales of physical goods accounted for 27.2 percent of total retail sales of consumer goods.

The growth of the digital economy has created new opportunities for fresh e-commerce while also intensifying the challenges faced by firms in this sector. Fresh food refers to primary agricultural products that are not subject to further processing steps such as cooking and preparation, and can be sold directly only through necessary preservation and simple treatment (Zan et al., 2020). Such as fruits, vegetables, eggs, poultry, meat, and aquatic products, fresh food are highly perishable and easily spoiled, which makes their marketing and distribution more difficult than those of many other products. These characteristics create challenges such as low customer loyalty, poor inventory control, and high loss rates (He et al., 2025). Fresh food e-commerce refers to the platforms provide customers with a channel to purchase fresh agricultural products online. Compared with shopping in physical stores, they offer a wider range of products, 24 hours ordering services, and convenient home delivery, which help customers save both time and effort (Wang, 2024). The digital economy is the main economic form after the agricultural and industrial economies, and is a new economic form that promotes greater unity between equity and efficiency, with data resources as the key element, modern information networks as the main carrier, and the integrated application of information and communication technologies and the digital transformation of all elements as the important driving force (State Council of the People's Republic of China, 2021). Fresh food e-commerce has become an important form of e-commerce in the digital economy era. Its development not only influences social and economic trends, but also contributes to the transformation of the fresh food industry. At the same time, consumer demand has changed significantly with the spread of digital technologies, which has reshaped market relations and business models (Gao, 2024).

In terms of transaction scale, according to Dianshubao (DT), the transaction scale of China's fresh e-commerce has grown significantly from 2017 to 2023. While the transaction scale in 2017 was RMB140.28 billion, this figure increased to RMB 642.76 billion in 2023, which is almost 4.6 times that of 2017, and during this period, the size of the user base also reached 513 million (Dianshubao (DT), 2024), showing a healthy growth

momentum. According to iiMedia Research (2021) data, the market size of China's fresh e-commerce industry will be 363.75 billion yuan in 2022, up 16.7% from 2021. With strong consumer demand for online fresh food purchases during the epidemic and deepening user trust in the fresh e-commerce industry, China's fresh food market is expected to reach RMB 630.20 billion in 2026. In terms of market share, according to Dianshubao (DT), between 2019 and 2022, China's urban residents' food consumption expenditure grew steadily from RMB 16,624 to RMB 21,690, while fresh e-commerce's market share also grew from 15.40% to 25.80% during the same period, significantly higher than the growth rate of traditional channels. This leapfrog growth highlights the importance and influence of fresh e-commerce in residents' daily consumption. By 2023, despite urban residents' food consumption expenditure falling to RMB 10,594, the share of fresh e-commerce further climbs to 27.60% (Dianshubao (DT), 2024) , this growth against the trend not only highlights the ability of fresh e-commerce to adapt to consumer needs, provide convenience, and optimize the shopping experience, but also reflects the resilience of e-commerce platforms and consumer loyalty to e-commerce purchasing methods under turbulent market conditions (COMNEWS, 2023) .

Driven by the expansion of the digital economy and shifting customer purchase behavior, e-commerce platforms have emerged as a primary platform for the fresh food market (He et al., 2025). The traditional fresh food purchasing model usually relies on offline channels, consumers need to go to supermarkets, farmers markets, or specialized fresh food shops to select and purchase, subject to time and space constraints, and the experience is more limited. Nowadays, consumers' shopping behaviour is undergoing an interesting fundamental change. They have gradually shifted from relying solely on brick-and-mortar shopping to a multi-channel model that combines online and offline, and more and more consumers are starting to use mobile apps and e-commerce platforms for shopping, which not only brings higher convenience, but also reduces the consumption of shopping time and energy.

In addition, consumers are no longer concerned only with product availability and price, but also pay increasing attention to product quality, source transparency, shopping convenience, delivery reliability, and overall shopping experience (Wang, 2024). Features such as ease of website use, information accessibility, and interactive functions may further shape consumer evaluations and purchase decisions. At the same time, the

perishable nature of fresh products places higher demands on supply chain coordination, logistics performance, and service consistency, making consumer trust a critical issue for fresh e-commerce firms. Under increasingly intense market competition and growing product homogeneity, firms can no longer rely solely on basic service provision, but need to create differentiated value that better responds to changing consumer expectations. Against this background, examining how value innovation in fresh e-commerce influences consumer purchase intention has both clear practical relevance and important theoretical value. Therefore, exploring the impact of value innovation on purchase intention is not only timely but critical, serving as the cornerstone for the significance of this investigation in both theoretical and practical views.

Despite the rapid growth of fresh e-commerce in China, many firms continue to face significant challenges, including increasing market competition, low customer loyalty, high customer acquisition costs, and growing product and service homogeneity. Under these conditions, firms can no longer rely solely on price competition or operational efficiency. Instead, creating differentiated customer value through value innovation has become a critical strategic approach for sustaining competitive advantage and enhancing consumer purchase intentions. However, limited research has examined how value innovation influences consumer purchase intention in the fresh e-commerce context.

1.2 Significance of the Study

1.2.1 Theoretical Significance

Grounded in the Stimulus Organism Response (SOR) model and 4I Marketing Theory, this study constructs and empirically tests a mechanism model explaining how value innovation in fresh e-commerce influences consumer purchase intention within the digital economy. Corresponding to the three contributions proposed at the outset of this thesis, the theoretical implications are elaborated below.

First, this study substantiates the integrated SOR–4I framework by revealing the heterogeneous pathways through which different dimensions of value innovation shape purchase intention. By positioning the four dimensions of 4I Marketing Theory as external stimuli, perceived value as the organism, and purchase intention as the response, the study demonstrates that value innovation does not operate through a single uniform mechanism. Perceived benefits account for the largest share of the mediating effect in the

individualization innovation pathway (49.06%), whereas perceived risk plays a substantially greater mediating role in the integration innovation pathway (42.33%) than in the interesting and interactivity pathways. This indicates that when innovation involves systemic solutions, consumers are more inclined to evaluate its potential risks, whereas innovation centred on emotional experience functions mainly by enhancing perceived benefits. The findings further clarify the relative importance of the four 4I dimensions: interestingness and interactivity innovation are positively associated with purchase intention and also exert indirect effects through perceived benefits, each exceeding 32%. This shows that emotional and experiential value remains influential even in a high-frequency, relatively planned consumption context such as fresh food purchasing, where consumers respond not only to functional attributes such as price, delivery speed, and availability, but also to enjoyable content, interactive communication, and reassuring service experiences (Wongkitrungrueng & Assarut, 2020; Zhang et al., 2020). By contrast, individualization innovation did not produce the strongest effect, suggesting that recommendation algorithms and personalized suggestions increase purchase intention only when they are closely aligned with consumers' practical goals such as freshness, safety, and delivery reliability—an interpretation consistent with recent research showing that AI-based personalization creates value only when perceived as useful, trustworthy, and contextually relevant (Davenport et al., 2020; Huang & Rust, 2021; Puntoni et al., 2021). Together, these results confirm that the integrated SOR–4I framework captures both whether and how value innovation influences purchase intention, an explanatory depth that neither theory achieves in isolation.

Second, this study advances the conceptualization of perceived value as a multidimensional construct comprising perceived benefits, perceived costs, and perceived risks, thereby offering a more complete account of the consumer evaluation process. Rather than treating perceived value as a single benefit-oriented judgment, the study models the trade-offs that characterise fresh food consumption and shows that its three components mediate the value-innovation–purchase-intention relationship in distinct ways. Perceived benefits act as the dominant mechanism in experience-oriented innovation pathways, whereas perceived risk becomes decisive when innovation involves systemic integration, and perceived cost exerts a comparatively weaker but consistent influence. This tripartite conceptualization demonstrates that the effectiveness of value

innovation cannot be understood through benefits alone, and that explicitly incorporating costs and risks yields a more realistic depiction of how consumers evaluate fresh e-commerce offerings.

Third, this study identifies consumer innovativeness and digital transformation attitudes as boundary conditions that determine the effectiveness of value innovation, thereby refining existing consumer behaviour research. On the one hand, consumer innovativeness exerts a significant buffering effect only on the relationship between perceived risk and purchase intention (H22 supported), while its moderating effects on perceived benefits and perceived costs are not significant. This indicates that, in high-risk and highly functional consumption decisions, innovativeness operates primarily as a "risk buffer" rather than a "value amplifier," clarifying the theoretical boundary of innovativeness and integrating perceived value theory with innovation diffusion theory. On the other hand, digital transformation attitudes significantly moderate the relationships between purchase intention and perceived benefits, perceived costs, and perceived risks (H24–H26 supported), and in a consistent direction: positive attitudes strengthen the effect of perceived benefits while weakening the negative effects of perceived costs and risks. This extends the "attitude" variable from the Technology Acceptance Model beyond a direct antecedent to a moderating contextual filter, revealing that consumers' acceptance of digital technology critically governs whether value innovation is translated into actual purchase intention. By introducing and validating these two boundary conditions, the study moves beyond the assumption that value innovation exerts a uniform effect and specifies the conditions under which its influence is amplified or constrained.

In conclusion, by integrating the SOR model and 4I Marketing Theory, this study deconstructs the pathways through which value innovation influences purchase intention, reconceptualises perceived value as a three-dimensional evaluative structure, and incorporates consumer innovativeness and digital transformation attitudes as boundary conditions within a unified analytical framework. The construction and empirical validation of this model provide a more explanatory account of consumer behaviour in fresh e-commerce in the digital economy, and directly fulfil the three theoretical contributions set out at the beginning of this thesis.

1.2.2 Practical Significance

This study provides practical guidance for the operation and management of fresh e-commerce enterprises. By examining the impact of value innovation on consumers' purchase intention, it helps enterprises better understand changes in consumer demand in the digital economy. The findings also offer suggestions for improving product quality, service models, and pricing strategies. In particular, enterprises can better meet consumers' demands for quality, freshness, convenience, and personalized experiences by improving product traceability, enhancing delivery efficiency, and strengthening personalized recommendations, thereby increasing purchase intention.

This study also helps fresh e-commerce enterprises develop more accurate marketing strategies. The 4I marketing theory, which emphasizes interesting, interactivity, integration, and individualization, is closely aligned with the business model of fresh e-commerce. By examining these dimensions, enterprises can design different marketing strategies for different consumer groups and strengthen users' connection with the platform. For example, by enhancing user interaction, organizing engaging activities, and launching personalized promotions, enterprises can improve user experience and satisfaction, thereby increasing user retention.

As an important part of the digital economy, fresh e-commerce not only contributes to the development of individual enterprises but also plays a positive role in the sustainable development of the fresh food industry and the digital economy as a whole. This study can provide a reference for practitioners and policymakers in the fresh e-commerce industry. It may also support the healthy and standardized development of the industry, thereby promoting the optimization of the fresh food supply chain and the improvement of the digital economy ecosystem.

Building on the empirical findings, this study provides several practical implications for fresh e-commerce enterprises. First, fresh e-commerce platforms should strengthen customer retention by improving consumers’ perceived benefits. The results show that interestingness innovation and interactivity innovation can enhance purchase intention through perceived benefits. Therefore, platforms should not rely only on price discounts or short-term promotions. Instead, they should create engaging shopping content, provide interactive communication, and offer reliable service experiences. These practices can help consumers perceive greater functional and emotional value, which may

encourage repeated purchases. Second, enterprises should improve personalized recommendation systems. The findings suggest that individualization innovation does not automatically lead to the strongest purchase intention. Personalized recommendations are effective only when they match consumers' real purchase concerns. In the fresh e-commerce context, consumers care about freshness, food safety, product quality, delivery timeliness, and after-sales protection. Therefore, recommendation systems should not only predict consumer preferences, but also provide useful and trustworthy product information. Third, fresh e-commerce enterprises should promote digital transformation from both the technological and consumer sides. The results indicate that digital transformation attitudes moderate the relationship between perceived value and purchase intention. This means that technological investment alone is not enough. Enterprises should also help consumers understand and accept digital tools. For example, platforms can provide clear user interfaces, transparent information, simple operating procedures, and trust-building mechanisms. These measures can reduce consumers' resistance to digital services and improve the effectiveness of value innovation. Fourth, platforms should strengthen customer experience management. The findings show that perceived risk plays an important mediating role, especially in the interactivity and integration innovation pathways. Since fresh food products are perishable and quality-sensitive, consumers may worry about product freshness, delivery conditions, return policies, and service reliability. Therefore, platforms should provide transparent product descriptions, visible quality assurance, reliable cold-chain logistics, and responsive after-sales service. These actions can reduce uncertainty and increase consumers' confidence in online fresh food purchases. Fifth, enterprises should develop differentiated platform strategies. The four dimensions of value innovation influence purchase intention through different mechanisms. Therefore, fresh e-commerce platforms should not simply imitate the same marketing practices used by competitors. Instead, they should choose a clear strategic focus according to their own resources and market positioning. Some platforms may compete through interactive and enjoyable shopping experiences, while others may focus on logistics integration, quality assurance, or personalized services. A clear differentiation strategy can help platforms build stronger competitive advantages.

Overall, these implications show that value innovation should be converted into concrete consumer value. Fresh e-commerce enterprises need to increase perceived

benefits, reduce perceived costs, and lower perceived risks. By doing so, they can transform innovation activities into stronger purchase intention, higher customer retention, and more sustainable competitive advantage.

1.2.3 Research Gap

While extensive research exists in the fields of fresh e-commerce, the digital economy, and consumer behavior, several research gaps remain to be explored in the further study.

Firstly, existing research lacks a deep focus on value innovation in e-commerce. Most of the research concentrate on operational aspects like product quality, distribution efficiency and service experience.They often overlook how companies can systematically create value to shape consumer perceptions and drive purchases. It remains unclear how fresh e-commerce platforms can use value innovative propositions to meet personalized demands and gain a competitive advantage.

Secondly, the 4I marketing theory has been highly ignored in the fresh e-commerce research. Existing research on fresh e-commerce heavily relies on the traditional 4P theory. While the 4I theory has been applied in some studies, which focused more on traditional retail and fast-moving consumer goods industries, with less attention to fresh e-commerce. 4I marketing theory emphasizes interesting, interactivity, integration, and individualization, elements that are highly compatible with fresh e-commerce in the context of the digital economy. However, there is a lack of systematic research on the application of 4I marketing theory to fresh e-commerce, especially in the exploration of how to promote value innovation through 4I marketing to increase consumers' purchase intention. Therefore, combining 4I marketing theory with fresh e-commerce and studying its value innovation path can help fill the theoretical gap in this field.

Thirdly, a comprehensive model explaining about consumer purchase intention is still lacking from the current literature. Existing studies on consumer purchase intention in fresh e-commerce often rely on traditional frameworks or focus on isolated variables, which lacks a multi-dimensional comprehensive analysis framework. In this respect, the Stimulus-Organism-Response (SOR) model offers a more systematic and dynamic perspective. It allow researchers to explain how external stimuli, such as value innovation implemented by e-commerce platform, influence consumers' purchase intention. In

particular, the psychological process through consumers' perceived value and then develop consumer purchase intention remains insufficiently verified in existing research.

Finally, the role of consumers' attitude toward digital transformation and consumer innovativeness in fresh e-commerce has not been sufficiently explored. In the context of the digital economy, consumer's traits are complex, especially their innovativeness and attitude toward digital transformation are critical factors that can shape their behavior. These attitudes determined not only their initial willingness to adopt fresh e-commerce platforms but also how they perceived the value offered by theses platforms. Therefore, this study examines consumers' innovativeness and attitudes toward digital transformation as moderating variables. It aims to test whether these factors influence the relationship between value innovation and purchase intention. This may provide useful guidance for fresh e-commerce firms in designing marketing strategies.

In summary, this study addresses these gaps by proposing and testing a integrated framework. This study combines the 4I marketing theory with the SOR model to explain how value innovation in fresh e-commerce influences consumer purchase intention through perceived value. At the same time, the study incorporates consumer innovation and attitudes toward digital transformation as moderating variables, so as to better capture the boundary conditions of this relationship. Based on the identified research gaps, this study proposes an integrated framework that combines value innovation, perceived value, consumer innovativeness, and digital transformation attitudes to explain consumer purchase intention in fresh e-commerce. The framework serves as the foundation for the development of research questions and objectives.

1.3 Statement of Research Questions

Based on the background of fresh e-commerce in section 1.1 and the gaps identified in previous studies section 1.2, this study focus on how value innovation influences consumers' purchase intention. It also examine the mediating role of perceived value, as well as the moderating roles of consumer innovativeness and customer attitudes toward digital transformation. The research questions are presented as follows.

RQ1: How does value innovation in fresh e-commerce related consumers' purchase intention?

The consumers' intention to buy fresh food is the ultimate goal for all the fresh e-commerce platform. As competition in fresh food e-commerce continues to grow, firms need to create value beyond basic product and price cuts. Therefore, firms should use value innovation - such as making the shopping experience more interesting, interactive, integrated, and individualized- to stand out. However, there still lack a clear understand of which specific innovations actually drive purchase intention. This question explores how these different innovative strategies influence consumers to make a purchase.

RQ2: How mediating role does perceived value play between value innovation and consumers' purchase intention?

The fresh e-commerce platform innovations do not automatically led to seals; they must first change how a customer thinks about the product. Consumers do not respond to platform products directly alone; they also form evaluations of what they gain and what they give up during the shopping process. In this study, perceived value includes three dimensions: perceived benefits, perceived risk and perceived costs. These perceptions are especially relevant in fresh e-commerce, where concerns about freshness, delivery reliability, and product uncertainty are common. It has been shown that perceived value plays an important mediating role between external stimuli, such as value innovations, and consumer behavioral responses, such as purchase intention. Therefore, this study examines whether perceived value mediates the relationship between value innovation and consumers' purchase intention.

RQ3: How do consumer innovativeness and digital transformation attitudes moderate the relationship between perceived value and purchase intentions?

Consumers show varying behaviors in fresh e-commerce shopping. To some extent, consumers' innovativeness and digital transformation attitudes play an important role in accepting and evaluating fresh e-commerce platforms, ultimately influencing their purchase decisions. Innovative consumers tend to be more inclined to accept new things, while consumers with positive digital transformation attitudes are more likely to make purchases on fresh e-commerce platforms. Existing research has paid insufficient attention to the moderating effects of consumer innovativeness and digital transformation attitudes in the relationship between consumers' perceived value and purchase intention, especially in the fresh e-commerce sector. Therefore, exploring the moderating effects of these two

variables can help fresh e-commerce firms to develop more personalized value innovation and marketing strategies based on consumer idiosyncrasies.

By answering the above research questions, this study will establish a complete theoretical framework to reveal how the value innovation of fresh e-commerce can influence consumers' purchase intention through the combined effect of perceived value, consumer traits, and other factors in the digital economy environment.

1.4 Statement of Research Objectives

Based on the above research questions, this study has three objectives.

RO1: To investigate how different dimensions of value innovation drive consumer purchase intention.

This study break down value innovation into its core dimensions, this objective systematically explore how these innovation dimensions relate consumers' purchase intention in the context of the digital economy, thus providing a theoretical basis for fresh e-commerce enterprises to enhance their market competitiveness.

RO2: To investigate the mediating role of perceived value between value innovation and consumer purchase intention in fresh e-commerce.

This study break down perceived value into 3 core dimensions, aims to determine whether perceived benefits, perceived risk, and perceived costs mediate the effect of value innovation on consumers' purchase intention in fresh food e-commerce. An in-depth study of how value innovation enhances purchase intentions by increasing consumers' perceived value of products and services and explores the different impacts of different dimensions on this process to reveal the important role of perceived value in this chain of influence.

RO3: To investigate the moderating role of consumer innovativeness and digital transformation attitudes in the relationship between consumers' perceived value and purchase intentions.

This study aims to analyze whether consumer innovativeness and customer's attitudes toward digital transformation change the strength of the relationship between perceived value and consumers' purchase intention. Because people adopt technology at different levels, this objective looks at the boundary conditions of the buying process. It analyzes how a consumer's willingness to innovate and their attitude toward digital tools

strengthen or weaken their purchase intention. This will help companies understand different user segments and create more targeted marketing strategies.

1.5 Methodology

To ensure the scientific rigour and depth of this study, it employs a quantitative research design. Questionnaire surveys and structural equation modeling are used to test the proposed hypotheses systematically. The research methods and technical approach are as follows:

This study adopted a quantitative research design. A structured questionnaire was used to collect data from consumers with fresh e-commerce shopping experience in Shanghai. The proposed relationships among value innovation, perceived value, consumer innovativeness, digital transformation attitudes, and purchase intention were tested using structural equation modelling and regression-based moderation analysis.

This study will draw theoretical support and background knowledge from a broad range of academic literature. The literature review will cover the concept of the digital economy, the development of the fresh food e-commerce industry, factors influencing consumer behaviour, and theoretical frameworks for value innovation. This review will help establish the theoretical foundation of the study, clarify the research questions, and identify knowledge gaps in cutting-edge research.

Based on the Stimulus Organism Response theoretical model, this study has designed a structured questionnaire. The questionnaire comprises of three sections. The first section introduces the purpose of the survey. The second part collects demographic information, including ten control variables such as gender, age, income, education level, and purchase frequency. The third part measures the core variables: value innovation, perceived value, purchase intention, consumer innovativeness, and attitudes toward digital transformation. All measurement items are adapted from well-established domestic and international scales, modified to fit the context of China fresh food e-commerce industry, and assessed using a five-point Likert scale.

SEM were used for data processing and hypothesis testing. The analysis proceeded in three stages. First, reliability and validity were assessed. Cronbach's alpha was used to examine internal consistency, and the overall scale showed reliability. Confirmatory factor analysis was then conducted to test construct validity. The results showed acceptable

convergent validity, with all AVE values above 0.5 and all CR values above 0.7. Discriminant validity was also supported, as the square root of each construct's AVE was greater than its correlations with other constructs. Second, Common method bias was assessed using Harman's single-factor test. VIF values were examined all values were below 10, indicating that the data did not exhibit severe common method bias. Third, hypothesis testing was assessed. Structural Equation Modelling (SEM) was used to examine the direct effects of the dimension of value innovation on purchase intention. The mediating effects of perceived benefit, perceived risk, and perceived cost were tested using the bootstrap method with 5,000 repeated samples. The moderating effects of consumer innovativeness and digital transformation attitudes were tested via hierarchical regression analysis.

Based on this procedure, the study analyzed 838 consumer responses collected in Shanghai. The purpose was to provide empirical evidence and theoretical support for value innovation strategies in fresh food e-commerce.

1.6 Definitions of Terms

This study defines and discusses four core constructs: purchase intention, perceived value, consumer innovativeness and consumer digital transformation attitudes.

Purchase intention is the key dependent variable in this study and represents consumers' willingness to buy fresh products through e-commerce platforms. According to the definition provided by Feng et al., (2006), purchase intention usually refers to the consumer's tendency and motivation to buy a particular product or service; it is a kind of attitude or intention of pre-purchase behaviour within the consumer. It reflects the strength of consumers' motivation to buy goods or services in a particular situation. In the context of this study, purchase intention refers to that consumers will choose to purchase fresh food through e-commerce platforms. It is used as the final outcome variable to examine whether value innovation can effectively encourage consumer purchasing behaviour.

Perceived value is the mediating variable in this study and reflects consumers' overall evaluation of the benefits, risks, and costs associated with fresh food e-commerce. According to the research by Ryu & Park (2020), perceived benefits are positive benefits perceived by consumers during the social media shopping process on three levels: instrumental, experiential, and symbolic, which can influence their loyalty to social media,

their actual use, and their willingness to spread positive word-of-mouth. Perceived risks, defined by Dayour et al. (2019), refers to the subjective assessment of potential negative consequences when consumers buy or use products and services. Furthermore, perceived costs, drawing on the perspective of Li et al. (2019), refers to the consumer's personal perception and assessment of all costs associated with the purchase decision process, these costs encompass not only monetary expenditure but also the consumption of resources such as time and effort. In this study, perceived value is used to explain how value innovation influences consumers' ultimate purchase intention through their internal evaluation.

Consumer innovativeness is a moderating variable in this study and used to captures an individual's inherent personality trait of being open to new ideas and technologies. According to the definition by Esfahani & Reynolds (2021), consumer innovativeness describes the extent to which consumers adopt new ideas earlier than other members of the system. In this study, this concept encompasses four dimensions—social, functional, hedonic, and cognitive—and is used to measure consumers' acceptance of and inclination towards new products, platforms, and service models.

Consumer digital transformation attitudes is a moderating variable in this study and refers to consumers' responses to the use of digital technologies in fresh food e-commerce services. According to the definition by Zhang & Qin (2022), this variable refers to consumers' perceptions, feelings, and reactions regarding the introduction of digital technologies and processes by enterprises in their operations and services (Zhang & Qin, 2022). In the context of this study, it reflects consumers' acceptance of digital features used by fresh food e-commerce platforms, such as intelligent recommendations, contactless delivery, and digital cold chain monitoring. This variable is included to examine whether consumers with different attitudes toward digital transformation respond differently to the relationship between perceived value and purchase intention.

1.7 Delimitation of the Thesis

To maintain a clear and manageable research scope, this study defines several delimitation in terms of geographical context, target population, industry focus, theoretical scope, and research method. Geographically, the study is limited to Shanghai, China, which is chosen as one of the most developed digital economies in the country,

characterized by high levels of internet use, online consumption, and a mature fresh food e-commerce market. Focusing on Shanghai provides a relevant context for examining how consumers respond to value innovation in fresh food e-commerce.

Demographically, the research targets consumers who have actual experience purchasing fresh agricultural products through e-commerce platforms. Individuals without such experience are excluded to ensure that responses are based on real consumption behavior rather than hypothetical judgment.

Industrially, the focus is restricted to the fresh food e-commerce sector. Other online retail categories, such as clothing, electronics, and general merchandise, are not included. Fresh food products have distinctive features perishability, strict delivery requirements, and heightened consumer attention to quality and safety—which make value innovation particularly critical in this sector.

Theoretically, the research is confined to the 4I marketing theory and the Stimulus Organism Response framework. Within these frameworks, the study examines five main constructs: value innovation, perceived value, purchase intention, consumer innovativeness, and digital transformation attitudes. Other potential antecedents of purchase intention fall outside the scope of this study.

Methodologically, a quantitative research design is adopted. data are collected through a structured questionnaire and analyzed using statistical methods, including structural equation modeling. These methodological boundaries maintain focus and support empirical testing of the proposed relationships. Overall, these delimitations establish the boundaries of the study and ensure internal consistency among its research objectives, conceptual framework, and empirical design.

1.8 Outline of the Thesis

To explore how value innovation influences purchase intention in the fresh food e-commerce, this thesis is organized into the following five chapters:

Chapter One introduces the research background and explains the purpose and significance of the study. It also defines the research questions and objectives while providing a overview of the methodology and the overall structure of the thesis.

Chapter Two reviews existing research on fresh e-commerce industry, value innovation, perceived value, consumer purchase intention, and consumer behavior.

Drawing on the 4I marketing theory and the Stimulus Organism Response model, this research establish a theoretical framework and propose a series of hypotheses to be tested int he study.

Chapter Three describes the research methodology. It explains the research design, sampling process, questionnaire development, and data collection procedure. It also presents the methods used to test reliability and validity and outlines the statistical techniques applied in the empirical analysis.

Chapter Four presents the empirical findings of the study. It begins with descriptive analysis, including reliability analysis, validity analysis, and the test of common method bias. It then reports the results of hypothesis testing, covering the main effects, mediating effect, and moderating effects in the proposed model. The chapter ends with a brief conclusion of the main results.

Chapter Five provides the discussion and conclusion of the study. It interprets the main findings and discusses their theoretical and practical implications. In addition, it offers strategic recommendations for fresh food e-commerce companies, as well as suggestions for policy makers and industry associations. Finally, the chapter addresses the limitations of the study and proposes directions for future research.

1.9 Conclusion

This chapter has introduced the background, significance, and overall design of the study. In the context of the digital economy, fresh food e-commerce has developed rapidly, but it also faces growing competition and changing consumer expectations. As a result, value innovation has become increasingly important for firms seeking to improve consumer purchase intention. Based on 4I marketing theory and the Stimulus Organism Response model, this study proposes a research framework to examine how value innovation influences purchase intention in fresh food e-commerce. It focuses on the mediating role of perceived value and the moderating roles of consumer innovativeness and digital transformation attitudes. The chapter has also presented the research questions, research objectives, methodology, key definitions, delimitations, and the overall structure of the thesis. Overall, this chapter provides the foundation for the rest of the study. The next chapter reviews the relevant literature and develops the theoretical framework and research hypotheses.

CHAPTER 2
LITERATURE REVIEW

This chapter reviews the literature relevant to this study and establishes its theoretical foundation. It first outlines the research context by examining the development of the digital economy, the fresh e-commerce industry, and consumer behaviour in digital settings. It then reviews the main theoretical foundations of the study, including the Stimulus Organism Response theory, the 4I marketing theory, and perceived value theory. After that, it discusses the key research variables: value innovation, consumer perceived value, consumer purchase intention, consumer innovativeness, and customer digital transformation attitudes. Based on this review, the chapter develops the conceptual framework and research hypotheses.

2.1 Contexts of the Study

This section provides the background for the present study from three related perspectives. It first reviews the development of the digital economy, with attention to both global digital transformation and the growth of the digital economy in China. It then examines the fresh e-commerce industry, including the importance of fresh food in the Chinese context, the role of innovation in fresh e-commerce, its main business models, and the challenges and opportunities faced by the sector. Finally, this section discusses consumer behaviour in the digital economy by looking at changes in shopping habits, general digital consumer characteristics, and the specific characteristics and buying behaviour of fresh e-commerce consumers. Together, these three parts build the contextual foundation for understanding value innovation and purchase intention in China's fresh e-commerce market.

2.1.1 Development of the Digital Economy

2.1.1.1 Global Digital Transformation

Global digital transformation represents a vital stage in contemporary economic development. It involves the widespread integration of digital technologies production, distribution, and consumption processes across industries, which fundamentally changing how value is created and delivered. A major feature of global digital transformation is the convergence of emerging technologies and innovation. The development of the digital economy depends on the continuous advancement and combination of technologies such as artificial intelligence, big data analysis, cloud computing, automation, and the Internet of Things. Dong et al. (2014) argue that digital technologies are progressing exponentially and generating powerful combination effects, through which different technologies reinforce one another and reshape industries. For example, the expansion of advanced digital infrastructure, including 5G networks, strengthens the technical foundation for IoT and industrial internet applications, making cross-industry digital integration increasingly feasible.

Beyond technology change, digital transformation also accelerating across industries globally. Traditional sectors such as manufacturing, retail, and financial services are increasingly using digital technologies to improve efficiency and redesign business models. According to a study by the World Economic Forum (World Economic Forum, 2018), digital transformation has become an important source of innovation in many industries. In manufacturing, for instance, the rise of Industry 4.0 reflects a major shift in production systems. Technologies such as digital twins and smart manufacturing allow firms to monitor operations in real time and optimize production more precisely.

At the same time, digital transformation is changing the structure of global value chains. Digital platforms are reshaping how firms organize production, exchange information, and reach consumers across borders. A report by the United Nations Conference on Trade and Development (2019) notes that the digital platform economy is changing the production and distribution models of multinational enterprises, making value creation more decentralized and networked. Large digital platforms such as Amazon and Alibaba have lowered transaction costs and improved the efficiency of resource allocation, which has changed the traditional organization of international business activities.

In addition, digital transformation has created new demands for governance and regulation. As digital technologies become more deeply embedded in economic and social life, governments have paid greater attention to issues such as data privacy and platform regulation. The Organization for Economic Cooperation and Development (2020) has emphasized the need for the digital economy to balance innovation and risk, particularly in areas such as data privacy and cyber security. The General data Protection Regulation in the EU and the California Consumer Privacy Act in the US are important examples of this trend.

Digital transformation is also closely linked to sustainable development. Digital technologies can improve resource efficiency, reduce waste, and support lower-carbon development. Research by the World Bank (World Bank, 2021) has shown that digital technologies can help reduce carbon emissions and optimize the use of resources. Examples such as smart cities and precision agriculture show how digital solutions can support environmental goals. However, the benefits of digital transformation are not evenly distributed.

Overall, the global experience shows that digital transformation is not only a technological process but also a broad economic and social change. It affects industries, institutions, and consumers in multiple ways. This broader context provides an important foundation for understanding the development of the digital economy and its impact on specific sectors such as fresh food e-commerce.

2.1.1.2 Development of the Digital Economy in China

As discussed in the previous section, digital transformation has become a major global trend and has reshaped economic activities across countries. Within this broader context, China's digital economy has developed rapidly and has become an important part of the global digital transformation process. Since the G20 Hangzhou Summit in 2016, China has treated the digital economy as a key driver of high-quality growth and long-term economic restructuring.

Firstly, strong policy support has played a central role in the growth of China digital economy. The Chinese government has given the digital economy a clear strategic position in national development planning. The 14th Five-Year Plan for the Development of the Digital Economy issued by the State Council of China (2021) explicitly proposes that the added value of the core industries of the digital economy will account for 10% of

GDP by 2025, and that the digital economy will become a dominant force in the national economy. According to a report by the China Academy of Information and Communication Research (2022), the overall scale of China's digital economy has grown rapidly from 27.2 trillion yuan in 2017 to 50.2 trillion yuan in 2022, and its share of GDP has risen from 32.9% to 41.5%.

Second, the rapid improvement of digital infrastructure has provided a solid foundation for digital economic growth. China has made large-scale investments in new digital infrastructure, especially in 5G networks, data systems, and intelligent technologies. The data from China Internet Network Information Centre (2023) showed that as of 2023, China has built the world's largest 5G network with over 2.6 million 5G base stations. This infrastructure provides strong support for the development of emerging technologies such as artificial intelligence and the Internet of Things. This infrastructure has created favorable conditions for the wider use of technologies such as artificial intelligence, big data, cloud computing, and the Internet of Things.

Thirdly, the digital transformation of traditional industries has further expanded the influence of the digital economy. In recent years, digital technologies have been widely adopted in sectors such as manufacturing, retail, logistics, and agriculture. In the manufacturing industry, for example, the 'Made in China 2025' strategy promotes the transformation of the traditional manufacturing industry into intelligent manufacturing. According to a report by the Alibaba DAMO Academy (2022), the digital transformation of the manufacturing industry has become a key path to enhancing international competitiveness.

At the same time, the rapid growth of the platform economy has accelerated the formation of digital ecosystems in China. Large platform companies such as Alibaba, Tencent, and JD.com have not only established a strong digital ecosystem at home, but also occupy an important position in the global digital economy map. According to a report by the China Internet Network Information Center (2023), the size of China's Internet users has reached 1.079 billion, with an Internet penetration rate of 76.4%, and the large group of Internet users provides an important foundation for building a digital ecosystem.This large user base has provided strong support for the continued expansion of the digital economy.

In addition, China has also strengthened its participation in international digital economic cooperation. The Digital Silk Road initiative demonstrates China's strategic vision in promoting international cooperation in the digital economy. According to the Ministry of Commerce, the scale of digital economy cooperation between China and countries along the Belt and Road continued to grow in 2022.This shows that China's digital economy is not only important domestically, but also increasingly connected to global digital development.

Against this background, the rise of fresh e-commerce can be understood as a direct result of China's digital economy development. As digital technologies have become more widely used, e-commerce platforms have introduced new business models and operating methods into the fresh produce market. Fresh food e-commerce firms have combined internet technology with logistics innovation to improve distribution efficiency and respond to consumers' demand for convenience, speed, and quality assurance. Common delivery models include home delivery, in-store pickup, community group buying, and subscription-based services.

The development of China's fresh e-commerce industry has generally gone through three stages. The first stage (2005-2011) was an exploration and start-up period, during which companies created a whole industry chain structure by building their own farms, logistics centres, and cold chain systems. The second stage (2012-2015) was a rapid development period, marked by the influx of social capital, the emergence of O2O models, and the expansion of product categories. The third stage (2016 to present) is a transformation and upgrading period, during which the market has gradually concentrated on mainstream e-commerce companies, with model innovations such as the front warehouse model, and new opportunities arising from the 2020 epidemic, including community group buying and live-streaming commerce. Overall, the fresh e-commerce market size has been growing year by year, but the industry still faces challenges and requires continuous exploration. Overall, the fresh e-commerce market in China has continued to grow, although the industry still faces challenges in profitability, service quality, and long-term sustainable development.

2.1.2 Fresh E-Commerce Industry

2.1.2.1 Importance of Fresh Food in the Chinese Perspective

Fresh food is important not only because it meets basic consumption needs, but also because it has become increasingly connected to changing lifestyles, market demand, and the development of fresh e-commerce.Fresh food is the basic form of farm goods, usually not processed beyond what is necessary to keep them fresh. They haven't been cooked or made into other products (Zan, 2020). Nowadays, most fresh agricultural products can be sold online. e-commerce platforms generally divide these products into six main categories: vegetables, fruits, meat, eggs and dairy, seafood, and baked goods (Wang et al., 2019). This classification is useful because it defines the main product scope of fresh e-commerce and shows that fresh food covers a wide range of daily consumer goods.

The importance of fresh food in China has become more evident as incomes and living standards have risen. As China's annual incomes have risen, living standards have significantly improved. This economic progression has led to a transformation in consumer attitudes toward fresh goods, evolving from a singular focus on basic consumption to a more diversified approach (Gao, 2024). Consumers now expect not only staple items, but also a wider range of products such as dairy items, meats, frozen foods, fruits, vegetables, and ready-to-cook or semi-prepared food. At the same time, they place more emphasis on freshness, nutrition, convenience, and timely availability. These changes have created strong market demand and opened up important opportunities for the development of fresh e-commerce. This evidence supports the argument that changes in consumer demand are one of the key driving forces behind the growth of China's fresh e-commerce market.

Fresh food also has broader economic and social importance in China. In traditional agricultural sales models, fresh food typically passes through multiple stages and an extended supply chain before reaching consumers. This lengthy distribution process often results in higher costs, which limit the profits that producers at the start of the chain can earn. As a result, producers may receive lower returns, while consumers often face higher prices. Problems such as difficulty in selling agricultural products and the high cost of purchasing fresh food therefore remain common (Zan et al., 2020). This argument is important because it shows that fresh e-commerce is not only a consumption channel, but

also a potential solution for improving supply-chain efficiency, increasing farmers' income, and reducing consumer purchase costs.

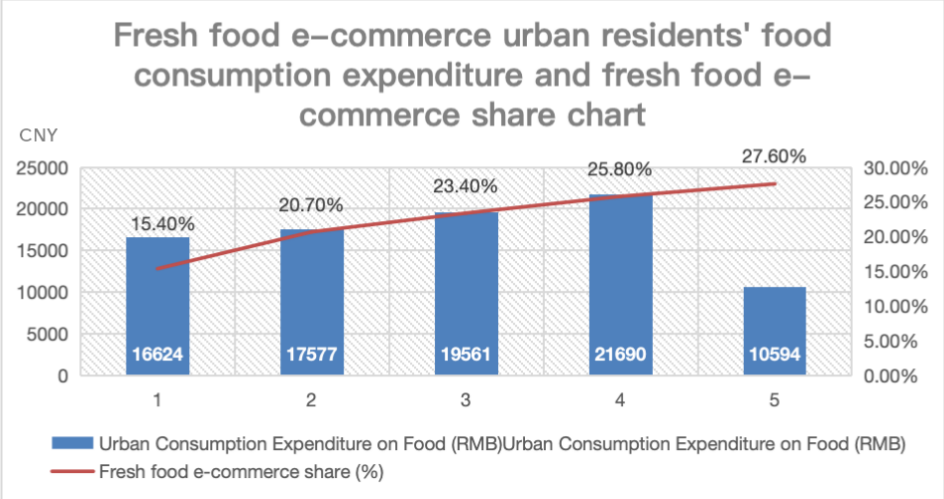


Figure 2.1 Urban Residents' Fresh Food Expenditure and Fresh E-commerce Penetration Note: data sourced from the Digital Economy Industry database, NetEase Economic Internet Economy Service Platform. https://www.100ec.cn/User/industrydata.html?name=sxds

Against this background, fresh e-commerce has become an increasingly important channel in China's fresh food market. In 2022, the transaction volume in China's fresh e-commerce sector reached 560.14 billion yuan, with the market continuing to expand (Li et al., 2024). By refining transaction systems, fresh e-commerce has the potential to significantly increase the overall value of fresh food while enhancing the efficiency of the supply chain. Overall, the growing importance of fresh food in China has not only reshaped consumer demand, but has also created strong momentum for the development of fresh e-commerce.

2.1.2.2 Importance of Fresh E-Commerce Innovation

Fresh e-commerce innovation is essential because it helps firms respond to changing consumer needs, improve operational efficiency, and build sustainable competitive advantage in a fast-changing digital market. As China's fresh e-commerce market continues to expand, innovation has become a key condition for long-term development. Existing studies show that the sector faces a number of structural challenges, including high cold-chain costs, unstable product quality, weak consumer trust, and intense market homogeneity (Gao, 2024). This innovation is not only necessary to meet evolving

consumer demands but also for maintaining competitiveness in a rapidly changing landscape. Li (2024) explored key strategies that emphasize the importance of understanding consumer preferences, optimizing logistics, and differentiating brands through innovative approaches in the Chinese market. Gao (2024) argued that fresh e-commerce firms need to reconstruct consumer value by improving service experience through digital tools. In practice, this means using technologies such as big data, intelligent recommendation systems, and digital platforms to better understand consumer preferences and provide more personalized services. When firms can match products, delivery options, and promotional content with consumer needs more accurately, they are more likely to improve satisfaction, strengthen trust, and increase repeat purchase intention.

Innovation is further important because it supports new retail transformation and helps firms develop more integrated business models. Liu and Chen (2025) in their case study of Dingdong Maicai, show that fresh e-commerce firms can create value through clearer value propositions, stronger product capability, front-warehouse systems, instant delivery, source-based procurement, and transparent supply chains. Their study suggests that innovation in fresh e-commerce is not limited to a single technology or marketing tool. Rather, it involves the coordinated improvement of value proposition, value delivery, and value realization. This broader form of innovation helps firms respond to consumer demand for convenience, freshness, and safety while also improving supply chain performance and customer experience. Despite the rise of online shopping, a substantial segment of consumers still prefers traditional offline purchasing methods. To convert these consumers into loyal online shoppers, fresh e-commerce companies must offer superior value through innovative marketing and service strategies. Providing value-added services, such as personalized promotions or guarantees on product quality, helps build trust and shifts consumer behavior from offline to online platforms. Enhancing market competitiveness through innovative marketing strategies is vital. Building professional online communities and leveraging new media channels for broader outreach are effective ways to attract diverse consumer segments. By engaging consumers through interactive platforms such as social media and live-streaming, companies can create vibrant online communities that foster brand loyalty.

Overall, innovation is important because it supports business model transformation. In the fresh e-commerce sector, innovation is not limited to technology

adoption or promotional activity. It also includes changes in value proposition, value delivery, and value capture. As firms explore new retail formats, front-warehouse systems, instant delivery services, and more transparent supply chains, innovation becomes a key driver of long-term competitiveness. Therefore, fresh e-commerce innovation is not only a response to current market pressure, but also a strategic path for future growth.

2.1.2.3 Business Models for Fresh E-Commerce

Fresh e-commerce in China has developed several business models to meet different consumer demands and market conditions. Fresh e-commerce in China has a number of different business models to suit various market demands and consumer preferences. Traditional e-commerce companies typically offer online shopping with delivery via express services, mainly targeting high-end and mid-to-high-end customers in first- and second-tier cities. Community e-commerce companies focus on shortening the delivery chain and providing faster delivery services to meet consumer demand, also primarily in first- and second-tier cities. Vertical fresh e-commerce emphasizes supply chain management and product quality to deliver differentiated services, usually targeting the high-end market. Platform-based e-commerce and the "shop and warehouse in one" model provide an integrated online and offline shopping experience, while front-loading e-commerce adopts a community front warehouse strategy to focus on instant delivery. The community group-buying model organizes group-buying activities within communities through online platforms, offering lower-priced products and targeting the mid-range market. Each model has its unique operational features. Traditional e-commerce relies on regional centre warehouses and owned or outsourced logistics, with citywide coverage and delivery times of one to two days. Community e-commerce uses city centre warehouses and free logistics distribution, achieving half- to one-day delivery. Vertical fresh e-commerce is directly operated, utilises multi-layer warehouse and distribution systems, and delivers within half a day to one day. The platform-based model and the "shop and warehouse in one" model combine in-store and online services, covering a one-to-three-kilometre radius with half- to one-hour delivery. Front-loading e-commerce deploys community warehouses that integrate storage, sorting, and distribution, shortening the supply chain and enabling half- to one-hour delivery. Community group-buying platforms are platform-operated, using central warehouses and community network warehouses with outsourced distribution, covering a 0.5-to-one-kilometre radius and

offering delivery within one to two days, with customers picking up goods at community pick-up points. Representative companies for each model include China Agri-Industries for traditional e-commerce; JD and Tmall Supermarket for community e-commerce; Hema (Freshippo) for the shop and warehouse in one model; Daily Fresh and Dingdong Maicai for front-loading e-commerce; and Meituan Select for community group-buying. This article synthesises a summary of business models in the fresh food industry based on relevant research reports (iiMedia Research, 2021; MobTech, 2022; Zhiyan Consultancy, 2023), providing a theoretical basis for the future study of value innovation and consumer behaviour in fresh e-commerce.

These business models differ in target customers, delivery speed, warehouse layout, and operational cost. Traditional and vertical e-commerce models often rely on central warehouses and standard distribution networks, while integrated retail and front-warehouse models place more emphasis on speed and local fulfillment. Community group-buying, by contrast, uses a lighter delivery structure and stronger community coordination. The coexistence of these models shows that fresh e-commerce is a highly dynamic sector, and that business model innovation is an important feature of its development.

2.1.2.4 Challenges and Opportunities

Although China fresh e-commerce industry has expanded rapidly in recent years, its development is still shaped by both major challenges and emerging opportunities. Existing studies show that the industry faces persistent pressure from logistics, cost control, market competition, and food safety management. At the same time, digital technology, changing consumer demand, and policy support have created favourable conditions for further development (Gao, 2024; Wang & Song, 2022; Zan, 2020). These studies provide a comprehensive background for understanding the current development conditions of China fresh e-commerce industry, including both its constraints and growth potential.

One of the most critical challenges is logistics and cold-chain distribution. Fresh products are highly perishable, sensitive to temperature, and difficult to store for long periods. This means that product quality depends heavily on efficient warehousing, transportation, and last-mile delivery. As several studies have noted, weaknesses in cold-chain logistics, limited delivery coverage, and insufficient standard remain major barriers to the sustainable development of fresh e-commerce in China. If logistics performance is

unstable, product freshness and customer satisfaction are likely to decline, which directly relates repeat purchase behaviour and platform trust.

Another challenge lies in high operating costs and supply chain management. Compared with many other e-commerce categories, fresh products involve higher costs in procurement, storage, packaging, refrigeration, and distribution. In addition, the fragmented nature of agricultural production and the unstable quality of fresh products make standard management more difficult. Previous research has pointed out that fresh e-commerce firms often face pressure from inventory loss, product damage, fluctuating supply, and weak coordination across the supply chain. These problems reduce efficiency and make profitability difficult to achieve, especially for firms that rely heavily on rapid delivery or front-warehouse operations.

Market competition also presents a major challenge. With the rapid expansion of the industry, competition now comes not only from vertical fresh e-commerce firms, but also from large integrated e-commerce platforms, traditional supermarkets, community group-buying platforms, and new retail enterprises. As a result, product and service homogeneity has become increasingly common. Some studies have argued that many firms still depend on price competition, subsidies, and rapid market expansion rather than on sustainable value creation. This has made the market more competitive and has increased the pressure on firms to differentiate themselves through quality, service, supply chain capability, and business model innovation.

Despite these difficulties, the industry also faces considerable opportunities. Firstly, the development of digital technologies has created new conditions for upgrading fresh e-commerce business models. Technologies such as big data, artificial intelligence, the Internet of Things, and cloud computing can improve demand forecasting, inventory management, product traceability, and delivery efficiency. They also allow firms to better understand customer preferences and provide more targeted services. In this sense, digital technology is not only a tool for operational improvement, but also an important driver of business model innovation and value creation. Secondly, consumption upgrading has created strong market potential for fresh e-commerce. As consumers become more health-conscious and quality-oriented, demand for fresh, safe, nutritious, and convenient food continues to grow. In urban areas especially, busy lifestyles and changing consumption habits have increased the acceptance of online fresh shopping. Consumers are now more

willing to pay for high-quality products, reliable delivery, and better shopping experiences. This creates favourable market conditions for firms that can combine freshness, quality assurance, convenience, and personalized service.

Overall, the fresh e-commerce industry operates in a context where challenges and opportunities coexist. On the one hand, logistics pressure, high costs, strong competition, and consumer trust issues continue to constrain industry development. On the other hand, digital innovation, consumption upgrading, and policy support provide strong momentum for transformation and growth. This dual context suggests that continuous innovation in value creation, value delivery, and service experience is essential for the long-term development of fresh e-commerce and also provides an important practial background for this study.

2.1.3 Consumer Behaviour in the Digital Economy

2.1.3.1 Changes in Shopping Habits

Existing studies show that the digital economy has significantly changed consumers' shopping habits. Hu (2024) argued that the continuous development of digital technologies—such as the mobile internet, big data, artificial intelligence, and online platforms—has fundamentally transformed consumption patterns. Rather than passively responding to basic survival needs, consumers now engage in a more active and diversified shopping process. Because digital platforms operate continuously, consumers are empowered to access product information at any time, compare alternative products more easily, and execute purchases without the traditional constraints of time and physical location. Similarly, Sun et al. (2025) emphasized the structural changes in shopping channels. They found that the development of the digital economy has deeply promoted online shopping and the widespread use of mobile payments. Furthermore, the integration of online and offline consumption scenarios allows consumers to flexibly switch between physical and digital spaces. This technological integration has ultimately made the daily shopping process significantly more convenient, efficient, and flexible.

Firstly, the popularity of e-commerce has changed consumers' shopping styles (Figueiredo et al., 2025). Consumers are no longer confined to brick-and-mortar shops, but rely more on e-commerce platforms and mobile applications to browse and purchase goods. This shift has been made possible by the widespread popularity of the Internet and smart devices, which allow consumers to shop anytime and anywhere, greatly

improving the convenience and timeliness of shopping. In particular, the rise of mobile shopping has enabled consumers to make full use of fragmented time for impromptu shopping and quick order placement, a shopping style that is very different from traditional centralised purchasing (Nam & Cho, 2026). This evidence supports the argument that mobile commerce has increased shopping flexibility and changed consumers' purchase timing, frequency, and decision making process.

Secondly, the application of intelligent recommendation systems and personalize technology under the digital economy has further influenced consumers' shopping habits (Putri & Milad, 2025). E-commerce platforms accurately push products to consumers that meet their needs based on big data such as users' browsing history, shopping records, and interests and preferences, thus enhancing user experience and purchase rates (Naim et al., 2025). This personalize shopping experience makes consumers gradually rely on the platform's recommendations, reducing the frequency of independent searches and price comparisons, and increasing the likelihood of impulsive spending (Putri & Milad, 2025). It explains how mobile shopping enables more immediate and fragmented consumption behaviour compared with traditional planned shopping.

Thirdly the rise of social media and short video platforms has also profoundly affected shopping habits (Vinodh et al., 2024). In the process of shopping decision-making, consumers pay more and more attention to the evaluation and recommendation of others, including the use and sharing of online celebrities, KOLs, and ordinary users. In particular, the popularity of emerging shopping methods such as live streaming and short video recommendation has made "planting grass" and "pulling grass" the new normal of shopping, and consumers tend to judge the quality and applicability of goods through the actual experience of others (Huang & Mohamad, 2025). This social shopping mode has enhanced the interactivity and sense of participation in shopping, making consumers' shopping decisions more easily influenced by the opinions of others (Zhu & Vijayan, 2025). Social commerce increases consumer engagement while also making purchase decisions more dependent on online communities and interpersonal influence.

At the same time, with the continuous upgrading of logistics and delivery services, consumers' demand for the timeliness of shopping has also gradually increased. From one-hour delivery to no-touch delivery, e-commerce platforms continue to optimise delivery efficiency to meet consumers' immediate needs for shopping experience (DHL,

2024). This innovation in delivery methods has made fresh products, daily necessities, and other goods with immediate needs an important category of online shopping, further expanding the scope and frequency of online shopping for consumers (Cunningham & Petzer, 2026). The argument states that improved delivery services have expanded the types of products suitable for online shopping, especially fresh food and daily necessities that require timely fulfilment.

In addition, consumers' shopping habits are also characterized by both price sensitivity and value sensitivity. On the one hand, consumers are more price-sensitive and often use price comparison websites, coupons, and promotions to get the most cost-effective products. On the other hand, consumers are paying more attention to the brand, quality, environmental protection, and other value elements of the product, no longer only pursuing low prices, but tend to pay a premium for high-value goods (Koc et al., 2025). This change in shopping habits has prompted brands and platforms to place more emphasis on product quality, service quality, and brand value in addition to promotional tactics.

Finally, changes in shopping habits under the digital economy are also reflected in the diversification and convenience of payment methods (Bian et al., 2024). With the popularity of mobile payments, consumers can easily complete payments, eliminating the tedious process of cash payments. At the same time, e-commerce platforms commonly use credit payment, instalment payment, and other payment methods, further lowering the threshold of consumption, enabling consumers to arrange their expenditures more flexibly and meet immediate consumption needs .

2.1.3.2 Digital Consumer Characteristics

The literature also suggests that digital consumers have distinct behaviour characteristics, that digital consumers tend to have stronger preferences for personalization, diversity, and convenience. They are more active in searching for information and more capable of making independent choices. Sun et al. (2025) further pointed out that digital economy development has encouraged consumers to pursue higher-quality, more intelligent, and more customized products and services. As a result, digital consumers are generally more information-sensitive, experience-oriented, and quality-conscious than traditional consumers.

In the era of the digital economy, the characteristics of consumers have changed significantly in many aspects, presenting unique attributes different from those of

traditional consumers. The characteristics of digital consumers mainly include high mobility, enhanced individualization, high information sensitivity, emphasis on privacy protection, and strong social attributes (Efendioğlu, 2024). These characteristics have prompted companies to pay more attention to user experience, information transparency, and privacy protection when providing products and services, so as to maintain competitiveness in the digital economy (Efendioğlu, 2024). Therefore, understanding the changing characteristics of digital consumers is essential for explaining how firms should adjust their marketing strategies, service design, and customer relationship management in the digital economy.

Firstly, digital consumers exhibit a high degree of mobility, as they are no longer loyal to a single shopping channel or brand, but switch between multiple platforms in search of optimal products and services (Alesanco-Llorente et al., 2025). This characteristic is facilitated by the transparency of digital information, which allows consumers to easily compare prices, reviews, and promotions across different platforms in order to choose the best purchasing channels and products among the competition (Shankar et al., 2024). This shows that consumer mobility is not only reflected in channel switching, but also in consumers' stronger ability to evaluate alternatives, which requires firms to improve platform experience, pricing strategies, and service consistency across different channels.

Secondly, significantly increased demand for individualization is another characteristic of digital consumers (Nurdianasari & Md., 2025). In an environment of massive quantities of goods and information, consumers expect a highly personalize shopping experience, and e-commerce platforms are able to provide consumers with personalize recommendations and customised services based on their historical behaviors and preferences through big data and artificial intelligence technologies (Nurdianasari & Md., 2025). Digital consumers are happy to receive such personalized recommendations that match their interests and needs, and this enhanced personalized service makes it easier for consumers to find products that match their personal preferences, increasing user stickiness and loyalty (Choi & Kim, 2025). Therefore, individualization has become an important basis for improving consumer satisfaction and loyalty, because digital consumers increasingly expect firms to understand their preferences and provide more relevant products, services, and communication.

In addition, digital consumers are more information-sensitive. The convenience of digitalization allows consumers to easily access and process a large amount of product information, including product features, user reviews, price trends, etc., which makes them more rational and cautious in their purchase decisions. Digital consumers actively use search engines, social media, and price comparison websites to conduct comprehensive information gathering for optimal purchase intention. Therefore, digital consumers' trust in merchants is to a certain extent based on the openness and transparency of information, and they place higher demands on the authenticity and completeness of the information provided by merchants (Kou et al., 2025). This indicates that information transparency directly affects consumer trust and purchase decisions, making accurate product descriptions, authentic reviews, and reliable platform information essential elements of digital marketing.

Furthermore, digital consumers generally value data privacy and information security. As digitization deepens, the collection and use of personal information has become a focus of consumer attention, especially in the context of personalized services, where consumers demand greater control and transparency of data. More and more consumers are aware of the importance of data privacy and expect merchants to provide personalized services with privacy protection, which also poses higher challenges to companies' data management and privacy protection (Choi & Kim, 2025). Thus, privacy protection has become a key condition for maintaining consumer trust, as firms must balance the benefits of personalized services with consumers' concerns about data security and information control.

Finally, digital consumers show a high degree of socialisation (Abdalla et al., 2025). Not only do they obtain consumption information through social media, but they are also willing to share their shopping experience, forming a social consumption mode (Abdalla et al., 2025). The shopping behaviour of digital consumers is no longer a single buying and selling process, but a kind of social interaction, and they get social recognition and satisfaction while sharing their experience (IDC, 2023). Therefore, in the marketing process, merchants can make use of user-generated content to enhance the social attributes and interactivity of the brand, in order to increase consumer engagement and loyalty (Ogilvy Social Lab, 2026). This suggests that digital consumption is increasingly embedded in social interaction, meaning that firms need to manage not only products and

services, but also online communities, consumer engagement, and user-generated brand communication.

2.1.3.3 Fresh E-Commerce Consumer Characteristics and Purchase Behaviour

Although the studies reviewed above do not focus specifically on fresh e-commerce, they offer a useful foundation for understanding consumer behaviour in this sector. In the digital economy, consumers increasingly expect convenience, efficiency, quality, and personalized service (Sun et al., 2025). These expectations are especially relevant in fresh e-commerce, where product freshness, food safety, delivery speed, and service reliability are central to purchase decisions. Therefore, fresh e-commerce consumers are likely to show strong sensitivity to platform performance, perceived value, and perceived risk, which directly influence their buying behaviour and purchase intention.

Fresh e-commerce consumers in China also display clear demographic characteristics, which help explain their purchasing behaviour and platform preferences. According to survey data reported by the Mob Research Institute (MobTech, 2022), fresh e-commerce consumers in China show several clear demographic characteristics. The typical fresh e-commerce consumer is a married, middle-aged professional residing in a major urban center, holding a college degree, and earning a middle-to-high income. Understanding these demographic characteristics allows fresh e-commerce companies to implement targeted value innovations, thereby better meeting consumer expectations and enhancing purchase intentions. Specifically, the consumer profile can be analyzed across five key dimensions:

Firstly, the gender distribution among fresh e-commerce consumers has shifted from a female-dominated space to a balanced demographic. In 2019, women accounted for approximately 70% of the user base. However, by 2022, the ratio equalized to nearly 50:50. Given that over 80% of these users are married, this shift suggests that men are increasingly participating in household grocery shopping, sharing family responsibilities through digital platforms.

Secondly, age demographics reveal a strong correlation between fresh e-commerce adoption and family caregiver roles. The majority of users are over 25 years old, with the 35-44 age bracket showing the highest engagement. Since more than half of these consumers live in households with three or more members, their purchasing behavior

is largely driven by the practical need to efficiently procure daily ingredients for their families.

Thirdly, the fresh e-commerce market is heavily concentrated in China's economically developed urban centers. Users primarily reside in Tier-1 and New Tier-1 cities. More than 60% of the user base is located in the top ten major cities, with regions like Beijing, Shanghai, Guangdong, and the Yangtze River Delta coastal belt accounting for over 75% of total engagement. This indicates that the fast-paced lifestyle in major economic hubs strongly drives the demand for convenient grocery delivery.

Furthermore, consumer purchasing power, indicated by income level and home-ownership, significantly influences platform preferences. While the foundational user base consists of middle-income earners (making between 3,000 and 10,000 RMB monthly), higher-income groups (earning over 20,000 RMB) show a particularly strong interest in this sector. Notably, home-owning consumers with higher incomes tend to favor premium platforms like Hema and RT-Mart YouFresh, reflecting a consumption focus on quality and brand reputation over mere price.

Finally, educational attainment serves as a key predictor of a consumer's platform choice. Over 86% of fresh e-commerce consumers hold an associate or bachelor's degree. Interestingly, education levels correlate directly with platform selection: highly educated consumers generally prefer high-end services like Hema, whereas those with intermediate education levels often lean towards community-based group-buying platforms like Meituan Select. This highlights the need for platforms to differentiate their market positioning.

In summary, the profile of the fresh e-commerce consumer is predominantly urban, family-oriented, and well-educated. These characteristics mean that users place a high value on convenience, product quality, and service reliability, which are critical factors that shape their buying behaviour and receptiveness to value innovation.

2.2 Parent Disciplines

2.2.1 Theories of Consumer Behaviour

The theory of consumer behaviour aims to study the psychological processes and behavioural patterns of individuals when making consumption decisions in order to better understand and predict consumer purchasing behaviour. This theory provides a basis for

the development of marketing strategies, enabling companies to enhance their market competitiveness by satisfying consumers' needs. In the study of consumer behaviour, the Stimulus-Organism-Response model, as an important theoretical framework, analyzes the decision-making process of consumers through the triple structure of Stimulus-Organism-Response. The Stimulus-Organism-Response model provides a powerful explanatory tool to understand the response mechanism of consumers in specific situations.

By introducing the Stimulus-Organism-Response model, the impact of value innovation in fresh e-commerce on consumers' purchase intention can be analyzed in more detail. Value innovations in fresh e-commerce can be regarded as external stimuli to consumers, affecting their cognitive, emotional, and other internal psychological states, thus further influencing their purchase decisions. The application of the Stimulus-Organism-Response model can help fresh e-commerce companies to deeply understand consumers' purchasing motives and behavioral patterns, and provide a theoretical basis for the development of personalized marketing strategies and optimization of user experience, which not only enhances the market competitiveness of enterprises, but also provides consumers with services that are more in line with their needs.

2.2.1.1 S-O-R Theory

The Stimulus-Organism-Response theoretical framework is based on the traditional stimulus-response model with the addition of an intermediate variable, organism, to explain the inner activities of human beings, and is one of the key theories in environmental psychology. The Stimulus-Organism-Response model as shown in Figure 2.1 (Hu et al., 2023). Donovan and Rossiter later applied the Stimulus-Organism-Response model to offline retail scenarios to study user purchasing behaviour and found that consumers develop acceptance or avoidance behaviours when stimulated by offline retail environments (Karim et al., 2021). Therefore, the Stimulus-Organism-Response model provides a useful theoretical basis for explaining how external environmental stimuli influence consumers' internal psychological states and further lead to behavioural responses.

The Stimulus-Organism-Response model consists of three core elements: Stimulus, Organism, and Response Stimulus, or "the influence that awakens the individual", stimulates and influences the internal state of the individual, and encompasses many aspects of the external environment. The organism refers to an individual's internal

sensory, perceptual, and thinking activities, which reflect a person's cognitive and affective states, and plays an intermediary role in connecting stimulus and response in the Stimulus-Organism-Response model. Response, on the other hand, is the final behaviour and attitude that an individual displays through his or her internal state under the effect of a stimulus (Wulansari & Sodikin, 2026; Mimanda, 2026). In this sense, the Stimulus-Organism-Response model explains consumer behaviour as a continuous process from external stimulation to internal psychological change and finally to behavioural response, which makes it suitable for analysing purchase intention in digital shopping environments.

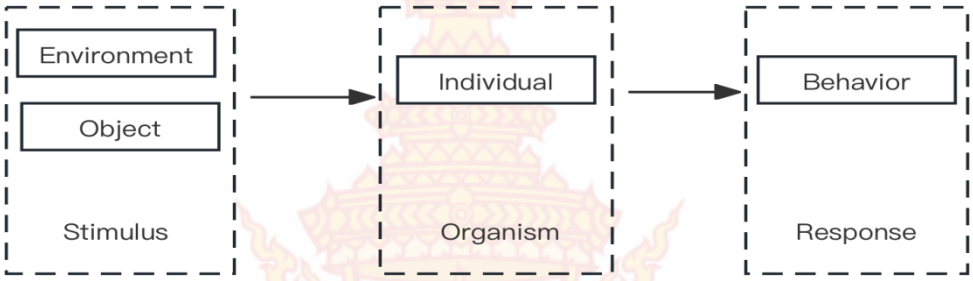


Figure 2.2 S-O-R Theoretical Framework

Based on the Stimulus-Organism-Response theoretical model, in the study of consumers' acceptance of stimuli on consumers' purchase intention, it was concluded that purchase intention is positively influenced by the shopping channel under the four dimensions of external stimuli: convenience, individualization, interesting and sociality of the e-commerce platform channel choice, and that the mind-flow experience plays a mediating role, the mind-flow experience refers to the pleasurable psychological sensation obtained by the consumer's deep integration into the e-commerce shopping platform.. Liu et al. (2020) noted limiting the shopping channel to webcasting, taking the characteristics of webcasting, interactivity, authenticity, entertainment, and visibility, as external stimuli, and the mediating variable adding the trust variable on the basis of emotion perception, the study concludes that interactivity, authenticity, entertainment, and visibility all significantly and positively affect consumers' pleasurable emotions, and authenticity and visibility significantly and positively affect consumers' trust perceptions. In the study of webcasting consumer purchase intention, selected external stimuli for the webcasting situation under the product characteristic factors and situational characteristic factors, concluded that the product and situational characteristic factors through perceived value

and perceived pleasantness positively relate consumer purchase intention, of which the product characteristic factors embodied in the quality of the product and the product promotions, the situational characteristics of the factors in the interactivity, the number of transactions, the number of viewers (Ji & Zhuo, 2020). Overall, these studies demonstrate that the Stimulus-Organism-Response model can effectively explain how different types of online shopping stimuli, such as platform features, live-streaming characteristics, product attributes, and situational cues, influence consumers' psychological perceptions and ultimately affect purchase intention.

Based on the Stimulus-Organism-Response theoretical model, in the study of consumer perceived value and perceived risks on consumer's purchase intention, Zhang (2017) studied consumer online purchase intention by taking online return policy leniency as the external environment, and perceived product quality and perceived shopping risk as the mediator variables, and empirically concluded that perceived risks does not affect consumer's purchase intention, while perceived product quality positively affects consumers' purchase intention. Liu et al. (2020) added trust variables on the basis of perceived risks and perceived value, and concluded that the external stimulus of online opinions would indirectly affect purchase intention through consumers' trust, perceived risks, and perceived value changes. In the context of online purchase of tourism products, external stimuli are categorized as price concessions, product information, website service quality, and online reviews, and it is empirically concluded that these four external factors affect consumers' purchase intention through perceived value and perceived risks, but perceived value plays a major role in purchase intention (Peng et al., 2019) . In the study of consumers' purchase intention in e-tailing companies, the social responsibility of e-tailing companies is used as an external stimulus, and it is concluded that the social responsibility of e-tailing companies affects purchase intention through perceived quality and perceived risks, and the mediating effect of perceived quality is greater than that of perceived risks (Wei & Wan, 2020). In the online group-buying environment, consumers' risk perception has a significant negative effect on their purchase intention. The study reveals that when group-buying platforms offer deeper price discounts and display a larger number of participants, consumers' risk perceptions of product quality and transaction process diminish. Correspondingly, a group-buying product with a less restrictive purchase limit policy, for example., a smaller number of participants, also reduces consumers' risk

perception of the product and the transaction process (Shi et al., 2017) . These external environmental incentives enhance consumers' willingness to participate in online group purchases by alleviating their concerns about potential adverse consequences.

By summarizing the above literature, it is shown in the table 2.1 below.

Table 2.1 Components of the S-O-R Model based on Consumer Purchase Intention

S-stimulation	O-organism	R-response	Description of the reaction	Source
Internet Return Policy Leniency	Perceived value, perceived risks	purchase intention	Perceived product quality positively influences purchase intentions	Zhang Beijia (2017)
Network infrastructure	Trust, perceived risks, perceived value	purchase intention	Online opinions indirectly influence purchase intentions through trust	Liu Junyue et al. (2020)
Price favorability, product information, website service quality, online reviews	Perceived value, perceived risks	purchase intention	External stimuli influence purchase intention through perceived value and perceived risks, with perceived value playing a major role	Peng, Z. et al. (2019)
Social Responsibility of E-tailers	Perceived quality, perceived risks	purchase intention	E-tailers' social responsibility affects purchase intentions through perceived quality and perceived risks, with perceived quality having a greater influence	Wei, H. et al. (2020)

In summary, since the Stimulus-Organism-Response theory was introduced to explain consumer behaviour, it has been extended to a wide range of domains such as food, education, tourism, e-intelligence, and online shopping. The stimuli of the external environment are no longer limited to the influence of the traditional environment, but extended to the influence of the online environment. At the same time, the scope of users' internal perception has also expanded from a single emotional change to multiple changes in the perception of things as well as emotions. The cognitive dimension now includes multiple dimensions such as perceived trust, perceived risks, perceived quality, perceived

usefulness, and perceived ease of use. Ultimately, based on the perceived changes, users will react by avoiding harm, i.e. actual behavioural choices, which have evolved from simple avoidance behaviours to a variety of forms such as refusal behaviours, use behaviours, purchase behaviours, and so on.

2.2.1.2 Theoretical Advantage of the S-O-R Theory

The Stimulus-Organism-Response theory provides a powerful framework for understanding and explaining consumer behaviour. Unlike the traditional stimulus-response model, the Stimulus-Organism-Response model introduces the intermediate variable of the organism, which allows the analysis to be not only limited to external stimuli and behavioral responses, but also delves into the consumers' internal psychological states, such as emotions, attitudes, and conditions (Song et al., 2022). This approach allows us to understand the consumer in a holistic manner. This approach allows for a comprehensive understanding of consumer purchasing behaviour and recognizes the role of individual differences in consumer responses, emphasizing the unique internal psychological processes of each consumer.

The introduction of the Stimulus-Organism-Response theory improves the accuracy of predicting consumer behaviour and is important for the development and optimization of marketing strategies (Baber & Baber, 2022). It promotes the development of personalized marketing and helps firms better understand the needs and preferences of target consumers and design more personalized products and services. Meanwhile, this theory supports firms to adopt diversified marketing strategies, such as emotional marketing and experiential marketing, to influence consumers' purchase intention.

The Stimulus-Organism-Response model is adaptable and can be applied not only to offline retail environments but also to online e-commerce and social media environments (Lin & Shen, 2023; Ma et al., 2022) . In today's digital and networked environment, this adaptability allows the Stimulus-Organism-Response theory to continue to maintain its practical value, helping companies to capture consumer needs more accurately and formulate effective marketing strategies in an era of information explosion and diversified consumer choices.

In summary, the Stimulus-Organism-Response theory provides a framework for understanding and predicting consumer behaviour, emphasizing the interaction between external stimuli and an individual's intrinsic state and its impact on behaviour.

However, there are limitations to the theory: its predictive power may be insufficient in complex or fast-changing markets; individual differences may lead to different responses to the same stimuli, and the theory fails to fully account for this heterogeneity; the quantification of intrinsic states is elusive, which may limit the application of empirical research; the causal relationships between stimuli, organisms, and responses in the theory may be complex and difficult to establish; the theory's cross-cultural applicability and completeness in specific scenarios also needs to be further verified. These limitations suggest that we should consider the potential limitations of the theory when applying it.

This study proposes to adopt the Stimulus-Organism-Response theory, which aims to explore how the value innovation of fresh e-commerce serves as a stimulus to consumers and how consumers' value perception serves as an indicator reflecting consumers' cognitive and affective states. Purchase intention is regarded as consumers' final purchase intention through perceived value under the stimulus effect of value innovation of fresh e-commerce.

2.2.2 4I Marketing Theory

Marketing theory provides an important basis for understanding consumer behaviour, designing marketing strategies, and creating customer value. In the digital economy, however, the marketing environment has changed significantly. Consumers are no longer passive receivers of information; instead, they interact with brands through multiple digital touch points, including social media, mobile applications, online communities, live-streaming platforms, and e-commerce websites. As Verhoef et al. (2021) argue, digital transformation has reshaped firms' business models, customer interactions, and value-creation processes. Therefore, marketing strategies in the digital era need to be more interactive, data-driven, integrated, and customer-oriented.

This change is particularly important in fresh e-commerce. Compared with general e-commerce products, fresh products are more sensitive to quality, freshness, delivery speed, food safety, and service reliability. Consumers' purchase decisions are influenced not only by price, but also by product presentation, trust, convenience, platform experience, and after-sales service. As a result, fresh e-commerce firms need marketing strategies that can attract attention, strengthen consumer participation, coordinate multiple channels, and provide personalized value.

Against this background, this study adopts an adapted 4I marketing framework consisting of four dimensions: interesting, interactivity, integration, and individualization. This framework is suitable for analyzing digital marketing practices because it reflects several key features of the contemporary online market: attention competition, consumer participation, channel convergence, and data based personalization. Previous research has shown that digital and social media marketing has become an important tool for firms to engage consumers, build brand relationships, and improve marketing performance (Dwivedi et al., 2021).

First, interesting refers to the ability of marketing content to attract consumers' attention and stimulate their interest. In digital markets, consumers are exposed to a large amount of information every day, and ordinary promotional messages are easily ignored. Therefore, creative, vivid, and emotionally appealing content is important for improving consumer attention. In fresh e-commerce, firms can use short videos, live-streaming, visual storytelling, recipe content, and product-origin stories to show the freshness and quality of products. Such content can make fresh products more attractive and encourage consumers to browse, share, and purchase.

Second, interactivity emphasizes two-way communication between firms and consumers. In the digital environment, consumers can comment, share, review, ask questions, and participate in brand-related activities. This changes marketing from one-way persuasion to continuous communication. Interactivity is especially important for fresh e-commerce because consumers often have concerns about freshness, delivery time, product quality, and refund policies. Through live-streaming, online customer service, user reviews, community groups, and social media interaction, firms can respond to consumer concerns more quickly and build stronger trust. Interactive marketing also helps firms collect consumer feedback and improve their products and services.

Third, integration refers to the coordination of different marketing channels and consumer touch points. In the digital economy, consumers often move between different channels before making a purchase. For example, they may see a product on social media, compare prices on an e-commerce platform, read reviews in an online community, and finally place an order through a mobile application. Therefore, firms need to integrate online and offline resources to provide a consistent consumer experience. Cai and Lo (2020) pointed out that integration is important because consumers increasingly expect

seamless experiences across different channels. For fresh e-commerce firms, integration may include the coordination of mobile apps, social media accounts, live-streaming rooms, offline stores, community group buying, and delivery services. Effective integration can reduce consumer friction and improve the overall shopping experience.

Fourth, individualization means providing personalized products, content, and services based on consumer preferences and behavioral data. With the development of big data and artificial intelligence, firms can analyse consumers' browsing history, purchase records, location, preferences, and feedback to offer more accurate product recommendations and marketing messages. Ameen et al. (2021) suggest that AI-enabled technologies can improve customer experience by supporting more personalized and responsive services. In fresh e-commerce, individualization can be reflected in personalized product recommendations, customized discount coupons, dietary preference suggestions, membership services, and location-based delivery options. These practices can improve consumer satisfaction and encourage repeat purchases.

Overall, the adapted 4I marketing framework provides a useful perspective for analyzing marketing strategies in fresh e-commerce. Interesting helps firms attract consumer attention; interactivity strengthens communication and trust; integration improves the consistency of the consumer journey; and individualization enhances the relevance of products and services. Together, these four dimensions explain how fresh e-commerce firms can create consumer value and improve marketing performance in the digital economy.

2.2.3 Consumer Psychology Theory

The theory of consumer psychology explores the psychological activities that consumers exhibit during the buying process and the factors that influence them. The theory emphasizes the importance of consumers' emotions, attitudes, and perceptions on their purchase intention and aims to reveal how consumers perceive, evaluate, and choose products. Consumer psychology theory is particularly important in the context of the rapidly developing digital economy, where consumer purchasing behaviour is influenced by a variety of factors, including how information is accessed, the effectiveness of brand communication, and social media engagement.

Within this theoretical framework, the Perceived Value theoretical model is particularly prominent. The model suggests that consumers' perceived value of a product

is a key determinant of their purchasing behaviour (Li & Shan, 2025). The theory emphasizes that consumers make purchase intentions not only on the basis of the actual price or quality of the product, but more on their subjective perception of the value of the product. Perceived value usually involves a consumer's trade-off between the benefits a product or service can provide and the price it demands. Understanding and applying Perceived Value theory will help companies optimize their marketing strategies as fresh e-commerce firms face high consumer expectations for product quality and buying experience in the digital economy.

2.2.3.1 Perceived Value Theory

The Perceived Value Theory suggests that consumers' perception of the value of a product is a key determinant of their purchasing behaviour, emphasizing that consumers base their purchase intention not solely on the actual price or quality of a product, but more on their subjective perception of the value of the product (Monfort et al., 2025). Perceived value usually involves a trade-off between the benefits a product or service can provide and the price it demands.

The understanding and research on consumer perceived value began in the 1990s. Scholars have different opinions on the concept of consumer perceived value. Zeithaml first formally articulated the theory of consumer perceived value from a consumer psychology perspective. He defined consumer-perceived value as the overall evaluation of the utility of a product or service when the perceived benefits of the product or service are weighed against the costs incurred by the consumer in acquiring the product or service (Zeithaml, 1988). He argues that consumer perception of value should be the determining factor in designing, creating, and delivering value to consumers from a consumer-oriented perspective. Consumer value is determined by the consumer rather than by the firm, and consumer value is actually consumer perceived value. This concept has two meanings. This concept has two meanings: firstly, value is personalized and varies from person to person, and different consumers do not perceive the same value for the same product or service; secondly, value represents a trade-off between utility and cost, and consumers make purchase intentions based on their own perceptions of value, rather than solely on a single factor.

It also stated that whether a consumer buys a good depends on the relative relationship between the benefits he derives from the product he wants to buy and the price

he has to pay for it (Prakash et al., 2021). In other words, a consumer's perceived value of a product is derived from the benefits derived from the product versus the price he has to pay in order to get the product. The greater the perceived benefit exceeds the perceived costs, the greater the perceived value of the consumer. The magnitude of perceived value depends on the relationship between perceived benefits and costs.

In addition, perceived risks as one of the costs that must be paid to obtain a product and argue that benefits, monetary costs, and perceived risks affect purchase intentions through the overall evaluation of the transaction. willingness (Wang, 2023). Price is the monetary amount that consumers must give up in order to obtain certain products or services, and perceived risk is the consumer's sense of uncertainty about the outcome and consequences of a purchase decision, so price is an immediately certain expense, while risk represents a future and uncertain possible expense or encounter, and the cost of risk should have a more significant effect on consumer behaviour.

According to Schendzielarz and Alavi (2022) study, consumers have two perceptions when purchasing a product: desired characteristics and unwanted characteristics, which can be subtracted to obtain the net perceived rewards, where the positive value is the perceived rewards and the negative value is the perceived risks. Perceived reward has the same meaning as perceived benefit, and what is called "net perceived reward" has the same meaning as perceived value. With the deepening of research, the perceived value theory has been widely used in the formulation of marketing strategies to help companies enhance the attractiveness of their products by improving the perceived value of consumers in a highly competitive market. In addition, the theory has also been used in various fields such as service marketing, e-commerce, and consumer behaviour research. In the study of perceived value of haze prevention cosmetics under haze pollution, it was found that perceived value played a partially mediating role between monetary value, social value, perceived haze awareness, and purchase intention, and a fully mediating role between brand value and purchase intention. This implies that perceived value is a key factor in the process of consumers' transition from perception to purchase behaviour (Song et al., 2019). Yu and Zheng (2022) explored the impact of perceived luxury value on customer engagement and purchase intention in live shopping, showing that perceived value has a positive impact on consumer behaviour in the context of luxury goods. Lai et al. (2021) investigated the generation of electronic word-of-mouth

in culinary tourism by combining the theory of the experience economy with the theory of perceived value, highlighting the positive influence of emotional value on tourists' satisfaction and memory. Finally, Xu et al. (2022) analyzed the impact of perceived value on the repurchase intention of green agricultural products, emphasizing the importance of safety value, functional value, and green value on the formation of consumer behavioral intention. Lin and Dong (2023) integrated the theory of planned behaviour, the perceived value theory, and environmental awareness to explore consumers' purchase intentions towards energy-efficient home appliances, highlighting the impact of functional value, price value, environmental value, and environmental awareness on consumer attitudes.

In summary, perceived value is the result of a trade-off between a consumer's perception of the utility provided by a product or service and the cost it incurs. It is a subjective evaluation that reflects the consumer's perception and understanding of the value of a product or service based on personal needs, preferences, experience, and socio-cultural context. Perceived value does not only depend on the physical attributes of the product or the functional characteristics of the service, but also includes the emotional experience, social impact, and personal emotional state associated with it. In actual purchase decisions, consumers typically weigh the expected benefits received against the costs they must pay . Perceived value therefore reflects both the economic considerations of the consumer and incorporates an emotional and psychological dimension to the assessment, and is a key factor influencing consumers' purchase intention.

2.2.3.2 Theoretical Advantage of Perceived Value Theory

A key advantage of perceived value theory is that it explains consumer judgement in a more comprehensive way. The theory argues that consumers do not evaluate products or services by simply adding up their objective attributes. Instead, value judgement is formed through a combination of subjective perception and the extent to which personal needs are satisfied. This makes perceived value theory more suitable for explaining actual consumer behaviour, especially in markets where purchase decisions are influenced by both functional and emotional considerations.

Another important strength of perceived value theory is that it captures the complexity of consumer psychology. Unlike the traditional rational choice model, perceived value theory emphasizes that consumer decisions are influenced by cognitive bias, emotional preference, and personal experience. As a result, the same product or

service may be valued very differently by different consumers. This helps explain why consumer responses are often diverse even under similar market conditions.

Perceived value theory is also useful because it provides strong support for market segmentation and customized marketing. By analysing the perceived value of different consumer groups, firms can better identify the needs and preferences of their target markets. This allows them to design more suitable products, services, and communication strategies. In competitive markets, such an approach can help firms build stronger customer relationships and gain strategic advantage.

In addition, perceived value theory highlights the importance of situational factors in shaping purchase intention. Consumer decisions are not made in isolation. They are often affected by contextual conditions such as the shopping environment, time pressure, and social influence. Therefore, firms need to consider these factors when developing marketing strategies. Doing so can improve communication effectiveness and increase the likelihood of successful purchase outcomes.

A further advantage of perceived value theory is that it offers a useful basis for evaluating marketing effectiveness. By comparing changes in consumers' perceived value before and after marketing activities, firms can better understand whether their strategies have achieved the intended results. This gives managers more reliable evidence for adjusting and improving later campaigns. In this sense, perceived value theory is not only explanatory, but also practical.

In summary, perceived value theory has important strengths in explaining and predicting consumer behaviour. It reveals the complexity of consumer judgement, supports market segmentation and customized marketing, draws attention to situational influences, and provides a useful tool for assessing marketing performance. For these reasons, the theory has strong application value in studies of consumer behaviour and purchase intention.

2.3 Immediate Disciplines

This section discusses the core variables that are directly related to the research model and helps explain consumer behaviour in fresh e-commerce. Based on the Stimulus-Organism-Response framework, this study focuses on how external marketing stimuli affect consumers' internal evaluations and behavioural responses. Among these variables,

value innovation in fresh e-commerce is treated as an important external stimulus because it can shape consumers' perceptions and influence their purchase decisions.

2.3.1 Value Innovation in Fresh E-Commerce

Value innovation in fresh e-commerce serves as the stimulus factor in the Stimulus-Organism-Response model and plays an important role in influencing consumer responses. In the Stimulus-Organism-Response framework, stimulus refers to external factors that can affect consumers' internal psychological states and behavioural intentions. In this study, value innovation in fresh e-commerce is regarded as a key form of external stimulus because it can influence consumers' perceived value and purchase intention. In practice, value innovation in fresh e-commerce is reflected in improvements in products, services, channels, and brand experience. Fresh e-commerce firms do not rely only on low prices or basic product supply. Instead, they try to create additional value by improving product quality, providing better services, optimizing purchasing channels, and building a stronger brand image. These efforts can attract consumers' attention, increase their interest in shopping, and create a more satisfying consumer experience. Therefore, value innovation is an important factor in understanding consumer behaviour in the fresh e-commerce context.

2.3.1.1 The Concept of Value Innovation

Value innovation is a key concept in modern business strategy because it emphasizes creating superior value for customers rather than competing only through technology or product features. Traditional competition often focuses on improving technical performance or outperforming rivals within an existing market. In contrast, value innovation highlights the importance of delivering new and meaningful value to customers as a way to achieve business growth and market success.

The concept of value innovation was developed by Kim and Mauborgne (2004), who argued that firms should shift their strategic focus from competitors to new market creation. Their view suggests that companies should not limit themselves to direct competition in existing markets. Instead, they should seek to create new market space or redefine existing markets by identifying and meeting customer needs in new ways. In this sense, the core of value innovation lies in using innovation and creativity to satisfy unmet customer needs and open up opportunities beyond traditional competition.

Value innovation requires a balance between value creation and innovation. In the absence of innovation, the focus of value is often on scale-up value creation, which provides value but is not sufficient to enable firms to stand out in the market. On the other hand, if a firm focuses only on innovation without creating value for customers, the result may be technology-driven development that customers do not fully accept or are unwilling to pay for. Therefore, value innovation is different from simple technological innovation or conventional marketing activities. Its core idea is to combine innovation with customer value in a way that supports both consumer satisfaction and firm competitiveness.

Value innovation plays a vital role in various industries. Woo et al. (2019) argued that service innovation is crucial in determining value in use and affects long-term relationships with business customers. Fager and Engberg (2023) consider Lean practices as an effective tool for identifying customer value through methods such as customer development, lean products, and lean innovation. Hajar et al. (2020) argued that value innovation activities in the wireless telecommunication services industry are critical to company performance and sustainable growth, and that the provision of high-value innovative services can increase customer satisfaction and loyalty. Anning-Dorson and Nyamekye (2020) argued that the engagement capabilities of service firms have been shown to have a positive impact on innovation intensity and firm performance, emphasising the importance of customer engagement in value creation. Ni et al. (2021) argues that intellectual capital is identified as a key factor in enhancing firm value, with a focus on the development of intellectual capital and corporate governance to improve competitiveness and customer relationships. Hung et al. (2020) examined the impact of corporate innovation on customer loyalty, demonstrating the contribution of aspects of innovation to consumer perceived value and satisfaction. Overall, these studies highlight the importance of value-based innovation in driving firm performance, customer satisfaction, and long-term relationships, emphasizing the importance of using innovative practices and engagement capabilities to create value for customers and enhance business outcomes.

Value innovation emphasizes the need to continuously provide different and higher-level products or services to meet customer needs and preferences, so that the customer gets a strong sense of profitability and thus achieves a leap in total customer value. Value innovation is characterized by the following key features.

First, product and service innovation based on deep customer needs. With the development of the economy, customer demand is also deepening. According to Maslow's hierarchy of needs theory, the rapid development of today's society has made most users more intense pursuit of individuality and catharsis. In this case, personalized products and services are more and more popular with users.

Second, product and service innovation focusing on user experience. The experience economy is now increasingly recognized and playing an increasingly important role, with experiences being a series of memorable events that occur when people spend time in an essentially personal way. When a service is personalized, it becomes memorable and thus an experience (Pine & Gilmore, 1998). Value innovation is about providing customers with the opportunity to personalize their services. The point of value innovation is to provide customers with unique experiences to gain access to customers and markets, and to increase customer transference value by reducing customer non-monetary costs. Research has shown that consumer engagement can have an impact on purchase intentions through community identification, especially on community group purchasing platforms. Consumers participate in community activities through information sharing, taking responsibility, and interpersonal interactions, which enhances community identity and thus purchase intention (Hongsuchon & Li, 2022). Therefore, user-experience-oriented innovation can create value not only through personalized products and services, but also through consumer engagement and community interaction, which together strengthen consumer identification, satisfaction, and purchase intention.

2.3.1.2 Value Innovation of Fresh E-Commerce based on 4I Theory

In a competitive market, fresh e-commerce companies must move beyond traditional business models to create unique value for consumers. The 4I theory provides a robust framework for this purpose. Therefore, this study operationalizes value innovation in fresh e-commerce through four distinct dimensions: Interesting, Interactivity, Integration, and Individualization. Each dimension contributes to enhancing the consumer experience and helps companies differentiate their offerings.

First ,interesting creates value by making the shopping process more engaging and enjoyable for consumers. In fresh e-commerce, value innovation is not limited to product function or price. It also includes the emotional and experiential aspects of shopping. Firms can introduce creative and novel elements into their products, services,

and marketing activities to attract consumer attention and improve user experience. For example, fresh e-commerce companies can use augmented reality to provide virtual trial experiences, such as allowing users to try out products through an app or platform, to increase consumer engagement and conversion rates. This type of interaction using augmented reality technology not only enhances users' shopping enjoyment, but also provides consumers with a novel shopping experience. In addition, interesting marketing activities on social media can further strengthen consumer participation and brand connection. Fresh e-commerce firms can use online challenges, check-in activities, or point-collection campaigns to encourage users to interact with the brand. This approach not only enables users to develop a deeper brand connection, but also effectively prompts viral spread of the brand through user-generated content (Pine & Gilmore, 1998). In this way, interesting can support both consumer experience and brand growth.

Second, interactivity creates value by building closer and more immediate connections between firms and consumers. In fresh e-commerce, consumers often care about product freshness, delivery arrangements, and service reliability. For this reason, real-time two-way communication is especially important. Tools such as online chatbots and live customer service can help firms solve consumer problems quickly and improve shopping comfort and satisfaction (Wang et al., 2020). Consumer communities also play an important role in improving interactivity. Online forums or social media groups can help users share their purchasing experiences and product insights with each other, thus increasing the social stickiness of the brand. For example, companies can create exclusive consumer interaction platforms and organize regular events or competitions to motivate users to share their purchasing experiences and life tips, which not only enhances users' sense of community belonging, but also increases brand trust and loyalty (Laroche et al., 2013). Thus, interactivity creates value not only through direct communication between firms and consumers, but also through community-based interaction among consumers, which helps firms build stronger relationships, improve engagement, and enhance long-term brand loyalty.

Third, integration creates value by connecting channels, resources, and supply chain activities in a coordinated way. Through the strategy of O2O, fresh e-commerce can effectively open up online and offline channels. For example, through a combination of online ordering, offline pickup, and fast delivery services, companies can

provide a one-stop shopping experience so that consumers can enjoy a seamless service process. This kind of coordination can improve service consistency and reduce friction during the buying process. Integration is also important for improving operational efficiency behind the consumer experience. Fresh e-commerce companies can also improve operational efficiency by integrating all aspects of the supply chain. With the help of big data and AI technology, companies can predict market demand more accurately, reduce inventory backlogs, and optimise the supply chain. Such data-driven management practices not only help reduce logistics costs, but also improve the accuracy and timeliness of services, which can effectively increase consumer satisfaction (Hua et al., 2024). Therefore, integration supports both front-end service quality and back-end operational performance.

Fourth, individualization creates value by allowing firms to meet the different needs of different consumers more accurately. Personalized service is the key to improving customer satisfaction. By analysing consumers' historical purchase data and behavioural patterns, fresh e-commerce companies can offer personalized recommendations and promotions to meet consumers' unique needs. For example, personalised recommendation systems based on data analytics can enhance the likelihood of purchase by providing personalized product and set suggestions as consumers browse for items (Kumar & Reinartz, 2018). In addition, personalized services can also strengthen long-term relationships between firms and consumers. Customized weekly or monthly subscription plans not only increase the revenue liquidity of the business, but also enable users to gradually cultivate a sense of attachment to the brand in their daily lives. For example, providing exclusive membership services, including special discounts and exclusive new product experiences, can increase users' brand stickiness and consumption willingness (Huang & Benyoucef, 2013). In this sense, individualization contributes not only to short-term sales, but also to long-term customer loyalty.

Overall, the 4I theory offers a clear framework for understanding value innovation in fresh e-commerce. In the fresh e-commerce industry, value innovation through the 4I theory is not only an innovation of the business model, but also an in-depth understanding of consumer needs. Through the innovation of interesting, interactivity, integration, and individualization, enterprises can create a more accurate and humane service experience, thus improving market competitiveness and customer loyalty. These

four innovative directions not only cracked some of the current operational difficulties of fresh e-commerce, but also pointed out the direction for the future development of the industry.

2.3.2 Consumer Perceived Value

Consumer perceived value (O) is the mediating variable between external value innovation stimulus (S) and final purchase intention (R). When perceived value increases, consumers' purchase intention also increases. This means that in order to increase consumers' purchase intention, fresh e-commerce companies need to invest in value innovation activities as a way to increase consumers' overall perceived value.

Consumer perceived value is a multidimensional concept that influences fresh food consumers' willingness to purchase fresh e-commerce in the context of the digital economy. It combines the actual utility provided by a product or service with the price consumers pay for it. Consumer-perceived value includes functional value, such as price and performance, which predicts customer satisfaction to some extent; emotional value, which is associated with consumers' emotional responses and personal preferences; and social value, which relates to consumers' need for social recognition and belonging. These factors influence fresh produce consumer satisfaction, loyalty, and behavioral intentions to varying degrees. When implementing a value innovation strategy, these dimensions need to be taken into account as critical to meeting fresh produce consumer needs, increasing satisfaction, and deepening brand loyalty.

2.3.2.1 Components of Consumer Perceived Value

Previous studies show that consumer perceived value is made up of several dimensions rather than a single form of value. Different scholars have explained the composition of perceived value in different ways, but most agree that consumers evaluate products and services from multiple perspectives.

Consumer choice is shaped by different types of value. Sheth et al. (1991), in their study of customer perceived value, argued that consumer decision-making operates at several levels, such as whether to buy, what type of product to buy, and which brand to choose. In this process, five types of value influence consumer choice: international, social, emotional, cognitive, and contextual values (Li et al., 2021). According to Sheth et al. (1991), situational value is derived from temporary interesting or social value, which

occurs in specific situations, and interesting value is derived from attributes such as reliability, durability, and price.

Later studies simplified this framework and focused on the value dimensions that are more relevant to actual consumption settings. Based on Sheth et al. (1991), Sweeney and Soutar (2001), using consumer durables as a research pair, concluded that the perceived value as described by Sheth et al. (1991) is related to the novelty of the product, the degree of curiosity aroused, which may be important for consumers who are eager to seek new experiences. For consumer durable, however, this is less important, while reliability and durability are often seen as indicative of product quality, and in some studies quality and price do not have the same effect on perceived value, with quality having a positive effect on perceived value and price the opposite. Finally, four types of perceived value were summarized, namely quality, price, emotional value, and social value, where quality and price can be seen as sub-dimensions of functional value (Lin & Hoang, 2023).

Other scholars have also emphasized the importance of functional, emotional, and social value in consumer evaluation. It also classified customer perceived value into three important categories of functional, emotional, and social value (Ullah, 2021) . In their framework, quality and price are often treated as sub-dimensions of functional value. This classification has been widely applied in studies of consumer behaviour because it is more practical and easier to use in empirical research. The study of anti-smog cosmetics under smog pollution also found that perceived value played a partially mediating role between monetary value, social value, perceived smog awareness, and purchase intention, and a fully mediating role between brand value and purchase intention. This implies that perceived value is a key factor in the process of consumers' transition from perception to purchase behaviour. In addition, price sensitivity has a significant negative moderating effect on perceived value and purchase intention, for example, when consumers are more price sensitive, their perceived value and purchase intention may decrease (Song et al., 2019) .Although different scholars have discussed the composition of perceived value in different ways, they all suggest that perceived value consists of several different attributes of value, which are mainly derived from a firm's products as well as services.

In this study, we will follow Sheth et al. (1991) discussion of value categorization to describe the composition of perceived value in terms of both products and services. In addition, consumers perceive value not only in terms of the products and services provided by the firm, but also in terms of the value created by their ongoing relationship with the firm (Ho et al., 2022). In a buyer-seller relationship between a consumer and a firm, the consumer may value the relationship with the firm more. If the relationship is perceived to be of sufficient value, the consumer and the firm are likely to come to an agreement even if the product or service is not the best. Nguyen et al. (2023) suggested that, in addition to the value derived from the product's own utility, emotional, service, and social values in the composition of the consumer's perceived value, there is also the value derived from the relationship constructed between the firm and the consumer. Therefore, while providing consumers with high-quality products and services, enterprises should also actively cultivate and develop good relationships with customers to enhance the value of consumer relationships and create favourable conditions for consumers to purchase products.

Based on the above discussion, this study understands consumer perceived value as a dynamic and multidimensional concept. In the context of fresh e-commerce, perceived value mainly includes functional value, emotional value, social value, and relationship value. However, the exact composition of perceived value is not fixed. It may change across product types, consumer groups, and consumption situations.

2.3.2.2 Characteristics of Consumer Perceived Value

Consumer perceived value has several important characteristics, including subjectivity, practicality, and dynamism. These characteristics help explain why different consumers may respond differently to the same product or service, and why perceived value changes across situations.

Firstly, consumer perceived value is highly subjective because it is based on consumers' judgments and experiences. Consumers are the main evaluators of perceived value. The value of a product or service does not exist only in the product itself; it is formed through consumer perception. Different consumers may assign different value to the same product because they differ in personal needs, purchasing power, lifestyle, culture, and consumption goals. For this reason, perceived value is not determined only by the firm. It is shaped by how consumers interpret what they receive.

Secondly, consumer perceived value has a practical basis because it is closely linked to actual consumption experience. Consumer perception of the value of the product or service is often based on the purchase experience, preferences, attitudes, and other subjective understanding of the basis, and these subjective understandings of the consumer are the consumer's past experience of buying, using, and experiencing the product as well as with the provision of the product by the enterprise service personnel in the process of contact. Consumers build knowledge about products, platforms, and service quality, and this knowledge affects how they judge future shopping choices. In this sense, perceived value is not only emotional or abstract. It is also grounded in real consumption practice.

Finally, consumer perceived value is dynamic because it may change across time, place, and context. The same consumer may perceive different value from the same product at different stages of the buying process. Before purchase, perceived value may be based mainly on product information, prior experience, and expectations. During or after use, consumers may re-evaluate the product based on actual experience. As a result, perceived value is not stable. It changes with consumers' psychological states, the external environment, and different stages of product consumption. This dynamic feature is especially important in fresh e-commerce, where freshness, delivery speed, and service quality can strongly affect post-purchase evaluation.

2.3.2.3 Consumer Perceived Value Dimension Analysis

In this study, consumer perceived value is analyzed through three core elements: perceived benefits, perceived costs, and perceived risks. In general, perceived value increases when consumers perceive greater benefits, and it decreases when they perceive higher costs and risks. Therefore, consumers form an overall value judgment by weighing what they gain against what they may lose in the purchase process.

(1) Perceived Benefits

Perceived benefits refer to the positive outcomes that consumers believe they can obtain from a product or service. Perceived benefits are positive benefits perceived by consumers during the social media shopping process, including functional, experiential, and symbolic dimensions, which can influence their loyalty to social media, actual use, and willingness to spread positive word-of-mouth (Ryu & Park, 2020) .

The literature generally suggests that perceived benefits are a key foundation of consumer perceived value. According to the study, that value is a perceived utility of a

product relative to the purchase price (Rintamäki & Saarijärvi, 2021), and this utility can be in the form of economic, technological, service, and social benefits. Perceived value is a trade-off between perceived benefits and perceived costs, and is a dynamic concept that includes: acquisition value, transaction value, use value, and redemption value (Pham et al., 2023). The definition of perceived value suggests that perceived value is the overall evaluation of products and services made by consumers based on perceived benefits and perceived costs. Thus, the composition of consumers' perceived value should be closely related to products and services. Usually, the products purchased by consumers should have certain utility, which is manifested in the function, quality, and social use of the products, etc. In addition, according to the quality of the enterprise's services, the products should be of high quality. In addition, based on the quality of the enterprise's services, a certain service utility will be formed in the minds of consumers. Therefore, in general, the consumer perceived value should be composed of the utility value of the product and the service value. Because of the dynamic nature of perceived value and the fact that consumers' perceived value changes with different products, the division of consumer perceived value is not fixed.

Recent studies further show that perceived benefits in digital commerce are multidimensional. Wu and Huang (2023) investigated the impact of consumers' perceived value on their continued purchase intention in live e-commerce and considered consumer trust as a mediating variable. The study proposes three dimensions of perceived value: utilitarian value, hedonic value, and social value, and uses consumer trust in the anchor and in the product as a mediator to investigate the effect of perceived value on consumers' continued purchase intentions. data for this study were collected through questionnaires and analysed using structural equation modelling. In the live-streaming e-commerce environment, utilitarian value refers to the utilitarian value that consumers experience when the features, price, and quality offered by a product or service are in line with the consumer's expected level of utility. The product authenticity and price discounts that consumers can perceive during live shopping can increase their trust in the host. Hedonic value refers to the degree of interest, pleasure, and enjoyment that consumers experience when watching live streams. Text-based chat rooms on live streaming platforms reinforce social connections that improve positive consumer emotions such as satisfaction and attachment, leading to emotional commitment. Social value has often been overlooked in

previous academic definitions of perceived value dimensions. In the increasingly social context of e-commerce, consumers are not only interested in utilitarian and hedonic values such as convenience and enjoyment, but are also beginning to seek the social value of interaction with others and self-actualization. Consumer Trust: In the field of marketing, trust research has been a topic that scholars have been unable to ignore, and with the development of the Internet, the diversity presented by traditional commerce in the process of transforming to e-commerce has made trust a growing focus of attention for scholars (Wu & Huang, 2023). The elaboration of perceived value by many scholars mentioned above indicates that perceived value is the comprehensive evaluation of a product or service based on the trade-off between perceived benefits and Perceived costs when consumers purchase the product or service. Perceived benefit refers to the benefits that consumers perceive from a product or service, which can satisfy their specific consumption needs and psychological needs, and enable them to obtain the feeling of value realization.

These findings suggest that perceived benefits are not limited to functional gains, but also include emotional and social rewards. In other words, when consumers purchase a product or service, they do not only seek usefulness. They also expect enjoyment, social connection, and a sense of value fulfillment. Therefore, perceived benefit refers to the gains that consumers obtain from a product or service that satisfy both consumption needs and psychological needs.

Studies in digital and online consumption further support the importance of perceived benefits in shaping consumer attitudes and intentions. Wang and Somogyi (2018) investigated the impact of innovation-adoption characteristics on Chinese consumers' adoption of online food shopping. A path analysis found that Chinese consumers' attitudes or purchase intentions were positively related to their perceived incentives for online food shopping and negatively related to perceived complexity. Agag and El-Masry (2016) explored consumers' intentions to join an online travel community and examined how this participation affects their intentions to purchase travel services online and to spread positive word-of-mouth. The study found that perceptions such as relative advantage and compatibility with the online travel community significantly influenced consumer attitudes. The ease of use of the community platform, perceived

usefulness, and trust in the online community were key determinants in shaping consumer attitudes and intentions to participate.

Based on the above studies, perceived usefulness and perceived ease of use can be regarded as two important aspects of perceived benefits, especially in online service settings. These two factors are widely used to explain how consumers evaluate digital platforms and whether they are willing to continue using them.

Perceived usefulness refers to consumers' judgement of how far a product or service can help them achieve a specific goal. In the context of fresh e-commerce, this may include aspects such as the freshness of the product, its nutritional value, and its ability to fulfil health or dietary requirements. Empirical studies show that perceived usefulness has an important effect on online purchase behaviour. Consumers' willingness to purchase through digital business model platforms is influenced by their perceived usefulness. Perceived usefulness has a significant impact on whether online shoppers continue to be attracted to shop online or rely on traditional methods in online shopping applications or tools (Tilahun et al., 2023) . Live streaming and online consumer reviews as social commerce modes can work together to influence consumers' purchase intentions, with customer engagement playing a mediating role, and perceived usefulness and perceived trust identified as antecedents of purchase intentions (Qin et al., 2023). In their study, perceived usefulness and perceived trust were identified as important antecedents of purchase intention.

Perceived ease of use refers to the degree to which consumers believe that using a product or service requires little effort. In online shopping, ease of use is especially important because it directly affects consumers' efficiency and comfort during the purchase process.

(2) Perceived Costs

Perceived costs refer to consumers' subjective assessment of all the costs involved in purchasing a product or service. These costs include not only the direct price paid for the product or service, but also the time, effort, and other resources spent during the purchasing process. In consumer decision-making, perceived costs are important because they influence whether consumers believe a purchase is worthwhile. Since most consumers are rational or semi-rational, they usually try to minimise transaction-related costs. Previous research has shown that consumers' perceived transaction costs have a

negative effect on their behavioural intentions in different online environments (Li et al., 2019). The literature shows that perceived costs are multidimensional rather than limited to monetary expense alone. In online shopping, consumers often evaluate several forms of cost at the same time. After reviewing the literature, perceived costs in this study can be divided into five main dimensions: economic cost, time cost, psychological cost, effort cost, and opportunity cost.

Economic cost is the most direct form of perceived cost because it refers to the financial payment required for a purchase. It includes the purchase price, shipping costs, installation costs, and any other visible charges. In an e-commerce environment, consumers usually compare the price of a product with competing alternatives and also consider whether additional fees are involved. Therefore, economic cost directly influences consumers' judgement of whether a product offers good value for money.

Time cost refers to the time consumers spend during the shopping and purchasing process. This includes the time used to search for product information, compare options, place an order, and wait for delivery (Berry et al., 2002) . For example, consumers' perceptions of hidden costs, which are often not apparent until the final stages of the shopping process, such as shipping and handling fees, can significantly affect consumers' perceived costs as well as their satisfaction and loyalty. This issue is especially important in the purchase of fast-moving consumer goods and fresh products, because the value of these products may decline if delivery takes too long.

Psychological cost refers to the negative emotions that consumers may experience during the purchase process. These emotions may include stress, uncertainty, anxiety, and possible regret (Sweeney & Soutar, 2001) . When choosing a fresh e-commerce company, consumers may worry that the product is not fresh or does not match the description. Such concerns can increase the complexity of decision-making and make the purchase feel more burdensome.

Effort cost refers to the physical or mental effort consumers must spend to find, buy, and use a product or service (Beatty & Smith, 1987) . Online shopping may require consumers to learn how to use a website or application, this can be especially burdensome for consumers who are less familiar with online technologies. Research on user interface design has shown that a clear and easy-to-navigate interface can significantly reduce consumers' perceived effort and time costs in online shopping (Zhao et al., 2012).

Opportunity cost refers to the value of the alternatives that consumers give up when choosing one product or service over another (Lichtenstein et al., 1988). For example, a consumer's choice to buy one brand of fresh produce may mean giving up other alternatives that may be cheaper or more convenient. In order to reduce consumers' perceived costs, e-commerce platforms may need to take measures such as optimizing user interface design, providing comparison shopping tools, offering fast delivery options, and efficient customer service, so as to enhance consumers' purchase intention. At the same time, providing incentives such as coupons, discounts, and membership rewards can also be effective in reducing consumers' perceived costs and increasing the perceived value of their purchasing behaviour (Voss et al., 1998) . Understanding the different dimensions of perceived costs is therefore important because it helps firms develop strategies to improve satisfaction and loyalty (Anderson & Srinivasan, 2003). In summary, perceived cost is a multidimensional construct encompassing psychological, effort, and opportunity costs, and by understanding these dimensions, fresh food e-commerce platforms can adopt targeted strategies, such as optimising interface design, offering comparison tools and efficient delivery, and providing price incentivesto reduce consumers' perceived costs and thereby enhance their perceived value and purchase intention.

(3) Perceived Risks

Perceived risk refers to consumers' subjective assessment of the potential negative consequences of purchasing or using a product or service. This type of risk is not one-dimensional, but includes several forms of uncertainty and possible loss (Dayour et al., 2019) . Perceived risks has a profound impact on consumers' purchasing behaviour and their satisfaction and loyalty to a product or service. When making decisions to purchase high-value or technologically complex goods, consumers perceive greater risk, which may prompt them to seek more information or rely on brand reputation as a means of mitigating risk. In particular, in social commerce and e-commerce platforms, the nature of non-face-to-face transactions and the asymmetry of information make consumers' perceived risks central to purchase decisions (Martins et al., 2014) . In addition, privacy concerns have been found to moderate the relationship between community identity and purchase intention, suggesting that consumers with insufficient privacy protection may display lower purchase intention (Hongsuchon & Li, 2022). The literature generally treats perceived risk as a multidimensional concept. Previous studies have identified several

major forms of risk, including performance risk, financial risk, social risk, psychological risk, time risk, and health risk. In the context of fresh e-commerce, the most relevant dimensions can be grouped into four main categories: product risk, service risk, financial risk, and social risk.

Product risk refers to the possibility that a product may fail to meet consumers' expectations in terms of quality, freshness, safety, or consistency with the product description. This is especially important in fresh e-commerce because consumers cannot physically inspect products before purchase. They may worry about spoilage, deterioration, low quality, or even harmful substances. As a result, product risk can strongly influence consumers' confidence in online fresh shopping. Service risk refers to the uncertainty associated with the service process surrounding the purchase. This may include delivery delays, product damage during transportation, difficulties in returns and exchanges, and poor customer service. These service-related problems can directly affect consumers' shopping experience and reduce their trust in the platform. In fresh e-commerce, service risk is particularly important because delivery speed and handling quality are closely linked to product condition. Financial risk refers to the possibility of monetary loss during the purchase process. Consumers may worry that the product is overpriced, that there are hidden charges, or that pricing is not transparent. In online shopping, financial risk can also be linked to payment security and refund uncertainty. If consumers believe that the financial consequences of the purchase are uncertain or unfair, their willingness to buy is likely to decline. Social risk refers to the possibility that a purchase may negatively affect a consumer's social image or be disapproved of by others. For example, consumers may worry that the products they choose do not meet environmental, ethical, or social responsibility expectations. Although social risk may be less direct than product or financial risk, it can still influence consumer choices, especially when shopping decisions are visible to others or connected with personal values.

Overall, perceived risk is an important factor that can reduce consumer perceived value and weaken purchase intention in the digital economy. In the fresh e-commerce sector, perceived risks are often more diverse and complex than in offline shopping. Online shoppers face greater risks than offline shoppers. Consumers' perceived risks are negatively correlated with their perceived value , thus directly or indirectly affecting purchase intention (Li et al., 2019). Consumers' concerns about the health and

freshness of products, the timeliness of delivery, the security of payment, and the protection of personal information are particularly important. To reduce these concerns, fresh e-commerce companies need to improve service transparency, ensure product quality, and strengthen data protection. These measures can help increase the perceived value of products and services and encourage consumers to purchase.

2.3.3 Consumer Purchase Intention

Consumer purchase intention is the final response variable in the Stimulus-Organism-Response model and reflects consumers' likelihood of making a purchase after evaluating external stimuli and internal perceptions. In the Stimulus-Organism-Response framework, purchase intention represents the behavioral response (R) that results from the interaction between external stimuli (S) and the consumer's internal state or perceived value (O). In the context of fresh e-commerce, consumer purchase intention is shaped by consumers' evaluation of product-related and service-related factors, especially perceived benefits, perceived costs, and perceived risks. Therefore, purchase intention can be understood as a comprehensive judgement that directly predicts whether consumers are willing to buy fresh products online.

Previous studies show that purchase intention is influenced by different forms of innovation and by consumers' responses to innovation-related attributes. Song et al. (2009) emphasized the importance of network externalities in enhancing consumers' perception of innovative attributes and hence market performance. Wu & Chen (2014) highlighted the impact of green marketing awareness on purchase intention, which outweighs the impact of perceived innovation. Furthermore, Wu & Chen (2014) demonstrated that the impact of perceived innovation on purchase intention by consumers is greater than brand awareness. The role of performance expectations, ethical awareness, and consumer innovation was emphasized in the study of factors influencing purchase intention for cloud computing services (Ratten, 2015). These studies suggest that innovation does not influence consumer behaviour in a simple way. Instead, its effect depends on how consumers interpret and evaluate innovation in specific consumption contexts.

Some studies further show that the relationship between innovation and purchase intention is indirect and may be shaped by mediating factors. Husen (2015) explored the mediating role of community neighbourhood attribute attractiveness between product innovation and consumer purchase intention. The results of the study showed that the

attractiveness of community neighbourhood attributes has a significant mediating role between product innovation and consumer purchase intention. This suggests that when consumer perceptions of product innovation are positive, it enhances the attractiveness of the community neighbourhood attributes. In turn, these attributes effectively mediated an increase in consumer purchase intentions (Husen, 2015). This finding is important because it shows that consumers do not respond only to innovation itself, but also to the added value created around the product, including its aesthetic and functional surroundings. This perspective provides useful implications for understanding how value innovation may influence purchase intention in fresh e-commerce settings.

Research on online food shopping also confirms that consumers' purchase intention is affected by both positive and negative perceptions of innovation-related features. A study of the impact of innovation adoption characteristics on Chinese consumers' adoption of online food shopping found that Chinese consumers' attitudes or purchase intentions were positively related to their perceived incentives for online food shopping and negatively related to perceived complexity. This study investigated purchase intention for low-technology innovative local products and found that consumer scepticism had a significant negative effect, while familiarity, information seeking, and aesthetic design had significant positive effects on purchase intention. These findings indicate that product familiarity, clear information, and attractive design can support purchase intention, while uncertainty and doubt may weaken it (Jethro et al., 2019).

Consumer innovativeness and motivational factors also play an important role in shaping purchase intention. Esfahani & Reynolds (2021) explored consumer innovativeness as a personality trait and the hedonic, social, cognitive and interesting motivational elements behind it. The study challenged the classic relationship between consumer innovativeness and the adoption of genuinely new products, as well as questioning the relationship between consumer learning, attitudes and intentions. The main findings suggest that attitudes positively influence understanding and intention. In addition, hedonic innovativeness positively influenced consumer attitudes, whereas there was a negative relationship between social innovativeness and attitudes. Regarding the motivational elements of innovations, all of them, except hedonic motivation, positively influenced purchase intention.

In the fresh produce context, market innovation and platform experience have also been shown to influence purchase intention. Based on the dual theory perspective, when studying consumers' willingness to purchase vegetables from the perspective of fresh produce market innovation, it was found that exploratory market innovation can improve consumers' perception of brand innovativeness when the brand relationship is distant, which in turn improves consumers' willingness to purchase vegetables (Hui, 2022) The When exploring the impact of Boxmart Freshman's processing experience on consumers' online purchasing behaviour, it was found that substantial incentives, such as product quality and price, are still crucial factors influencing consumers' online purchasing behaviour (Xu & Chen, 2020). The study found that individual characteristics are another important factor influencing consumer purchase intention. Previous studies have shown that age, occupation, income, and personality can all affect consumers' purchase decisions because different individuals have different needs, preferences, and consumption habits. Different individuals have different needs and preferences for products or services, and individual differences play a key role in purchase decisions (Yahya et al., 2022). This study was conducted in the Klang Valley, Malaysia. This study, conducted in the context of coffee culture in Klang Valley, Malaysia, quantitatively analysed online survey results from 398 respondents and revealed significant associations between four individual factors, namely, age, occupation, income, and personality, and consumers' purchase intention, with personality being the most significant factor influencing consumers' purchase intention.

In terms of product characteristics, product characteristics have an important influence on purchase intentions. Product quality, features, price, and brand awareness all influence consumers' purchase intention (Harris et al., 2020). High-quality products tend to enhance consumer satisfaction and trust and increase purchase intention; unique product features can satisfy specific consumer needs, thus attracting specific market segments; a reasonable pricing strategy can increase the market competitiveness of the product and attract price-sensitive consumers; and strong brand awareness can increase consumers' brand awareness and build brand loyalty. These factors work together to influence consumers' purchasing behaviour and decision-making process.

The market environment and marketing strategies also play a key role in shaping consumer purchase intention. Marketing strategies are crucial in shaping purchase

intentions (Sheth & Sisodia, 2002). Factors such as advertising, promotions, pricing strategies, and distribution channels can directly influence consumers' purchase intention. Innovations in marketing activities can stimulate the desire to buy. In the study of purchase intention of fresh products under the community new sales model, it was found that consumer trust and consumer identification significantly and positively affect purchase intention. In addition, there are multiple mediating effects of product quality, logistics service quality, and after-sales service quality in it. In addition, product quality, logistics service quality, and after-sales service quality have several mediating effects (Ma et al., 2022). In the context of the digital economy, consumers' digital literacy and online shopping experience have a significant impact on their purchase intention. Consumers need to adapt to the changing digital landscape and understand how to use digital tools to make more informed purchase intentions. Brand new features of digital technologies, such as social media, personalized recommendation systems, and virtual reality, have changed the way consumers shop. These new technologies provide consumers with more information and interactive opportunities to better understand products and services, thereby influencing their purchase intention.

Overall, the existing literature provides an important foundation for understanding consumer purchase intention, but several gaps still remain. Most previous studies have focused on the effect of single factors on purchase intention, while fewer studies have examined how multiple factors interact in a fresh e-commerce context. In particular, more research is needed to explain how value innovation and perceived value jointly shape purchase intention under the Stimulus-Organism-Response framework. Therefore, this study further explores consumer purchase intention by focusing on key factors in fresh e-commerce, especially value innovation and perceived value. This approach helps fill current research gaps and provides practical guidance for fresh e-commerce firms seeking to improve consumer purchase intention through market strategies and service design.

2.3.4 Consumer Innovativeness

Consumer innovativeness is an important individual difference that influences how consumers respond to new products, services, and market changes. It is generally viewed as a personal trait that makes some consumers more willing and quicker than others to accept new ideas, try new products, and adapt to change. It involves consumers' acceptance of change, tolerance of the unknown, and motivation to try new things. Consumers with

high innovativeness are more willing to try new products and services emerging in the market, while consumers with low innovativeness may be more inclined to stick to traditional or known products and services.

Previous research suggests that consumer innovativeness can be understood through several motivational dimensions. The study of consumer innovativeness variables can be unfolded through the elements of consumer motivation for innovation (Esfahani & Reynolds, 2021). They examined consumer motivation for innovation through dimensions such as social, hedonic, functional, and cognitive innovativeness. These dimensions help explain why consumers differ in their responses to innovation. Rather than treating innovativeness as a single trait, this perspective shows that consumers may adopt innovative products for different reasons, including social recognition, practical problem-solving, emotional enjoyment, and information-based evaluation. This multidimensional view is useful for understanding consumer behaviour in fresh e-commerce, where purchasing decisions are often shaped by both product characteristics and digital shopping experiences.

Social innovativeness refers to consumers' motivation to adopt new products in relation to their social image, identity, and interactions with others, including the pursuit of status and the need for support (Statuto & Colby, 2026). Consumers may hope to impress others or present a desirable image by purchasing new products. However, when a really new product is not yet familiar in the market, consumers may find it difficult to imagine owning or using it in the near future. Therefore, social innovativeness is an important component of consumer innovativeness, which describes how consumers form attitudes and purchase intentions towards innovative products through social interactions and perceptions of others (Esfahani & Reynolds, 2021). In fresh e-commerce, social innovativeness is especially relevant because many consumers are influenced by social media, online communities, and lifestyle trends. Products with social value, such as organic, premium, or environmentally friendly fresh products, may appeal to consumers who want to show taste, responsibility, or uniqueness through their purchases.

Functional innovativeness refers to consumers' motivation to adopt products that can solve practical problems and improve consumption outcomes. It focuses on whether a product or service can meet real needs, increase efficiency, or provide useful solutions in daily life (Kalender & Guzmán, 2025). Intriguing needs refer to the ability of a product to

actually solve a specific problem faced by the user, for example, to help the user perform a task that cannot be accomplished with existing products. This type of need focuses not only on the basic functionality of the product, but also on its practical value and the specific help it brings to the user. Information processing theory confirms that emphasizing the functionality of a product and using a variety of stimuli in the promotion of the product can influence the purchase intention of the consumer (Esfahani & Reynolds, 2021). In the context of the digital economy, the fresh e-commerce industry is faced with increasing consumer expectations and market competition. This study aims to provide insights into how value innovation can influence consumers' purchase intention by satisfying their functional needs. functional needs refer to the ability of a product or service to solve practical consumer problems, such as providing faster delivery services or ensuring the freshness and safety of food. This study uses a questionnaire to collect data to analyse how consumers assess the interesting features offered by fresh e-commerce companies and to explore how these features translate into purchase intentions. For example, innovations that maintain food freshness through improved packaging technologies significantly increase consumer satisfaction with the product and may directly influence their purchase decisions. In addition, the introduction of smart logistics systems not only optimizes delivery efficiency, but also enhances consumers' trust in e-commerce platforms. Through comprehensive analyses, the study will reveal the central role of functional innovation in satisfying consumer demand and provide insights into how fresh e-commerce companies can maintain their competitive advantage through technological and service innovations in the digital economy. These findings will not only help to understand the drivers of consumer purchasing behaviour, but also provide fresh e-commerce companies with empirical evidence to develop effective market strategies.

Hedonic innovativeness refers to consumers' desire for sensory pleasure, enjoyment, and emotional satisfaction during the consumption process. It highlights the role of fun, excitement, and positive feelings in the adoption of innovative products and services (Kieling & Boeing, 2025). Hedonic motivation particularly affects technology acceptance and adoption of innovative products, due to the fact that when individuals feel pleasure and satisfaction when using products, they are more likely to have positive attitudes towards these products and may adopt these innovations as a result. For example, if individuals enjoy the clothing shopping experience, they are likely to be more innovative

in their shopping choices. Thus, hedonic primarily describes individuals' pursuit of sensory and emotional gratification during the consumption process, which influences their attitudes towards products and purchasing behaviours. Hedonic dimensions can be used to explore the sensory enjoyment and emotional gratification that consumers seek when purchasing through fresh e-commerce platforms in the context of the digital economy. Hedonic needs emphasise the pleasurable experience that a product brings, which is particularly important in fresh e-commerce as consumers seek not only utility but also pleasure in the shopping process. For example, fresh e-commerce companies can attract consumers by providing high-quality visual content, user-friendly interactive interfaces, and personalised shopping experiences. These elements enhance consumers' emotional engagement and increase their perceived value of the product, thereby promoting purchase intent. Through quantitative surveys and behavioural data analysis, this study will assess how hedonic factors influence consumer choice and satisfaction, and how they can be used to enhance the market competitiveness of fresh e-commerce companies. This will not only help understand consumers' behavioural patterns on fresh e-commerce platforms, but also provide companies with strategic recommendations on how to design more attractive products and services by increasing consumers' enjoyment of shopping.

Cognitive innovativeness refers to consumers' tendency to process, evaluate, and learn new information when facing innovative or uncertain products. It is related to the mental effort consumers make to understand novel product features, assess possible risks, and determine potential usefulness, especially when products are unfamiliar or involve higher uncertainty (Xu et al.,, 2025). The novelty of new products creates uncertainty in the minds of adopters, which requires them to increase their cognitive effort to understand this uncertainty, as well as to learn how to use these products to solve problems that cannot currently be solved with existing products. Cognitive processes, which include the reception, processing and comprehension of information, are a manifestation of the mental mechanisms of how individuals identify, analyse, and respond to new situations and challenges. Thus, cognition plays a central role in understanding and adopting new products, especially in situations where the product itself poses a high level of risk and requires in-depth understanding (Esfahani & Reynolds, 2021). The Cognitive dimension explores how consumers process and evaluate information about novel products and technologies offered by fresh e-commerce companies. This dimension is particularly

critical to understanding how consumers make purchase intention in the context of the digital economy, as consumers need to evaluate the usefulness and potential value of products. Cognitive innovativeness is particularly important in the fresh e-commerce environment because consumers are dealing with perishable products and their purchase decisions often need to be based on a quick cognitive assessment of product freshness and quality. For example, consumers may need to assess whether a product using a novel preservation technology actually leads to better food safety and durability. My research will use surveys and experiments to analyse how this cognitive processing affects consumers' purchase intentions, and to explore how increased transparency of product information can help consumers better understand product characteristics and thus enhance their purchase intentions. This will not only help fresh e-commerce companies to optimize their product presentation and information delivery methods, but also increase consumer satisfaction and loyalty.

Overall, consumer innovativeness provides an important basis for understanding consumers' acceptance of value innovation in fresh e-commerce. As an individual difference variable, it helps explain why some consumers are more willing than others to adopt innovative products, services, and shopping formats. Based on the literature above, consumer innovativeness in this study is mainly discussed through four key dimensions: social, functional, hedonic, and cognitive innovativeness. These dimensions support a more detailed understanding of how different innovation-related motivations may influence consumers' perceptions and purchase intention. Therefore, consumer innovativeness offers an important theoretical supplement to the analysis of value innovation and consumer behaviour in fresh e-commerce.

2.3.5 Customer Digital Transformation Attitudes

Customer digital transformation attitudes refer to customers' overall perceptions, feelings, and responses to the use of digital technologies in a company's operations and services. This concept reflects how customers view the digital changes introduced by firms, such as online platforms, mobile applications, digital payment systems, and intelligent customer service. In general, customer attitudes toward digital transformation are important because they influence how customers respond to new digital services and whether they are willing to continue using them. In the context of fresh e-commerce, these attitudes are especially relevant because the shopping process depends heavily on digital

systems, including online ordering, product information display, payment, logistics tracking, and after-sales service.

From the consumer perspective, customer digital transformation attitudes can be understood through several key aspects, including acceptance, satisfaction, expectations, trust, and adaptability. Acceptance refers to how open customers are to new technologies and digital services. For example, it reflects whether consumers are willing to use online shopping platforms, mobile applications, or virtual customer service. Satisfaction refers to customers' evaluation of the service quality and experience after digital transformation. This includes whether the website or application is easy to use, whether the response is fast, and whether the service is reliable. Expectations refer to what customers believe digital transformation should deliver, such as faster service, more personalize recommendations, and more efficient transactions. Trust refers to the degree to which customers believe that the company can protect their data privacy and ensure transaction security in a digital environment. Adaptability refers to customers' ability and willingness to adjust to digital changes, such as learning to use new tools, functions, or service processes. Together, these aspects provide a useful way to understand how consumers react to digital transformation in practice.

From the enterprise perspective, customer digital transformation attitudes are also related to how firms use digital capabilities to interact with and serve customers. The first is customer data utilization capability, which refers to how effectively firms collect, analyse, and use customer data to improve products and services. The second is the degree of digitization in sales and service, which reflects the extent to which firms integrate digital technologies into customer interaction, communication, and transaction processes. The third is customer digital media capability, which refers to the ability of customers to use the digital platforms and technologies provided by the firm (Schumacher et al., 2016). These aspects show that customer attitudes toward digital transformation are not shaped by customer factors alone, but are also influenced by how firms design and manage their digital systems.

Understanding customer digital transformation attitudes is important because these attitudes can affect the success of digital transformation strategies. Overall, customer digital transformation attitudes provide an important perspective for understanding consumer responses to digital service innovation. They help explain why some consumers

are more willing to accept digital changes and engage with fresh e-commerce platforms, while others may be more cautious or resistant. As a result, this concept offers useful support for analyzing consumer behaviour in the digital economy and helps connect digital transformation with perceived value and purchase intention in the fresh e-commerce context.

2.4. Hypotheses Statement and Theoretical Model

2.4.1 Conceptual Framework Construction

The S O R (Stimulus Organism Response) model provides a foundational theoretical lens for understanding how external factors shape consumer behaviour. This model posits that environmental stimuli (S) affect an individual's internal organismic state (O), which in turn leads to behavioural responses (R). Based on this theoretical logic, a conceptual framework is constructed to investigate the mechanism through which value innovation in fresh e-commerce influences consumers' purchase intention in the digital economy context (refer to Figure 2.3 for detail) .

In the Stimulus-Organism-Response model, the stimulus part of the environment and object will act on the person's internal state (Jin et al, 2022). Firstly, drawing on the 4I marketing theory model, the innovation of fresh e-commerce is subdivided into four dimensions, namely, interesting, interactivity, integration, and Individualization, which are the stimulus factors of the Stimulus-Organism-Response model. Together, they affect the competitive advantage, sustainable growth, consumer satisfaction, and purchase intention of the enterprise, and at the same time have a positive impact on the profitability and market share of the enterprise.

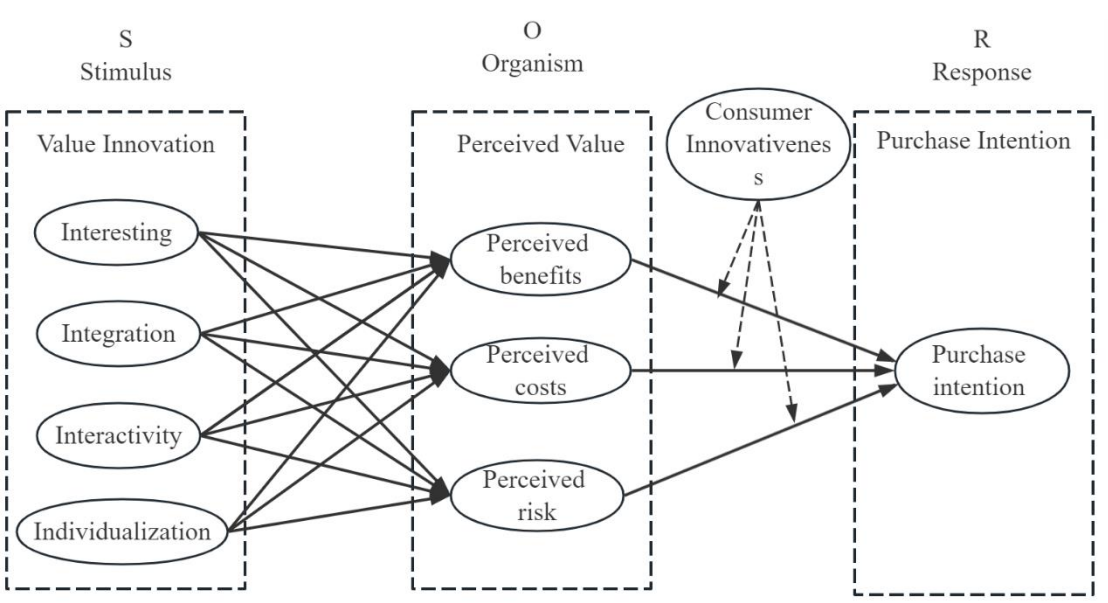


Figure 2.3 Path model of value innovation on consumer purchase intention

In the Stimulus-Organism-Response model, the organism part includes the state of cognitive and affective dimensions within a person (Zhang et al., 2023). According to the Stimulus-Organism-Response model, perceived benefits, perceived risks, and perceived costs are taken as organism factors. The perceived value response of the organism acts as a mediator in the Stimulus-Organism-Response model, influencing an individual's purchase intention by measuring the benefits, risks, and costs of a product or service through perceived value innovations in fresh e-commerce.

In the Stimulus-Organism-Response model, the Response part refers to the final behaviours and attitudes that an individual exhibits through his or her internal state in response to a stimulus (Zhang et al, 2023). According to the Stimulus-Organism-Response model, an individual's purchase intention is the response factor of the Stimulus-Organism-Response model. Consumers' purchase intention is influenced by perceived value,for example, by perceived benefits, perceived risks, and perceived costs. If more benefits are perceived, purchase intention may increase. Conversely, if higher risks and costs are perceived, purchase intention may decrease, while individual purchase intention may also be influenced by personal characteristics, needs, and shopping experience.

In summary, the theoretical framework and theoretical model of this study are constructed as shown in Figure 2.4.

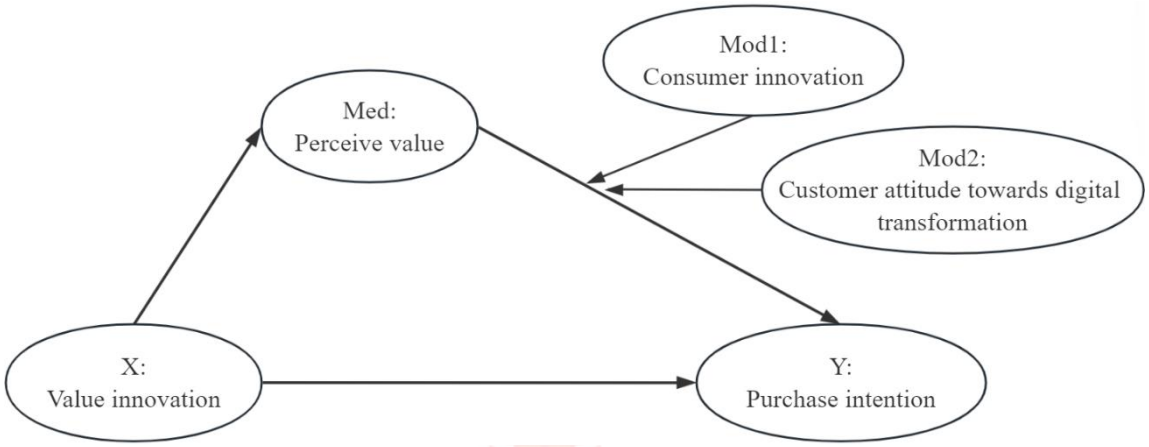


Figure 2.4 Theoretical model of value innovation and purchase intention

2.4.2 Research Hypotheses

2.4.2.1 Value Innovation and Purchase Intention

1. Hypotheses of interesting innovation and purchase intention

In recent years, with the rapid development of the fresh e-commerce industry, the platform's interesting has gradually become one of the important factors to attract users. interesting not only involves the richness and interactivity of product display, but also covers the user's pleasant experience in the shopping process. Many scholars have found that interesting plays a key role in enhancing user experience, increasing user stickiness, and driving purchase intention. Perceived interesting and joint matching had a significant effect on co-brand evaluation and purchase intention, confirming that consumers' perception of interesting and the degree of inter-brand matching when brands are joined can positively influence their purchase intention. Lu et al. (2023) focused on how perceived hedonistic in short video advertisements serves as a key factor in promoting consumers' purchase intention, pointing out that the pleasurable emotions generated by users during the enjoyment process are an important driving force in forming purchase intention . Xu and Liang (2021) pointed out that the impact of interpersonal interaction on consumers' impulse purchase intention in live e-commerce has also been widely discussed, and it was found that interpersonal interaction can effectively increase consumers' goodwill and trust in the product, which in turn promotes their purchasing behaviour. Through these studies, we can see that interesting is an important factor influencing consumers' purchase intention. interesting not only increases the attractiveness of a

product or service, but also promotes consumer purchase behaviour by increasing the pleasantness of the consumer experience. Thus, hypothesis H1 is proposed as follows.

H1. Fresh e-commerce interesting innovation positively influences consumers' purchase intention.

2. Hypotheses of interactivity innovation and purchase intention

In the current research field of fresh e-commerce, interactivity is widely recognised as one of the key factors in enhancing consumers' purchase intention. For example, based on research data from 377 consumers in Nanchang City, a study constructed a structural equation model to test the mechanism of interactivity's influence on consumers' purchase intention, and the results showed that there is a significant positive relationship between interactivity and consumers' perceived usefulness, which in turn positively affects consumers' purchase intention (Li & Cheng. 2023). Another study analysed consumer purchase intention of fresh produce on a live-streaming e-commerce platform using 417 valid samples, and found that positive consumer perceptions of the anchor's characteristics and product consistency enhance perceived value, which in turn is a key factor driving purchase intention, demonstrating the important role of interactivity in live-streaming e-commerce platforms (Wu, 2020). In addition, a study focusing on the impact of interpersonal interactions on consumers' impulse purchase intentions in live e-commerce broadcasts pointed out that interactions between consumers and anchors and among consumers not only directly drive consumers' impulse purchase intentions, but also indirectly affect them through mediating variables such as the mind-flow experience and perceived risks, suggesting that the impact of interactivity is multidimensional and involves both direct and indirect effects (Xu & Liang, 2021). From these studies, it is clear that interactivity is a key factor influencing consumers' purchase intention, both in live e-commerce platforms and other fresh e-commerce models. Interactivity positively affects purchase intention by enhancing consumers' perceived usefulness, perceived value, and providing a mind stream experience. Thus, hypothesis H2 is proposed as follows.

H2. Fresh e-commerce interactivity innovation positively influences consumers' purchase intention.

3. Hypotheses of integration innovation and purchase intention

In the development process of fresh e-commerce, the integration of content and services gradually shows its importance. Integration refers to the coordination and

unity of the e-commerce platform between different functional modules, between different product categories, and between online and offline services. A highly integrated fresh e-commerce platform can bring consumers a seamless shopping experience, increase user satisfaction and loyalty, and thus enhance purchase intention. Ihzaturrahma and Kusumawati (2021) showed that integrated marketing communication has a significant impact on increasing consumers' purchase intention for local fashion products by enhancing brand awareness and brand image. It shows that the use of multi-channel marketing communication strategies can be effective in engaging target customers, thereby increasing the likelihood that they will purchase locally branded products. A study by Swoboda and Winters (2021) explored the impact of online-offline as well as offline-online channel integration services perceived by consumers as the most useful and demonstrated that channel integration services significantly increased consumers' purchase intent. By seamlessly connecting the online and offline shopping experience, consumers are able to enjoy a more convenient and personalized shopping process, which increases their trust and satisfaction with the brand, which in turn promotes purchase intentions. Nguyen (2021) explored how the quality of channel integration affects the customer experience, and thus their purchase intentions. The study noted that high-quality channel integration enhances the consistency of the customer experience in a multichannel retail environment, leading to greater customer satisfaction, which in turn increases their purchase intentions. Through seamless online and offline interactions, the customer's shopping experience is optimized, enhancing overall loyalty and repeat purchase likelihood. Thus, the integration of platforms influences consumers' purchase intention in multiple dimensions by improving ease of operation, information transparency, and consumer trust, hypothesis H3 is proposed as follows.

H3. Fresh e-commerce integration innovation positively influences consumers' purchase intention.

4. Hypotheses of individualization innovation and purchase intention

In the field of fresh e-commerce, personalized service has gradually become an important factor influencing consumers' purchase intention. Individualization refers to platforms that provide consumers with customized services such as recommendations, promotions, and product displays based on their needs, preferences, and purchasing behaviour. This personalized experience can significantly increase consumers' purchase

intentions by enhancing the sense of exclusivity and convenience for users. Lau and Ki (2021) showed that through gamified and personalised interactive experiences, consumers can feel more satisfied and engaged, which directly contributes to their intention to make a purchase within the app. Nguyen et al. (2023) study focuses on the impact of Facebook ad features on purchase intentions in emerging markets. The study identifies and tests key factors that have a direct impact on customers' online purchase intentions and examines the mediating role of attitudes towards advertising. The results highlight the importance of personalized advertisements in shaping customers' attitudes towards advertisements and their purchase intentions. Odzic and Bozkurt (2023) explored the important relationship between Individualization of online shopping and consumer purchase intentions. They emphasize that a tailored online experience significantly increases the likelihood of a consumer making a purchase. They argue that Individualization acts as a catalyst in online shopping environments, facilitating more engaging and responsive interactions between consumers and platforms. In an increasingly competitive online marketplace, this relationship is critical for e-commerce platforms aiming to increase conversion rates and maintain consumer interest. Thus, hypothesis H4 is proposed as follows.

H4. Fresh e-commerce individualization innovation positively influences consumers' purchase intention.

2.4.2.2 Consumer Innovativeness and Perceived Value, Purchase Intention

In many cases, customer innovativeness has a significant impact on purchase intention. Mohamed & Wee (2020) highlighted the positive effect of consumer innovativeness on online purchase intention, highlighting the importance of customer characteristics in driving purchase behaviour. The study demonstrated that consumer innovativeness has a significant positive effect on influencing online purchase intention. Specifically, it was found that consumers' innovativeness traits motivate them to accept and adopt new fashions more quickly, thus enhancing their online purchase intentions. Furthermore, consumer innovativeness was associated with their intention to purchase trendy and popular items, emphasising the importance of considering consumer innovativeness in digital marketing and product strategies. Furthermore. Esfahani and Reynolds (2021) demonstrated how hedonic innovativeness positively influences customer attitudes, further highlighting the link between customer innovativeness and purchasing behaviour. In the article, it is noted that consumer innovativeness as a

personality trait can significantly influence their adoption of new products. More specifically, consumer innovativeness positively influences purchase intentions through their attitudes. Li et al. (2021) conducted an in-depth study on the impact of consumer innovativenes behavioral control,to purchase sustainable products. The researchers explored the impact of consumer innovativeness on purchase intentions for sustainable products, specifically high and low engagement sustainable products. It was found that consumer innovativeness partially mediated the relationship between consumer innovativeness and purchase intention in high involvement products through the four factors of the theory of planned behaviour: attitude, subjective norms, perceived behavioral control and personal norms. In contrast, in low involvement products, these factors fully mediated the relationship between consumer innovativeness and purchase intention. The article mentions that consumer innovativeness enhances consumers' purchase intention by promoting their perceptions, attitudes, and normative perceptions of sustainable products. Thus, hypothesis H5 is proposed as follows.

H5. Consumer innovativeness positively influences purchase intention.

Moreover, customer innovativeness has a significant impact on perceived value. Sajid et al. (2022) explored the changes in consumers' online shopping behaviour during the COVID-19 period. The study used the Technology Acceptance Model and theory of planned behaviour and found that consumers' perceived benefits, ease of use, enjoyment, and social influence significantly and positively influenced their purchase intentions. These perceived benefits include tangible benefits from product performance, as well as benefits in terms of time savings, low prices, and convenience through online shopping. Research has shown that consumers' perceptions of these benefits enhance their purchase intention. In a digital and technology-driven market environment, consumers who are highly innovative are more likely to have a variety of conveniences and benefits brought about by new technologies, thus increasing their purchase intention. Individual innovativeness, as defined by Rogers, is the extent to which an individual adopts an innovation earlier relative to others in society. Xie and An (2020) pointed out that consumers with greater innovativeness usually have a more substantial economic base, extensive social activities, and stronger psychological qualities, characteristics that enable them to bear the financial and emotional losses of decision failures at a higher level. As a result, the perceived risks of such consumers are relatively low, which makes them more

likely to adopt new technology products, such as new energy vehicles. In response to the impact of consumer innovativeness on the Perceived costs of Xu and Li (2022), they pointed out that consumer innovativeness is usually associated with lower Perceived costs. Highly innovative consumers tend to be open to new products and technologies and are more likely to believe that the long-term benefits of these innovations outweigh the initial costs. As a result, this type of consumer typically has lower Perceived costs because they are more able to recognise the long-term rewards of investing in green or innovative products. This awareness helps to reduce their sensitivity to product costs, which reduces the impact of perceived costs and increases purchase intention. Thus, hypothesis H6, H7 and H8 is proposed as follows.

H6. Consumer innovativeness positively influences perceived benefits

H7. Consumer innovativeness negatively influences perceived risks

H8. Consumer Innovativeness Negatively Influences Perceived Costs

2.4.2.3 Mediating Effect of Perceived Benefits

Perceived benefits play an important mediating role in consumer behaviour research, especially in influencing purchase intentions. Recent studies have shown that perceived benefits not only influence consumers' assessment of product attributes, but also regulate their purchase decisions. In the relationship between interest and purchase intention, perceived benefits stimulate consumers' desire to try and buy by enhancing product appeal. For example, Zahid and Ahmed (2017) explored the impact of image value and functional value on developing consumer purchase intentions and word-of-mouth marketing. The study showed that consumers' perceived benefits, including interesting perceptions of the product, enhance purchase intentions through positive attitudinal mediation. In terms of interactivity, consumers tend to be more interested in products that offer an interactive experience.

Perceived benefits also play an important role between integration and purchase intention. Products that are highly integrated often satisfy multiple consumer needs, and the value-added effect of this perceived benefit contributes to purchase intentions. Based on the Stimulus-Organism-Response model, a study by Yen (2023) aimed to explore how channel integration affects the intention to use food delivery platform services through perceived value. The study found that channel integration influences intention to use through perceived usefulness, perceived pleasure, and

perceived price. In addition, the study tested the moderating effects of individual innovativeness and experience in the modelled relationships.

Individualization has become an important factor influencing consumers' purchase intention. The mediating role of perceived benefits between Individualization and purchase intention is reflected in the fact that Individualization enhances consumers' experience of exclusivity and increases their perceived value. A study by Kang and Namkung (2019) explored how individualization affects continuance intention through the lens of privacy trade-offs in a food service mobile application. The study found that Individualization enhanced consumers' perceived benefits, and this perceived benefit acted as a mediating variable to positively influence users' intention to continue using the service. Thus, hypothesis H9, H10, H11 and H12 is proposed as follows.

H9. Perceived benefits mediate the relationship between interesting innovation and purchase intention.

H10. Perceived benefits mediate the relationship between interactivity innovation and purchase intention.

H11. Perceived benefits mediate the relationship between integration innovation and purchase intention.

H12 Perceived benefits mediate the relationship between individualization innovation and purchase intention.

2.4.2.4 Mediating Effect of Perceived Risks

Perceived risks plays a crucial mediating role in the consumer decision-making process, not only by having a direct effect on consumers' purchase intentions, but also by mediating the effects of interesting, interaction, integration, and Individualization on purchase intentions. Recent studies have shown that perceived risks often inhibit consumers' purchase intention by increasing uncertainty.

perceived risks also plays a significant mediating role between interactivity and purchase intention. While interactivity enhances consumers' sense of brand experience, information overload and privacy and security concerns in highly interactive situations may elevate perceived risks, which in turn affect purchase intentions. Isip and Lacap (2021) examined the relationship between social media use and purchase intentions, exploring the mediating roles of perceived risks and trust. The study found that social

media use indirectly enhanced consumers' purchase intentions by increasing trust and reducing perceived risks.

While personalised services enhance the consumption experience, they may also increase perceived risks due to data security and privacy concerns, which in turn affects purchase intentions. A study by Kang and Namkung (2019) discusses the impact of individualization on intentions to persist in food service mobile applications, particularly from the perspective of privacy trade-offs. Their study argues that perceived risks mediate the relationship between personalized services and users' intention to continue using them. In short, while personalized services improve user experience and satisfaction, they also increase users' perceived privacy risk, and this perceived risk affects their intention to continue using them. Thus, hypothesis H13, H14, H15 and H16 is proposed as follows.

H13. Perceived risks mediate the relationship between interesting innovation and purchase intention.

H14. Perceived risks mediate the relationship between interactivity and purchase intention.

H15. Perceived risks mediate the relationship between integration innovation and purchase intention.

H16. Perceived risks mediate the relationship between individualization innovation and purchase intention.

2.4.2.5 The Mediating Effect of Perceived Costs

Perceived costs are an important consideration for consumers in the purchase decision process, acting as a mediating variable that influences the role of interest, interaction, integration, and Individualization on purchase intention. Recent studies have shown that perceived costs include not only monetary costs, but also time, energy, and psychological costs, which have a complex impact on consumers' purchase intention.

In the relationship between interest and purchase intention, although the interest of a product may enhance consumers' interest, if the perceived costs are too high, consumers may abandon the purchase. According to Wu et al. (2022) study that the key to consumers' continued use lies not only in utilitarian values such as cheap price and convenience, but also in spiritual hedonic values, and the pleasure of the shopping process can stimulate consumers to make repeated purchases. When the services or products

provided by community group-buying platforms are perceived to be interesting, consumers may adjust their purchase intentions due to Perceived costs.

Perceived costs also play a mediating role between integrability and purchase intentions. In a more general sense, integration can be viewed as reducing transaction costs and complexity, thus positively affecting purchase intention. It explored the relationship between consumers' perceived value and their offline-to-online channel migration behaviour in a multichannel environment, revealing how consumers trade-off costs and benefits in a multichannel shopping environment. When consumers perceive that migrating from offline to online channels will result in higher value, they are more likely to overcome perceived cost barriers and show stronger purchase intentions. Oh et al. (2012) explored the impact of information technology-facilitated retail channel integration on firm performance. Through integration, firms can provide a coherent customer experience across physical and virtual channels, thereby influencing customers' purchase intentions by reducing perceived costs and minimizing friction.

Finally, Individualization can significantly enhance the customer experience, but the perceived costs of its implementation, such as personal information disclosure or setup complexity, may inhibit consumers' purchase intentions. According to Yang (2023), perceived costs mediate the relationship between Individualization services and cross-border e-commerce purchase intention, suggesting that the costs that consumers consider when evaluating Individualization services may hinder their purchase intention. In short, although personalized services provide a customised experience, high perceived costs may reduce consumers' purchase intentions. Thus, hypothesis H17, H18, H19 and H20 is proposed as follows.

H17. Perceived costs mediate the relationship between interesting innovation and purchase intention.

H18. Perceived costs mediate the relationship between interactivity innovation and purchase intention.

H19. Perceived costs mediate the relationship between integration innovation and purchase intention.

H20. Perceived costs mediate the relationship between individualization innovation and purchase intention.

2.4.2.6 The Moderating Effect of Consumer Innovativeness

Consumer innovativeness as a personality factor is one of the most important factors influencing consumer purchasing behaviour. Despite the many uncertain-oriented risks associated with online fresh produce purchasing, individuals who love the pursuit of new things adopt an approach strategy that may have a stronger willingness to purchase online fresh produce. Whereas preventive-oriented consumers are prone to have an avoidance attitude towards new things and may be reluctant to try online channels for fresh produce purchases. Based on the above derivation, the extent to which consumers with high individual innovativeness perceive the risks of online fresh produce leading to a reduction in purchase intention is weakened compared torisks,umers with low individual innovativeness. Min (2022) emphasized that when innovativeness is associated with negative impacts, it may impair purchase intention. This suggests that the relationship between consumer innovativeness, perceived risks and purchase intention is complex and may vary depending on the context and nature of the innovation. Kamalanon et al. (2022) explored the moderating effect of consumer innovativeness on purchase intentions for green products. Specifically, it was found that consumer innovativeness positively moderated the relationship between perceived consumer efficacy and green purchase intention. This suggests that consumers with high innovativeness are more willing to purchase green products when they perceive that their personal behaviour has a positive impact on the environment. In addition, consumer innovativeness was found to play a positive moderating role in the relationship between a company's perceived green image and green purchase intention, implying that high or low consumer innovativeness may influence how they adjust their purchase behaviour according to a company's green image. Khazaei and Tareq (2021) explored the influencing factors of personal innovativeness and driving experience on the adoption of electric vehicles in Malaysia. The research in this article was analyzed through Structural Equation Modelling method, focusing on the moderating role of personal innovativeness between perceived costs and purchase intention. The results of the study show that personal innovativeness significantly moderates the effect of perceived costs on purchase intention, where consumers with higher personal innovativeness are less sensitive to perceived costs, which may enhance their purchase intention. Thus, hypothesis H21, H22and H23 is proposed as follows.

H21. Consumer innovativeness has a moderating effect between perceived benefits and purchase intention. The more innovative the consumer is, the higher the perceived benefits and the stronger the purchase intention. The stronger the effect of perceived benefits on purchase intentions.

H22. Consumer innovativeness has a moderating effect between perceived risks and purchase intention. The greater the consumer innovativeness, the lower the perceived risks, the greater the purchase intention, and the weaker the effect of perceived risks on purchase intention.

H23. Consumer innovativeness has a moderating effect between Perceived costs and purchase intention. Consumer innovativeness has a moderating effect between Perceived costs and purchase intention. The stronger the consumer innovativeness, the lower the perceived costs, the stronger the purchase intention, and the weaker the effect of perceived costs on purchase intention.

2.4.2.7 The Moderating Effect of Customer Digital Transformation

According to customer digital transformation attitudes, different subjects have different perceptions of customer digital transformation, and in this research, this study examines customer digital transformation from the consumer's perspective.

Zhang and Qin (2022) conducted a survey experiment on urban digital transformation in Shanghai and found that in urban digital transformation, policy narratives containing different participant subjects with perceived descriptions of benefits acted on their propensity to support behaviours by influencing public attitudes; the size and maturity items of the Industry 4.0 maturity model developed by Schumacher et al. (2016), included customer digital transformation as a typical measurement entry for the degree of digital transformation of an enterprise, and measures the measurement items of customer digital transformation in terms of customer data utilisation capability, sales/service digitization degree, and customer digital media capability. By analyzing the internal logic and external performance of customer digital transformation, it can be concluded that customers' positive attitude towards digital transformation enhances their perceived benefits of products or services. This increase in perceived benefits further enhances customers' purchase intention. Positive customer attitudes digital transformation attitudes can diminish their perceived risks and mitigate their perceived costs of using new

technologies or digital services. Thus, hypothesis H24, H25 and H26 is proposed as follows.

H24. Customer digital transformation attitudes have a moderating effect between perceived benefits and purchase intentions. Stronger customer attitudes toward digital transformation lead to higher perceived benefits and higher purchase intentions

H25. Customer digital transformation attitudes have a moderating effect between perceived risks and purchase intention. The stronger the customer's digital transformation attitude, the lower the perceived risks, the stronger the purchase intention, and the weaker the effect of perceived risks on purchase intention.

H26. Customers' attitude towards digital transformation has a moderating effect between perceived costs and purchase intention. The stronger the customer's attitude towards digital transformation, the lower the perceived costs, the stronger the purchase intention, and the weaker the impact of perceived costs on purchase intention.

2.4.2.8 Summary of Research Hypotheses

The literature collated above resulted in a total of 26 hypotheses in this study, of which a total of 8 were direct hypotheses, 12 were hypotheses of mediating roles, and 6 were hypotheses of moderating roles (see Tables 2.2 for details).

Table 2.2 Summary of Research Hypotheses

Item	Hypotheses Statement
H1	Fresh e-commerce interesting innovation positively influences consumers' purchase intention.
H2	Fresh e-commerce interactivity innovation positively influences consumers' purchase intention.
H3	Fresh e-commerce integration innovation positively influences consumers' purchase intention.
H4	Fresh e-commerce individualization innovation positively influences consumers' purchase intention.
H5	Consumer innovativeness positively influences purchase intention.
H6	Consumer innovativeness positively influences perceived benefits
H7	Consumer innovativeness negatively influences perceived risk
H8	Consumer Innovativeness negatively Influences Perceived Costs

Table 2.2 (continued)

Item	Hypotheses Statement
H9	Perceived benefits mediate the relationship between interesting innovation and purchase intention.
H10	Perceived benefits mediate the relationship between interactivity innovation and purchase intention.
H11	Perceived benefits mediate the relationship between integration innovation and purchase intention.
H12	Perceived benefits mediate the relationship between individualization innovation and purchase intention.
H13	Perceived risks mediate the relationship between interesting innovation and purchase intention.
H14	Perceived risks mediate the relationship between interactivity and purchase intention.
H15	Perceived risks mediate the relationship between integration innovation and purchase intention.
H16	Perceived risks mediate the relationship between individualization innovation and purchase intention.
H17	Perceived costs mediate the relationship between interesting innovation and purchase intention.
H18	Perceived costs mediate the relationship between interactivity innovation and purchase intention.
H19	Perceived costs mediate the relationship between integration innovation and purchase intention.
H20	Perceived costs mediate the relationship between individualization innovation and purchase intention.
H21	Consumer innovativeness has a moderating effect between perceived benefits and purchase intentions. The more innovative the consumer, the higher the perceived benefits and the stronger the purchase intention. The stronger the effect of perceived benefits on purchase intention, the stronger the effect of perceived benefits on purchase intention.

Table 2.2 (continued)

Item	Hypotheses Statement
H22	Consumer innovativeness has a moderating effect between perceived risks and purchase intention. The greater the consumer innovativeness, the lower the perceived risks, the greater the purchase intention, and the weaker the effect of perceived risks on purchase intention.
H23	Consumer innovativeness has a moderating effect between Perceived costs and purchase intention. Consumer innovativeness has a moderating effect between Perceived costs and purchase intention. The stronger the consumer innovativeness, the lower the perceived costs, the stronger the purchase intention, and the weaker the effect of perceived costs on purchase intention.
H24	Customer digital transformation attitudes have a moderating effect between perceived benefits and purchase intentions. The stronger the customer's attitude towards digital transformation, the higher the perceived benefits and the stronger the purchase intention
H25	Customer digital transformation attitudes have a moderating effect between perceived risks and purchase intention. The stronger the customer's digital transformation attitude, the lower the perceived risks, the stronger the purchase intention, and the weaker the effect of perceived risks on purchase intention.
H26	Customer digital transformation attitudes have a moderating effect between perceived costs and purchase intentions. Customer digital transformation attitude has a moderating effect between perceived costs and purchase intention. The stronger the customer's digital transformation attitude, the lower the perceived costs, the stronger the purchase intention, and the weaker the effect of perceived costs on purchase intention.

2.4.3 Theoretical Model

Based on the comprehensive literature review and theoretical deduction presented above, this study constructs an integrated theoretical model grounded in the Stimulus-Organism-Response framework, as illustrated in Figure 2.5. In this model, the stimulus dimension comprises the four dimensions of value innovation in fresh e-commerce derived from the 4I marketing theory—namely, interesting innovation, interactivity innovation,

integration innovation, and individualization innovation. These four external stimuli are hypothesized to influence consumers' internal organism states, which are conceptualized as perceived benefits, perceived risks, and perceived costs. The response dimension is represented by consumers' purchase intention. Furthermore, the model incorporates two moderating variables, consumer innovativeness and customer digital transformation attitudes, which are theorized to moderate the relationships between the organism variables and purchase intention. This conceptual framework systematically delineates how value innovation in fresh e-commerce, as an external environmental stimulus, activates consumers' internal value perception processes, which subsequently shape their ultimate purchase responses, while also accounting for individual difference factors that may strengthen or weaken these pathways.

The hypothesized path model explicitly traces both direct and indirect effect pathways among the constructs. Direct paths (H1–H4) propose that each of the four value innovation dimensions positively influences purchase intention. Direct paths are also posited for consumer innovativeness on perceived benefits (H6, positive), perceived risks (H7, negative), perceived costs (H8, negative), and on purchase intention (H5, positive). The mediating roles of perceived benefits (H9–H12), perceived risks (H13–H16), and perceived costs (H17–H20) are specified as intervening mechanisms linking each value innovation dimension to purchase intention. Finally, the moderating effects (H21–H26) propose that consumer innovativeness and customer digital transformation attitudes each moderate the relationships from perceived benefits, perceived risks, and perceived costs to purchase intention.

2.5 Conclusion

This chapter provides an in-depth study of the fresh e-commerce industry in the context of the development of the digital economy. Starting from the global digital transformation and the development trend of China's digital economy, this chapter analyzes in detail the development status quo, business models, challenges and opportunities of the fresh e-commerce industry, as well as the characteristics of consumer behaviour in the digital economy. On this basis, this chapter combines consumer behaviour theory, marketing theory, and consumer psychology theory to construct a theoretical model containing value innovation, consumer perceived value, consumer innovativeness,

customer attitude towards digital transformation, and consumer purchase intention, and puts forward relevant research hypotheses. Through systematic sorting and theoretical analysis, this chapter provides a solid theoretical foundation for the subsequent empirical research, and provides an important reference for understanding the operation strategy of fresh e-commerce companies and enhancing consumer purchase intention in the digital economy environment.

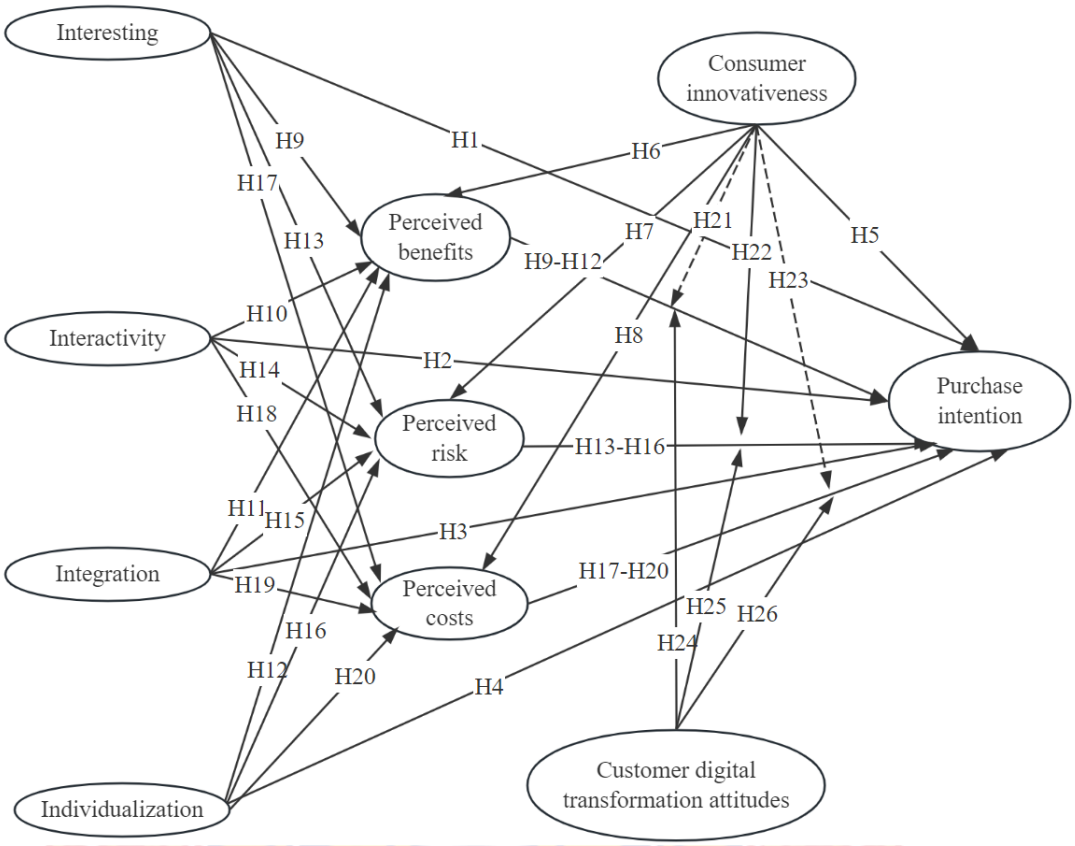


Figure 2.5 Proposed model Diagram

CHAPTER 3
METHODOLOGY

Following the theoretical model and research hypotheses developed in Chapter Two, this chapter presents the methodology of the study. It explains the research paradigm, data collection procedures, research design, variable measurement, and data analysis methods used to examine the proposed model. It also outlines the pilot study, formal survey, and ethical considerations. Together, these elements provide the methodological foundation for the empirical analysis in the following chapters.

3.1 Overview and Justification of Research Paradigm

The research paradigm provides the philosophical foundation for a study. It shapes how the research problem is understood, how data are collected, and how findings are interpreted. In this study, a post-positivist paradigm is adopted. This paradigm is suitable because it allows the researcher to examine social phenomena through empirical observation while also recognising that reality is complex and cannot be understood with complete certainty. Since this study aims to test the relationships between fresh e-commerce value innovation and consumer purchase intention, post-positivism offers an appropriate basis for hypothesis testing and quantitative analysis.

3.1.1 Ontology of Post-Positivism

The ontological position of post-positivism is that reality exists independently of human perception, but it can only be known imperfectly. In other words, there is an objective reality, yet people understand it through their own experiences, knowledge, and social context. This view is relevant to the present study because the fresh e-commerce market and consumer behaviour in the digital economy are both complex and dynamic. The effect of value innovation on consumer purchase intention is not a simple or one-dimensional issue. Instead, it involves many interacting factors, such as technology, consumer experience, culture, and individual preferences. Therefore, this study treats the

research context as a multi-layered reality that can be examined through careful data collection and analysis.

3.1.2 Epistemology of Post-Positivism

Post-positivist epistemology emphasizes the interplay between subjectivity and objectivity in the research process. In the process of value innovation in postgraduate fresh e-commerce, a researcher's own experience, background, and perspective will inevitably affect the perspective and interpretation of the research. For example, a researcher may have preconceived assumptions about consumers' purchase motivations based on their own shopping habits and preferences. Quantitative data was combined with a theoretical framework through questionnaires and statistical analyses in order to test the hypotheses. This epistemological balance helps to ensure the comprehensiveness and credibility of the research findings.

3.1.3 Methodology of Post-Positivism

The methodological orientation of post-positivism usually supports the use of quantitative methods to test hypotheses and identify patterns across a large group of respondents. This approach is appropriate for the current study because the research aims to measure relationships among defined variables and examine their significance. Specifically, a questionnaire survey is used to collect data on consumer behaviour in the fresh e-commerce sector under the digital economy context. The collected data are then analyzed using statistical software such as Structural Equation Model (SEM). Through these tools, the study tests the proposed relationships and possible influence paths among the variables. Overall, this methodological design enables the research to address the research questions in a systematic and evidence-based way, and it provides empirical support for value innovation strategies in fresh e-commerce enterprises.

3.2 Methodology

3.2.1 Data Collection Administration

This section explains how the data were collected for the study and how the overall data collection design supports the reliability and validity of the research findings. Data collection was carried out through a structured questionnaire survey targeting consumers of fresh food e-commerce platforms in Shanghai, China. The design included both pilot

and formal surveys to ensure that the measurement tools and the collected data were suitable for quantitative analysis.

Before the formal survey, a pilot test was conducted to assess the clarity, reliability, and preliminary validity of the questionnaire. A total of 130 questionnaires were distributed, and 108 valid responses were obtained. The pilot sample size was considered adequate because it exceeded the commonly recommended minimum of 100 cases for preliminary reliability and exploratory validity assessment. The results were used to refine the wording of items and remove items with low corrected item–total correlations.

After the pilot test, the formal survey was conducted in December 2024. The questionnaire distribution followed the combining stratified sampling with convenience sampling method, based on Shanghai's administrative division of inner-ring, outer-ring, and suburban districts. Six districts were selected—Jing'an, Xuhui, Putuo, Minhang, Songjiang, and Fengxian—to ensure coverage of different residential and socioeconomic groups. The sample size for each district was determined according to its share of the population, as shown in Table 3.8.

In order to obtain a sufficient number of valid responses for structural equation modelling, this study planned to distribute 1,000 questionnaires through both online and offline channels. The planned distribution size was not intended to represent the final number of valid questionnaires. Rather, it was set by considering the complexity of the research model, the number of measurement items, and the possibility of invalid or incomplete responses during the data collection process. The questionnaire contained 61 measurement items, and the research model included multiple latent constructs as well as mediation and moderation effects. Therefore, a larger initial distribution size was necessary to ensure that the final valid sample would be adequate for reliable model estimation. Among the 1,000 questionnaires distributed, 905 were returned, resulting in a response rate of 90.5%. During data screening, 67 questionnaires were excluded because they were incomplete or presented patterned responses. As a result, 838 valid questionnaires were retained for the formal analysis. The valid response rate was 83.8% of the total distributed questionnaires. This final sample size exceeded the commonly recommended minimum sample size for structural equation modelling and was sufficient for reliability testing, validity assessment, path analysis, mediation testing, and moderation testing in this study.

The questionnaire consisted of three parts. The first part introduced the purpose of the study and assured participants of data confidentiality. The second part collected demographic and behavioural information, such as gender, age, education, income, and purchase frequency. The third part included measurement scales of key variables: value innovation, perceived value, purchase intention, consumer innovativeness, and digital transformation attitudes. All scale items were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was available in Chinese, following a forward–backward translation procedure to ensure linguistic equivalence.

Data collection strictly followed ethical research principles. Participation was voluntary and anonymous, and respondents were informed that their answers would be used only for academic purposes. The final cleaning and coding of data were completed before formal statistical analysis using SEM.

Overall, the data collection administration combined systematic planning, rigorous sampling, and ethical control procedures to ensure that the obtained data were reliable, representative, and appropriate for quantitative modelling.

3.2.2 Variable Definition

This section explains the research design used to examine the relationships among value innovation, perceived value, consumer innovativeness, and purchase intention. It includes the definition of the main variables in the research model and the methods used to measure them. Clear variable definition is necessary for ensuring the consistency and validity of the empirical analysis.

This study defines and measures all variables based on existing literature and the specific characteristics of fresh food e-commerce platforms. After reviewing relevant studies on fresh food e-commerce and consumer behaviour, this research adopted widely used definitions of key constructs and adjusted them where necessary to fit the context of fresh food e-commerce. This approach helps maintain theoretical consistency while improving the practical relevance of the measurement items.

After collecting and collating literature related to fresh e-commerce, on the basis of existing definitions of relevant variables in the research model by external scholars, and taking into account the special characteristics of the fresh e-commerce platform itself, this study defines the variables covered by the research model as follows.

(1) Definition of core variables

Core variables include independent and dependent variables. The independent variable is the variable that is controlled, manipulated, or changed by the researcher in a study and is usually the cause or explanatory factor of the study to observe how it affects other variables. The dependent variable is the response variable in a study, whose change is affected by the independent variable, and is usually the outcome of the study, used to assess the extent to which the independent variable affects its change. The relationship between the independent and dependent variables is the central focus of the study to reveal their linkages and interactions

In this study, the "stimulus" factor of value innovation in the Stimulus-Organism-Response model is the independent variable (see Table 3.1 for details), and the "response" factor of purchase intention in the Stimulus-Organism-Response model is the dependent variable.

Table 3.1 Definition of Independent and Dependent Variables

Variable type	Variable	Define	Source
Independent variable	Value Innovation	Value innovation, as a new mode of business thinking, requires companies to start from customer value and continuously seek and maximize value through innovation as a way to gain competitive advantage and market success.	Kim & Mauborgn (2004).
Dependent variable	purchase intention	purchase intention usually refers to the consumer's tendency and motivation to buy a particular product or service, is a kind of attitude or intention of pre-purchase behaviour within the consumer. It reflects the strength of consumers' motivation to buy goods or services in a particular situation.	Feng et al. (2006)

(2) Definition of mediating variables

A mediating variable is a variable that lies in the causal path between the independent variable and the dependent variable, and helps to explain how or why the independent variable influences the dependent variable. Rather than simply showing that a relationship exists, a mediating variable reveals the underlying process through which the effect is transmitted. By identifying such a variable, this study is able to explain the internal mechanism that links the independent and dependent variables, rather than describing only their direct association. The mediating variables used in this study are defined in Table 3.2.

Table 3.2 Definition of Mediating Variables

Variable type	Variable	Define	Source
Mediating variable	Perceived benefits	Perceived benefits are positive benefits perceived by consumers during the social media shopping process on three levels: informational, experiential, and symbolic, which can influence their loyalty to social media, their actual use, and their willingness to spread positive word-of-mouth.	Ryu & Park (2020)
	Perceived risks	Perceived risks is the subjective assessment of potential negative consequences when consumers buy or use products and services. This risk is not just one-dimensional, but multidimensional.	Dayour et al. (2019)
	Perceived costs	Perceived costs are the consumer's personal perception and assessment of all costs associated with the purchase decision process. These costs include not only the price that the consumer pays directly to acquire a product or service, but may also include the consumption of time, effort, and other resources.	Li et al. (2019)

(3) Definition of moderating variables

A moderating variable is a variable that is used to moderate or modify the relationship between an independent variable and a dependent variable. In research, moderating variables are often used to explore whether the relationship between the independent and dependent variables changes under different conditions, or under what conditions the relationship is stronger or weaker. Moderating variables contribute to a more complete understanding of the relationship between the independent and dependent variables to reveal the complexities and conditional changes involved. The definitions of moderating variables in this study are detailed in Table 3.3.

Table 3.3 Definition of Moderating Variables

Variable type	Variable	Define	Source
Moderating variable	Consumer innovativeness	Consumer innovativeness describes the extent to which consumers adopt new ideas earlier than other members of the system. The concept is divided into two main streams: innate innovativeness and realised innovativeness.	Esfahani & Reynolds (2021)
	Customer digital transformation attitudes	Perceptions, feelings, and reactions to the introduction of digital technologies and processes into a business or organisation's operations and services	Zhang & Qin (2022)

3.2.3 Measurement Scales

3.2.3.1 Measurement of Value Innovation

(1) Interesting innovation scale

Referring to Xu (2024) study, the interesting scale has three items for the interesting dimension, each of which was measured on a 5-point Likert scale. The interestingness scale is shown in Appendix I, Table 1.

(2) Interactivity innovation scale

Interactivity scale referenced Leiner and Quiring (2008) study, the interactivity scale dimension has 11 question items. Each question item was measured using a 5-point Likert scale. The interactivity scale is shown in Appendix I, Table 2.

(3) Integration innovation scale

Integrative scale referenced Oh et al. (2012) study, the integrative scale has 12 question items. Each question item was measured using a 5-point Likert scale. The integrative scale is shown in Appendix I, Table 3.

(4) Individualization innovation scale

The individualization scale refers to the study of Xu et al. (2011), and the Individualization scale dimension was set up with 3 question items. Each question item was measured using a 5-point Likert scale. The individualization scale is shown in Appendix I, Table 4-

3.2.3.2 Measurement of Perceived Value

In terms of the measurement of consumers' perceived value, this study sets up a total of three dimensions: perceived benefits, perceived risks, and perceived costs.

(1) Perceived benefits

Perceived benefit identifies perceived usefulness and perceived ease of use as the two dimensions that capture perceived benefit, with perceived usefulness primarily referenced by Davis (1989). Perceived usefulness is mainly based on Davis (1989), which demonstrates the improvement in consumers' life efficiency by adopting the online channel to purchase fresh produce. Perceived ease of use is mainly based on Davis (1989). It shows how easy consumers perceive it is to search for information and how easy it is to operate and use the fresh e-commerce platform. There are 12 question items in the perceived benefit dimension. Each question item was measured using a 5-point Likert scale. The perceived benefit scale is shown in Appendix I, Table 5.

(2) Perceived costs

Perceived costs scale referring to the study of Li et al. (2019), the perceived costs dimension has 3 question items, each of which is measured using a 5-point Likert scale. The consumer perceived costs scale is shown in Appendix I, Table 6.

(3) perceived risks

Perceived risks scale references Cui et al. (2023), the perceived risks dimension has 8 question items and each item is measured using a 5-point Likert scale. The scale of consumer innovative question items is shown in Appendix I, Table 7.

3.2.3.3 Measurement of Purchase Intention

This study references Esfahani & Reynolds (2021) 's scale, in terms of the measurement items of consumer purchase intention, there are three items, each of which is measured using a 5-point Likert scale. The consumer purchase intention scale is shown in Appendix I, Table 8.

3.2.3.4 Measurement of Consumer Innovativeness

In this study, the consumer innovativeness scale developed by Esfahani & Reynolds (2021), which focuses on assessing consumer acceptance of new products, was synthesized. This scale contains four main dimensions: social, interesting, hedonic, and cognitive. The social dimension focuses on consumers' tendency to use new products to enhance social status and attract attention. The interesting dimension assesses the extent to which consumers choose new products based on their utility and interesting. The hedonic dimension captures the personal pleasure and satisfaction consumers derive from using novel products. The cognitive dimension explores consumer behaviour in purchasing new products to satisfy intellectual challenges and thinking needs. Together, these dimensions form a comprehensive framework for understanding and analysing consumer attitudes towards novel and innovative products and their acceptance behaviour. The scale has 18 items, each measured on a 5-point Likert scale. The scale for consumer innovativeness is shown in Appendix I, Table 9.

3.2.3.5 Measurement of Customer Digital Transformation Attitude

In this study, with reference to Zhang and Qin (2022) scale, there are three items for the measurement of customer attitude towards digital transformation, and each item is measured using a 5-point Likert scale. The customer digital transformation attitude scale is shown in Appendix I, Table 10.

3.2.3.6 Control Variables

This study includes several control variables to describe the basic characteristics of current users of online fresh food shopping.

The selection of control variables was mainly based on the user profile presented in Mob Research Institute's 2022 Consumption Insight Report on China Fresh E-commerce Industry (MobTech, 2022). To better fit the purpose of this study, the demographic indicators were adjusted and refined. As a result, ten control variables were included: gender, age, educational level, marital status, occupation, monthly disposable income, frequency of online purchases of fresh agricultural products, the type of fresh agricultural products purchased most often, the number of available online platforms, and the platform used most often. These variables were used to capture respondents' personal and consumption-related characteristics.

The first group of control variables describes respondents' demographic background. Gender was coded as a categorical variable, with 1 representing male and 2 representing female. Age was also coded categorically: 1 = under 18 years old, 2 = 18–24 years old, 3 = 25–30 years old, 4 = 31–40 years old, and 5 = over 40 years old. Educational level was measured with five categories: 1 = high school or below, 2 = high school or technical secondary school, 3 = junior college, 4 = bachelor's degree, and 5 = master's degree or above. Marital status was coded as 1 = unmarried, 2 = married, 3 = divorced, and 4 = widowed. Occupation was measured as 1 = student, 2 = government or public institution employee, 3 = corporate staff, 4 = self-employed, and 5 = other. Monthly disposable income was divided into five groups: 1 = RMB 3,000 and below, 2 = RMB 3,001–5,000, 3 = RMB 5,001–10,000, 4 = RMB 10,001–20,000, and 5 = above RMB 20,000.

The second group of control variables reflects respondents' online fresh food shopping behavior. The frequency of online shopping for fresh agricultural products was coded as 1 = almost never, 2 = once a month, 3 = two to three times a month, 4 = one to two times a week, and 5 = more than three times a week. The type of fresh agricultural products purchased most often online was coded as 1 = vegetables and bean products, 2 = fruits, 3 = meat and poultry, 4 = seafood, 5 = eggs and milk, and 6 = other. The platform used most often for online fresh food shopping was coded as 1 = Dingdong Maicai, 2 = Hema Fresh, 3 = JD Daojia, 4 = RT-Mart Youxian, 5 = Meituan Youxuan, and 6 = other. Finally, the number of available platforms for online shopping of fresh agricultural products was measured as 1 = one platform, 2 = two platforms, 3 = three platforms, 4 = four platforms, and 5 = five platforms or more.

3.2.3.7 Questionnaire Design

The questionnaire survey was conducted in the field, and the target respondents were consumers of fresh produce. The data were collected through a field questionnaire survey, and the main variables involved in the study were: stimulus variables, organism variables, response variables, and external variables (Table 3.4 for details).

The questionnaire was divided into three parts to improve clarity and response quality. The first part introduces the purpose and usage of the survey, through the textual introduction of the questionnaire and the verbal introduction of the investigator, to let the respondents know the main content of the survey and the purpose of the survey, so as to reduce the preventive mentality of the respondents, and to obtain more realistic data information through effective investigation. The first part of the questionnaire also provides additional explanations of the main content involved in the questionnaire to facilitate the understanding of the respondents. The second part of the questionnaire is the basic information survey of consumers, mainly to understand the basic personal situation of the respondents, such as gender, age, education level, occupation, monthly disposable income, etc., and also to make a detailed survey on the frequency of respondents' online purchase of fresh agricultural products as well as the type of fresh agricultural products that are purchased most online. The third part is the main part of the questionnaire, which mainly consists of measurement question items for the variables of value innovation, perceived value, consumer innovativeness, and purchase intention involved in the conceptual model. In order to ensure the scientificity and accuracy of the measurement scales, the variable measurement scales in this study adopt the mature scales widely used by previous researchers with good reliability and validity, and the scales are appropriately modified based on the characteristics of the current development of fresh e-commerce in China and the cultural background and language habits of China. These mature scales are mainly based on a five-point Likert scale to evaluate the measurement items, in which 1-5 points represent strongly disagree, basically disagree, uncertain, basically agree, and completely agree, respectively. The control variables were mainly measured in the form of dummy treatment and categorical variables.

Table 3.4 Summary of Variables

Stimulus variable (S)	Organism variable (O)	Response variable (R)	Moderator variable
Interesting, Interactive, Integrative, Individualization	Perceived benefits, Perceived risks, Perceived costs	Purchase intention	Consumer innovativeness; Customer digital transformation attitudes

3.2.4 Pilot Study

To ensure the quality, clarity, and measurement reliability of the questionnaire, a pilot study was conducted before the formal survey. The purpose of the pilot study was to examine whether the questionnaire items were understandable to respondents, whether the measurement items showed acceptable internal consistency, and whether the data were suitable for subsequent factor analysis. The preliminary questionnaire was measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The pilot questionnaire was distributed to 130 fresh produce consumers. After excluding invalid and incomplete responses, 108 valid responses were retained for analysis.

(1) Reliability analysis of the pilot questionnaire

The reliability of the pilot questionnaire was examined using Cronbach's alpha and corrected item–total correlation, namely CITC. Reliability refers to the consistency and stability of a measurement instrument. In this study, Cronbach's alpha was used as the main indicator of internal consistency reliability. A higher Cronbach's alpha value indicates that the items within a scale are more consistent in measuring the same underlying construct.

In general, a Cronbach's alpha value of 0.70 or above is considered acceptable for social science research. More specifically, an alpha value of 0.80 or above indicates good internal consistency, while an alpha value between 0.70 and 0.80 indicates acceptable to good reliability. If the alpha value is between 0.60 and 0.70, the scale may still be acceptable in exploratory research, but further improvement of the items is usually required. When the alpha value is below 0.60, the reliability of the scale is generally considered weak, and the measurement items should be carefully reviewed or revised.

In addition to Cronbach's alpha, CITC was used to evaluate the relationship between each item and its corresponding scale. CITC indicates the degree to which each item is consistent with the overall scale score. A higher CITC value suggests that the item contributes well to the measurement of the construct. In this study, items with a CITC value below 0.50 were carefully examined. Items with low CITC values, negative CITC values, or items whose deletion could improve the internal consistency of the scale were considered for removal. The decision to remove items was made by considering both statistical results and the conceptual relevance of the items.

The reliability analysis was conducted using SEM. The overall Cronbach's alpha of the pilot questionnaire was 0.951, indicating a very high level of internal consistency. This result suggests that the questionnaire as a whole had strong reliability in the pilot test. However, since the questionnaire contained multiple constructs, the reliability of each construct was also examined separately. The results showed that most constructs achieved acceptable or good reliability. For several constructs, some items showed relatively low or negative CITC values, suggesting that these items were not sufficiently consistent with the corresponding construct. Therefore, these items were further reviewed and removed before the formal survey.

The detailed results of the reliability analysis are shown in Table 3.5.

Table 3.5 Pre-Survey Questionnaire Reliability Analysis

Variant	Item	CITC	Cronbach's Alpha if Item Deleted	Cronbach's Alpha of Initial Scale
Interesting innovation	IIA1	0.794	0.727	0.853623
	IIA2	0.722	0.8	
	IIA3	0.67	0.847	
Interactivity innovation	IIB1	0.842	0.813	0.852004
	IIB2	0.815	0.817	
	IIB3	0.599	0.836	
	IIB4	0.744	0.824	
	IIB5	0.445	0.847	
	IIB6	0.763	0.822	

Table 3.5 (continued)

Variant	Item	CITC	Cronbach's Alpha if Item Deleted	Cronbach's Alpha of Initial Scale
	IIB7	0.678	0.829	
	IIB8	0.161	0.872	
	IIB9	-0.194	0.896	
	IIB10	0.782	0.821	
	IIB11	0.594	0.835	
Integration innovation	IIC1	0.775	0.706	0.767789
	IIC2	0.765	0.71	
	IIC3	0.61	0.732	
	IIC4	0.712	0.718	
	IIC5	0.602	0.729	
	IIC6	0.73	0.717	
	IIC7	0.671	0.723	
	IIC8	0.139	0.784	
	IIC9	-0.093	0.807	
	IIC10	-0.108	0.805	
	IIC11	0.574	0.734	
	IIC12	-0.085	0.807	
Individualization innovation	IID1	0.676	0.738	0.815324
	IID2	0.711	0.7	
	IID3	0.616	0.798	
Perceived costs	PC1	0.851	0.768	0.884071
	PC2	0.844	0.773	
	PC3	0.658	0.932	

Table 3.5 (continued)

Variant	Item	CITC	Cronbach's Alpha if Item Deleted	Cronbach's Alpha of Initial Scale
Perceived risks	PR1	0.734	0.674	0.754650
	PR2	0.577	0.709	
	PR3	0.695	0.684	
	PR4	0.59	0.702	
	PR5	0.696	0.684	
	PR6	0.661	0.691	
	PR7	0.147	0.79	
	PR8	-0.183	0.84	
Perceived benefits	PB1	0.863	0.86	0.886370
	PB2	0.691	0.872	
	PB3	0.589	0.877	
	PB4	0.717	0.87	
	PB5	0.334	0.89	
	PB6	0.791	0.865	
	PB7	0.509	0.882	
	PB8	0.749	0.868	
	PB9	0.505	0.882	
	PB10	0.726	0.869	
	PB11	0.489	0.883	
	PB12	0.105	0.901	
Purchase intention	PI1	0.745	0.687	0.823127
	PI2	0.768	0.663	
	PI3	0.541	0.881	
Customer digital transformation attitudes	DTA1	0.709	0.675	0.805345
	DTA2	0.682	0.708	
	DTA3	0.58	0.805	

Table 3.5 (continued)

Variant	Item	CITC	Cronbach's Alpha if Item Deleted	Cronbach's Alpha of Initial Scale
Consumer innovativeness	CI1	0.771	0.932	0.936494
	CI2	0.845	0.929	
	CI3	0.465	0.936	
	CI4	0.332	0.939	
	CI5	0.683	0.933	
	CI6	0.872	0.929	
	CI7	0.749	0.931	
	CI8	0.731	0.932	
	CI9	0.713	0.932	
	CI10	0.021	0.942	
	CI11	0.524	0.935	
	CI12	0.727	0.932	
	CI13	0.828	0.929	
	CI14	0.819	0.93	
	CI15	0.75	0.931	
	CI16	0.716	0.932	
	CI17	0.443	0.936	
	CI18	0.588	0.934	
	CI19	0.573	0.934	
	CI20	0.398	0.937	

(2) Validity Analysis of the Pilot Questionnaire

After the reliability analysis, the validity of the pilot questionnaire was assessed. Validity refers to the extent to which a measurement instrument accurately measures the construct that it is intended to measure. In this study, the validity of the questionnaire was mainly examined from two aspects: content validity and preliminary construct validity.

First, content validity was ensured through the development process of the questionnaire. The measurement items used in this study were adapted from mature scales in previous studies. These scales had been widely used in related research areas and had demonstrated acceptable measurement quality. In addition, the questionnaire was reviewed and revised based on expert suggestions to ensure that the items were appropriate for the research context of fresh produce consumption and digital transformation. Therefore, the questionnaire had an acceptable level of content validity.

Second, preliminary construct validity was examined using the Kaiser–Meyer–Olkin measure, namely KMO, and Bartlett's test of sphericity. The KMO value is used to evaluate whether the sample data are suitable for factor analysis. A KMO value above 0.60 generally indicates that the data are acceptable for factor analysis. Bartlett's test of sphericity examines whether the correlation matrix is significantly different from an identity matrix. A significant Bartlett's test result, namely $p < 0.05$, indicates that the variables are sufficiently correlated and suitable for factor analysis.

The validity analysis was conducted after the initial screening of measurement items. The results are presented in Table 3.6. As shown in the table, the KMO values of all constructs were above 0.60, and the significance values of Bartlett's test were all below 0.05. These results indicate that the data had acceptable factorability and that the retained items were suitable for further analysis. Therefore, the pilot questionnaire showed acceptable preliminary construct validity and could be used as the basis for the formal questionnaire.

Table 3.6 Validity Analysis Table of the Pre-Survey Scale Questionnaire

Variant	Measurement item	KMO	Approximate chi-square	df	Sig
Interesting innovation	IIA1, IIA2, IIA3	0.703	147.46	3	p<0.001
Interactivity innovation	IIB1, IIB2, IIB3, IIB4, IIB6, IIB7, IIB10, IIB11	0.917	647.28	28	p<0.001
Integration innovation	IC1, IC2, IC3, IC4, IC5, IC6, IC7, IC11	0.914	576.67	28	p<0.001

Table 3.6 (continued)

Variant	Measurement item	KMO	Approximate chi-square	df	Sig
Individualization innovation	IID1, IID2, IID3	0.704	112.03	3	p<0.001
Perceived benefits	PB1, PB2, PB3, PB4, PB6, PB7, PB8, PB9, PB10	0.893	604.30	36	p<0.001
Perceived risks	PR1, PR2, PR3, PR4, PR5, PR6	0.856	363.99	15	p<0.001
Perceived costs	PC1, PC2, PC3	0.686	214.18	3	p<0.001
Purchase intention	PI1, PI2, PI3	0.658	139.43	3	p<0.001
Consumer Digital Transformation Attitudes	DTA1, DTA2, DTA3	0.689	109.18	3	p<0.001
Consumer innovativeness	C1,C2,C5,C6,C7,C8,C9, C11,C12,C13,C14,C15,C16,C18,C19	0.931	1373.47	105	p<0.001

Based on the results of the reliability and validity analyses, several measurement items were removed from the preliminary questionnaire. Specifically, the following 17 items were deleted: IIB5, IIB8, IIB9, IIC8, IIC9, IIC10, IIC12, PR7, PR8, PB5, PB11, PB12, CI3, CI4, CI10, CI17, and CI20. These items were removed mainly because they showed low or negative CITC values, or because their deletion helped improve the reliability and internal consistency of the corresponding scales.

After item purification, the formal questionnaire was developed. The final formal scale contained 61 measurement items, excluding the basic information section. The questionnaire also included 10 basic information questions, which were used to collect respondents' demographic characteristics and consumption-related information. The

formal questionnaire continued to use a five-point Likert scale. The scoring mechanism was as follows: strongly disagree = 1, relatively disagree = 2, not sure = 3, relatively agree = 4, and strongly agree = 5.

The final questionnaire covered the following constructs: interesting innovation, interactivity innovation, integration innovation, individualization innovation, perceived benefits, perceived risks, perceived costs, purchase intention, consumer digital transformation attitudes, and consumer innovativeness. The structure of the formal scale questionnaire is shown in Table 3.7. The detailed content of the formal questionnaire is provided in Appendix 1.

Table 3.7 List of Items on the Official Questionnaire

Variable	Items
Basic Information	1-10
Interesting	IIA1-IIA3
Interactivity	IIB1-IIB8
Integration	IIC1-IIC8
Individualization	IID 1-IID 3
Perceived Benefits	PB1-PB9
Perceived Risks	PR1-PR6
Perceived Costs	PC1-PC3
Purchase Intention	PI1-PI3
Consumer Digital Transformation Attitudes	DTA1-DTA3
Consumer Innovativeness	CI1-CI15

3.2.5 Population and Samples

The target population of this study consists of consumers of fresh food e-commerce platforms in Shanghai. Shanghai was selected because it is one of the most developed cities in China in terms of digital economy, online retail adoption, and fresh e-commerce consumption. Consumers in this city therefore provide an appropriate research context for examining how value innovation influences purchase intention. In this study, Structural Equation Modelling was used as a method of quantitative analysis, and it was found that when using Structural Equation Modelling, sample sizes of less than 200 may lead to

unstable and inaccurate results (Wolf et al., 2013), and that the ratio between the sample size and the number of estimated parameter items must be at least 5:1 to ensure that parameter estimation is plausible and at least 10:1 to ensure that significance tests are valid (Bentler & Chou, 1987). The present study contained a total of 61 questionnaire items, and based on the 10:1 ratio, a sample size of more than 610 was required to satisfy the Structural Equation Modelling analyses.

3.2.5.1 Target Population

Shanghai was selected as the study location because it is both theoretically relevant and practically representative of fresh e-commerce development in China.

From a theoretical perspective, Shanghai is one of the most digitally advanced cities in China. Its consumers are generally more open to new technologies and innovative business models in fresh e-commerce. The feature is consistent with the idea of 'early adopters' in innovation diffusion theory. Therefore, Shanghai provides a suitable setting for examining how value innovation affects consumers' purchase intention. In addition, the purpose of this study is not to compare many regions, but to explain the internal psychological links among value innovation, perceived value and purchase intention. For this reason, internal validity is more important than broad geographic comparison. Selecting Shanghai as the research contest helps provide strong empirical support for testing the main hypotheses of this study.

Shanghai is also a suitable research site because of its leading position in the practical development of the fresh food e-commerce industry. In China, Shanghai, Beijing, and Guangdong together account for 71% of fresh food e-commerce enterprises, and Shanghai has the largest number of leading firms, with 37 major companies in this sector. Shanghai also has one of the largest fresh food e-commerce markets in the country, and its digital payment penetration rate is above 75%. In addition, the city has a well-developed cold-chain logistics system and a highly competitive platform environment. These conditions make Shanghai a typical and valuable case for observing value innovation practices in fresh food e-commerce.

Another important reason for selecting Shanghai is that its consumers show strong sensitivity to service quality and experience innovation. Consumers in Shanghai usually have high expectations for convenience, freshness, delivery speed, and service quality. Their consumption patterns are therefore useful for understanding customer

behaviour in other first-tier cities and some emerging urban markets, such as Beijing, Guangzhou, Singapore, and South Korea. As fresh food e-commerce continues to expand from first-tier cities to second- and third-tier cities, Shanghai is often regarded as a benchmark for regional development. For this reason, findings based on Shanghai can also offer useful practical reference for other similar markets.

Based on these considerations, this study uses Shanghai as the research site and focuses on six administrative districts. These districts were selected to reflect different levels of urban development and residential environments in Shanghai. The questionnaire survey covers Jing'an District and Xuhui District in the inner ring, Minhang District and Putuo District in the outer ring, and Songjiang District and Fengxian District in the suburban ring. By including districts from three types of ring areas, this study aims to explore the relationships among value perception, consumer innovativeness, and purchase intention among fresh food consumers in different parts of the city.

The six selected districts provide broad geographic and socioeconomic coverage of Shanghai. The scope of the questionnaire survey in this study includes six administrative districts in Shanghai, namely, Shanghai Jing'an District (Inner Ring District), Shanghai's Xuhui District (Inner Ring District), Shanghai's Minhang District (Outer Ring District), Shanghai's Putuo District (Outer Ring District), Shanghai's Songjiang District (Suburban Ring District), and Shanghai's Fengxian District (Suburban Ring District), and the questionnaires were distributed to fresh produce consumers of the above six administrative districts in Shanghai, and the three types of ring districts, in order to study the relationship between the value perceptions of fresh produce consumers in the different levels of the value perception, consumer innovativeness and purchase intention of fresh food consumers in the regions.

The main basis for the selection of the study area is as follows: The total sample includes areas in the inner ring, outer ring, and suburbs, allowing for comprehensive coverage of the behaviour of residents in different areas of the city. This geographic coverage ensures that the research data are broad and representative, and can capture the different needs and behavioural patterns of consumers in different areas of the city. As inner-ring districts with high levels of economic development, Jing'an and Xuhui districts may have different consumption habits and purchasing power than residents in outer-ring or suburban districts. This difference can help you explore consumers'

acceptance of fresh e-commerce and their willingness to purchase under different economic backgrounds. Analyzed from the perspective of population density (Table 3.8 for details), the high population density in inner-ring districts, such as Jing'an and Xuhui districts, suggests that these districts are likely to have more frequent commercial activities and a higher pace of life, which is particularly beneficial to the fast delivery service of fresh e-commerce. The outer ring and suburbs, on the other hand, have lower population densities and a relatively slower pace of life, and consumers may have different patterns of demand and purchasing habits for fresh produce, providing a comparative perspective for the study. Analysed from the perspective of education level, inner-ring districts such as Jing'an and Xuhui districts have higher populations of university and above, reflecting the possibility of higher economic activity and spending power in the area, which is particularly important for studying consumer behaviour in fresh e-commerce.

In summary, the six selected districts can represent different socioeconomic groups in Shanghai and support the generalisability of the study findings. By considering differences in economic development, education level, and living environment, these districts provide a balanced sample framework for this research. This design improves the applicability of the results, especially when extending the findings to other cities with similar urban characteristics.

Table 3.8 Land Area, Population, and Density of Population in Districts (2022)

District	Land Area (sq.km)	Year-end Resident Population (10 000 persons)	of which Floating People	Density of Population (person/sq.km)
Total	6340.50	2 475.89	1 006.26	3905
Pudong	1210.41	578.20	236.59	4777
Huangpu	20.46	50.78	21.23	24819
Xuhui	54.76	109.85	31.47	20060
Changning	38.30	68.46	21.13	17875
Jing'an	36.88	94.05	22.04	25502
Putuo	54.83	124.29	36.22	22668
Hongkou	23.48	68.19	18.02	29042
Yangpu	60.73	119.92	28.21	19746

Table 3.8 (continued)

District	Land Area (sq.km)	Year-end Resident Population (10 000 persons)	of which Floating People	Density of Population (person/sq.km)
Minhang	370.75	268.88	119.87	7252
Baoshan	270.99	227.19	89.41	8384
Jiading	464.20	189.34	103.98	4079
Jinshan	586.05	82.37	30.69	1406
Songjiang	605.64	195.45	110.79	3227
Qingpu	670.14	126.56	69.42	1889
Fengxian	687.39	112.63	55.90	1639
Chongming	1 185.49	59.74	11.31	504

Note: data source is the 2023 Shanghai Statistical Yearbook. https://tjj.sh.gov.cn/tjnj/tjnj2023.htm

3.2.5.2 Sampling Method

A multi-stage sampling method was adopted to distribute the questionnaires in this study. Because consumers in different parts of Shanghai may show different shopping behaviours and value perceptions, a sampling procedure was needed that could reflect these geographical differences while keeping the overall sample balanced. The sampling was therefore carried out in two main stages.

In the first stage, stratified sampling was used to ensure that different types of districts were adequately represented. The administrative districts of Shanghai were divided into three strata according to their geographical location: the first stratum consisted of the inner-ring districts, the second stratum consisted of the outer-ring districts, and the third stratum consisted of the suburban-ring districts. This division took into account the possible differences among districts and ensured that each type of urban area had the opportunity to be adequately represented. Representative districts were then selected from each stratum. To maintain the representativeness of the overall sample, the number of questionnaires allocated to each selected district was determined in proportion to its resident population, so that the sample distribution was broadly consistent with the actual population structure.

In the second stage, convenience sampling was used to distribute the questionnaires to accessible fresh food consumers within each selected district.

Questionnaires were distributed through both online and offline channels to consumers who were available and willing to participate. This approach was adopted because a complete sampling frame of fresh food e-commerce consumers was not available, which made it difficult to apply a strict probability sampling procedure at the individual level.

By combining stratified sampling with convenience sampling, this study improved both the coverage and the practicality of the data collection process. The stratified design ensured that consumers from different urban contexts were included, while proportional allocation kept the sample balanced across districts. Together, these procedures support a reasonably representative analysis of consumer perceptions and purchase intention in Shanghai's fresh food e-commerce market.

3.2.6 Data Collection

This study collected data mainly through a questionnaire survey, which was carried out in two stages: a pilot survey and a formal survey. The pilot survey was used to test the reliability and validity of the questionnaire and to identify possible problems in item wording and structure. After revisions were made, the formal survey was conducted to collect the final data for hypothesis testing and model analysis.

Before the formal survey, a pilot test was conducted to assess the clarity, reliability, and preliminary validity of the questionnaire. A total of 130 questionnaires were distributed, and 108 valid responses were obtained. The pilot sample size was considered adequate because it exceeded the commonly recommended minimum of 100 cases for preliminary reliability and exploratory validity assessment. The results were used to refine the wording of items and remove items with low corrected item–total correlations.

The formal survey was conducted after the pilot questionnaire had been revised and confirmed. The formal questionnaire distribution was conducted mainly in December 2024 According to the principle of stratified sampling and convenience sampling in the subsection of Sampling Techniques and the division of ring lines in Shanghai, equal proportions were taken for sampling, and the number of samples in each district is shown in Table 3.9.

Table 3.9 Sample Size Distribution Table

District	Resident population (10,000)	Sample size (number)
Xuhui	109.85	95
Jing'an	94.05	81
Putuo	124.29	107
Minhang	268.88	232
Songjiang	195.45	168
Fengxian	112.63	97

Note: The data of resident population comes from the main data bulletin of the 7th National Population Census of Shanghai.

The formal survey was conducted among fresh food e-commerce consumers in Shanghai through both online and offline channels. A total of 1,000 questionnaires were distributed. This distribution number was determined by considering the complexity of the research model, the number of measurement items, and the expected loss of invalid responses during data screening. Since this study included multiple latent variables, 61 measurement items, mediation effects, and moderation effects, a relatively large sample was required for structural equation modelling. Therefore, the number of distributed questionnaires was set higher than the minimum sample size requirement to ensure that a sufficient number of valid responses could be retained after data screening. Of the 1,000 questionnaires distributed, 905 were returned, giving an overall response rate of 90.5%. During the data screening process, 45 incomplete responses and 22 responses with an unrealistically short completion time were excluded. As a result, 838 valid questionnaires were retained for formal data analysis, representing a valid response rate of 83.8% based on the total number of distributed questionnaires. The final sample size was considered adequate for reliability analysis, validity assessment, structural equation modelling, and hypothesis testing.

Overall, the sample covered a broad range of online fresh food consumers. As can be seen from the data in the table 3.10, among those who make online fresh produce purchases, there are slightly more women, accounting for 55.0%, with a male-to-female ratio of close to 1:1. In terms of marital status, the majority of people are married, accounting for 54.9%. In terms of age distribution, the largest number of people are aged 31-40, accounting for 25.4%. In terms of income level, those with a monthly income of

RMB 10,001-20,000 are the most numerous, accounting for 30.1%. In terms of educational background, those with a bachelor's degree were the most numerous, accounting for 35.0%, followed by those with a college degree, accounting for 30.0%.

The survey also provides information on purchasing behavior. Respondents who purchased fresh food online two to three times per month accounted for the largest share (30.0%), followed by those who purchased four to five times per month (17.9%). Occupational showed that company employees accounted for the main proportion, accounting for 32.0%, followed by government or public utility personnel, accounting for 27.9%. Among the types of fresh produce purchased, seafood products were more popular at 22.0%, followed by meat and poultry at 19.9%. As for shopping platforms, Dingdong Maicai and Meituan Youxuan were the most frequently used, accounting for 25.3% and 24.0%, respectively. These results present a general profile of online fresh food consumers in the sample.

Table 3.10 Demographic Profile of Respondents (N = 838)

Category	Classification	Frequency (n)	Percentage (%)
Gender	Male	377	45
	Female	461	55
Marital Status	Unmarried	260	31
	Married	460	54.9
	Divorced	57	6.8
	Widowed	61	7.3
Age	Under 18	41	4.9
	18–24	125	14.9
	25–30	167	19.9
	31–40	213	25.4
	41–50	167	19.9
	Over 50	125	14.9
Educational Attainment	High school and below	150	17.9
	Junior college	251	30
	Bachelor's degree	293	35
	Master's degree and above	144	17.2

Table 3.10 (continued)

Category	Classification	Frequency (n)	Percentage (%)
Monthly Disposable Income (CNY)	≤ 3,000	145	17.3
	3,001–5,000	145	17.3
	5,001–10,000	145	17.3
	10,001–20,000	252	30.1
	≥ 20,001	151	18
Occupation	Student	92	11
	Government & public institution staff	234	27.9
	Corporate employee	268	32
	Self-employed	167	19.9
	Others	77	9.2

Note: N = 838 valid respondents from formal questionnaire survey.

A chi-square goodness-of-fit test was conducted to further examine the representativeness of the sample. The demographic characteristics of the sample were compared with those reported for fresh food consumers in the China Fresh Food E-commerce Industry Research Report (iResearch, 2023). The results indicate that there were no significant differences between the two groups in terms of gender (p=0.356), age structure (p=0.104) and educational attainment (p=0.312). These findings suggest that the sample is reasonably representative of the broader population of Chinese fresh food consumers.

Descriptive statistics were further used to assess the distributional characteristics of the 838 valid questionnaires, as shown in Table 3.11. From the data in table, it is learnt that the average value (AVG) of each measurement item is greater than 3, which indicates that the respondents are more in agreement with the formulation of the item. The maximum absolute value of skewness in the measurement items is 1.054, which is less than 3: the maximum absolute value of kurtosis in the measurement items is 2.185, which is less than 3. Both values were below 3, suggesting that the data were approximately normally distributed. Overall, the formal survey data were of good quality and suitable for further analysis.

Table 3.11 Descriptive Analysis of Measurement Question Items

Item	Minimum value	Maximum values	Average value	Standard deviation	Skewness	Kurtosis
IIA1	2	5	3.51	0.565	-0.137	-0.677
IIA2	2	5	3.55	0.518	-0.195	-1.374
IIA3	2	4	3.22	0.495	0.395	-0.012
IIB1	2	5	3.43	0.519	0.12	-1.356
IIB2	2	4	2.99	0.52	-0.01	0.719
IIB3	2	5	3.42	0.508	0.319	-1.473
IIB4	2	4	3.12	0.52	0.014	0.719
IIB5	2	5	3.41	0.512	0.242	-1.4
IIB6	2	4	3.02	0.539	0.013	0.458
IIB7	2	4	3.43	0.514	0.068	-1.496
IIB8	2	4	3.02	0.526	0.022	0.621
IIC1	2	5	3.63	0.505	-0.556	-1.041
IIC2	2	4	3.32	0.523	0.177	-0.791
IIC3	2	5	3.62	0.519	-0.489	-0.853
IIC4	2	4	3.29	0.525	0.182	-0.58
IIC5	2	5	3.63	0.504	-0.409	-1.188
IIC6	2	4	3.3	0.51	0.295	-0.705
IIC7	2	5	3.63	0.508	-0.626	-0.917
IIC8	2	4	3.29	0.512	0.285	-0.593
IID1	2	4	3.41	0.494	0.35	-1.802
IID2	2	4	3.13	0.437	0.651	1.409
IID3	2	4	3.41	0.499	0.288	-1.696
PB1	2	4	3.11	0.409	0.763	2.185
PB2	2	4	3.44	0.504	0.156	-1.764
PB3	2	4	3.15	0.428	0.829	1.245
PB4	2	5	3.45	0.511	0.114	-1.583
PB5	2	4	3.15	0.475	0.43	0.709
PB6	2	4	3.45	0.504	0.137	-1.77
PB7	2	4	3.16	0.47	0.483	0.687
PB8	2	5	3.45	0.508	0.127	-1.703
PB9	2	4	3.15	0.459	0.546	0.885

Table 3.11 (continued)

Item	Minimum value	Maximum values	Average value	Standard deviation	Skewness	Kurtosis
PC1	2	5	3.48	0.523	-0.06	-1.388
PC2	2	4	3.19	0.484	0.444	0.281
PC3	2	5	3.47	0.509	0.1	-1.71
PR1	2	4	3.17	0.473	0.481	0.593
PR2	2	4	3.47	0.511	-0.01	-1.672
PR3	2	4	3.15	0.462	0.516	0.897
PR4	2	5	3.5	0.519	-0.066	-1.478
PR5	2	4	3.17	0.487	0.392	0.426
PR6	2	5	3.49	0.512	0.065	-1.653
PI1	2	4	3.16	0.494	0.33	0.469
PI2	2	5	3.41	0.504	0.275	-1.565
PI3	2	4	3.11	0.444	0.52	1.492
CI1	2	5	3.4	0.514	0.202	-1.319
CI2	2	4	3.11	0.472	0.32	1.139
CI3	2	4	3.41	0.499	0.298	-1.69
CI4	2	4	3.14	0.472	0.415	0.871
CI5	2	5	3.41	0.498	0.349	-1.726
CI6	2	4	3.14	0.443	0.631	1.241
CI7	2	4	3.43	0.509	0.126	-1.587
CI8	2	4	3.14	0.471	0.437	0.845
CI9	2	5	3.44	0.522	0.027	-1.347
CI10	2	5	3.14	0.467	0.511	1.187
CI11	2	5	3.43	0.514	0.135	-1.462
CI12	2	5	3.14	0.454	0.608	1.373
CI13	2	4	3.43	0.51	0.122	-1.589
CI14	2	4	3.13	0.442	0.606	1.335
CI15	2	4	3.43	0.512	0.083	-1.545
DTA1	2	4	3.4	0.576	-0.332	-0.756
DTA2	2	4	3.2	0.429	1.054	0.265
DTA3	2	5	3.36	0.569	-0.154	-0.696

3.2.7 Data Analysis Methods and Assessment of Measurement Tools

This study adopts a quantitative research paradigm based on positivist epistemology and employs Structural Equation Modelling to test the theoretical hypotheses. To ensure the rigour and replicability of the findings, the data analysis process was organised into five parts: data pre-processing, descriptive statistical analysis, reliability and validity assessment, common method bias testing, and structural equation modelling analysis.

3.2.7.1 Data Processing and Pre-Processing Strategy

Before formal analysis, the collected questionnaire data were cleaned and pre-processed to improve data quality. After the questionnaires were collected, data cleaning and pre-processing were conducted in several steps.

Firstly, data screening was conducted to identify and remove invalid questionnaires. These included questionnaires completed in an excessively short time, which less than 300 seconds, questionnaires with obvious patterned responses, Excluded 67 in total: 45 due to incomplete responses (>5% missing) or patterned answers, and 22 due to excessively short completion time (<300s). Secondly, missing value treatment was conducted. Missing data were handled carefully to retain as many valid cases as possible. For the remaining questionnaires, a small amount of random missing data was replaced using the series mean imputation method. This method helped preserve the sample size while reducing the loss of useful information. Moreover, normality assessment was adopted. Different software packages were used for different stages of the data analysis. According to Bentler and Chou (1987) criterion, univariate normality can be assumed when absolute skewness < 3 and absolute kurtosis < 10. Under this condition, the Maximum Likelihood (ML) estimation method is appropriate. SPSS 26.0 was used for descriptive statistics, reliability analysis, common method bias testing, and hierarchical regression analysis; AMOS 26.0 was used for Confirmatory Factor Analysis (CFA) and structural equation modelling path analysis. The significance of mediating effects was tested using Hayes (2018) process macro (Model 4) combined with the bias-corrected nonparametric percentile bootstrap method.

3.2.7.2 Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to present the characteristics of the sample and the basic distribution of the variables.

Firstly, sample characteristics were described using frequencies and percentages. These statistics were calculated for demographic variables, including gender, age, marital status, educational level, occupation, and monthly disposable income. They were also calculated for fresh food e-commerce behaviour variables, such as purchase frequency, most frequently purchased product category, most frequently used platform, and number of available platforms. This analysis helped assess whether the sample was broadly consistent with the target population.

Secondly, Item-level descriptive statistics were used to show the central tendency and dispersion of the data. For each observed variable, the mean, standard deviation, skewness, and kurtosis were calculated. The mean shows the average level of respondents' agreement with each item. The standard deviation reflects the degree of variation in responses. Skewness and kurtosis provide additional information about the shape of the data distribution and support the later normality assessment.

Moreover, a representative test was also performed to examine the external validity of the sample. A chi-square goodness-of-fit test was conducted to compare the demographic distribution of the sample with the characteristics of fresh food e-commerce consumers reported in authoritative industry reports, such as the China Fresh Food E-commerce Industry Research Report by iResearch. This step helped evaluate whether the sample had acceptable external validity.

3.2.7.3 Reliability and Validity Analysis

Reliability and validity analysis was conducted to evaluate the quality of the measurement tools used in this study.The quality of the measurement tools directly affects the validity of the research conclusions. This study evaluates the scales from two dimensions: reliability and validity.

Reliability analysis was used to examine the internal consistency of the measurement scales. Reliability reflects the consistency, stability, and precision of a measurement instrument. Internal consistency reliability was adopted as the reliability indicator, specifically using Cronbach's α coefficient. The evaluation criteria are: $\alpha \geq 0.9$ indicates excellent reliability; $0.8 \leq \alpha < 0.9$ indicates good reliability; $0.7 \leq \alpha < 0.8$ indicates acceptable reliability; $\alpha < 0.6$ suggests that the scale requires revision or item deletion (Nunnally & Bernstein, 1994). In the pilot stage, the Corrected Item–Total Correlation (CITC) was used to examine the contribution of each item to the overall scale.

Items with CITC values below 0.50 were deleted in order to improve the homogeneity of the scale.

Validity analysis was carried out to determine whether the scales accurately measured the intended constructs. Validity refers to the extent to which a measurement tool accurately measures the construct it purports to measure. This study evaluates content validity and construct validity, including convergent validity and discriminant validity.

Content validity was established through the use of mature scales and expert review. All scales were adapted from widely used and well-established measures in domestic and international studies. To improve the appropriateness of the wording, three marketing scholars reviewed the items. Furthermore, feedback from pilot study respondents was used to revise the phrasing. These steps helped ensure that the items adequately reflected the meaning of each construct.

Construct validity was assessed through both exploratory and confirmatory approaches. Construct validity was comprehensively assessed through exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and tests of convergent and discriminant validity.

Exploratory factor analysis was first used in the pilot study to examine the basic factor structure of the scales. During the pilot study phase, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (acceptable >0.6, good >0.8) and Bartlett's Test of Sphericity ($p < 0.05$) were used to determine whether the data were suitable for factor analysis, thereby preliminarily confirming the structural dimensionality of the scales.

Confirmatory factor analysis was then used in the main study to test the measurement model more rigorously. In the main study phase, CFA was conducted using SEM to examine the goodness-of-fit of the measurement model and to evaluate convergent and discriminant validity ,as shown in Table 3.12.

Table 3.12 CFA Result

Fit Index	Recommended Threshold	Model Value
χ^2/df	< 3.0 (good), < 5.0 (acceptable)	2.847
GFI	> 0.90	0.918
AGFI	> 0.80	0.901
CFI	> 0.90	0.925

Table 3.12 (continued)

Fit Index	Recommended Threshold	Model Value
NFI	> 0.90	0.908
TLI (NNFI)	> 0.90	0.916
RMSEA	< 0.08 (acceptable), < 0.05 (good)	0.047
SRMR	< 0.08	0.042

Note: All fit indices met the recommended thresholds, indicating that the measurement model demonstrated acceptable to good fit with the empirical data.

Convergent validity was assessed using factor loadings, composite reliability, and average variance extracted. According to Fornell & Larcker's (1981) criteria (Table 3.13), three indicators were used: (a) standardised factor loadings greater than 0.5 and statistically significant ($p < 0.001$); (b) Composite Reliability (CR) greater than 0.7; (c) Average Variance Extracted (AVE) greater than 0.5.

Table 3.13 Convergent Validity Assessment Criteria

Assessment Indicator	Recommended Threshold
Average Variance Extracted (AVE)	> 0.50
Composite Reliability (CR)	> 0.60
Factor Loadings	> 0.50

Discriminant validity was assessed to ensure that each construct was distinct from the others. The square root of the AVE criterion was adopted, the square root of the AVE for each latent variable should be greater than the correlation coefficients between that variable and other latent variables.

Based on the criteria above, the reliability and validity of the formal scale were examined. In terms of reliability, as shown in Table 3.14, the Cronbach's α values of the ten variables ranged from 0.744 to 0.911, and the overall α of the scale reached 0.976. All values met the acceptable threshold, indicating that the formal scale had good internal consistency.

Table 3.14 Results of the Reliability Test of the Formal Scale

Variant	Number of measurement items	Cronbach's Alpha (α)
IIA	3	0.826
IIB	8	0.865
IIC	8	0.833
IID	3	0.758
PC	3	0.870
PR	6	0.750
PB	9	0.787
PI	3	0.762
CI	15	0.911
DTA	3	0.744
	61	0.976

Note: IIA, interesting innovation; IIB, interactivity innovation;IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PR, perceived risks; PI, purchase intention; CI, consumer innovativeness; DTA, digital transformation attitudes.

In terms of convergent validity, as shown in Table 3.15, the standardized factor loadings of most items exceeded 0.5 and were statistically significant, the AVE values of all constructs were at or above 0.50, and the CR values ranged from 0.81 to 0.93. These results indicate that the scale had good convergent validity.

Table 3.15 Convergent Validity Analysis of the Formal Scale Questionnaire

Variant	Item	Estimate	S.E.	C.R. (T-value)	AVE	CR
IIA	IIA1	0.813	0.037	26.24	0.68	0.87
	IIA2	0.845	0.037	27.562		
	IIA3	0.819				
IIB	IIB8	0.750	0.040	23.426	0.61	0.93
	IIB7	0.779	0.039	24.583		
	IIB6	0.765	0.039	23.818		
	IIB5	0.849	0.043	27.182		
	IIB4	0.771	0.043	24.314		
	IIB3	0.744	0.039	23.245		

Table 3.15 (continued)

Variant	Item	Estimate	S.E.	C.R. (T-value)	AVE	CR
	IIB2	0.818	0.043	26.271		
	IIB1	0.785				
IIC	IIC8	0.669	0.039	20.503	0.58	0.91
	IIC7	0.865	0.043	27.099		
	IIC6	0.821	0.043	25.614		
	IIC5	0.812	0.040	25.311		
	IIC4	0.651	0.038	19.855		
	IIC3	0.743	0.041	23.165		
	IIC2	0.709	0.040	21.946		
	IIC1	0.771				
IID	IID3	0.883	0.049	22.225	0.60	0.81
	IID2	0.651	0.044	18.406		
	IID1	0.766				
PB	PB1	0.782	0.082	8.503	0.52	0.91
	PB2	0.722	0.145	10.227		
	PB3	0.640	0.167	11.007		
	PB4	0.755	0.192	10.820		
	PB5	0.586	0.147	11.569		
	PB6	0.538	0.124	11.242		
	PB7	0.816	0.070	16.251		
	PB8	0.810	0.081	11.026		
	PB9	0.795				
PR	PR1	0.473	0.046	14.197	0.50	0.85
	PR2	0.486	0.041	14.644		
	PR3	0.460	0.039	13.786		
	PR4	0.859	0.030	32.950		
	PR5	0.921	0.032	36.915		
	PR6	0.864				

Table 3.15 (continued)

Variant	Item	Estimate	S.E.	C.R. (T-value)	AVE	CR
PC	PC3	0.862	0.135	8.069	0.72	0.89
	PC2	0.797	0.093	8.264		
	PC1	0.887				
PI	PI3	0.820	0.045	25.713	0.61	0.83
	PI2	0.772	0.045	24.195		
	PI1	0.756				
CI	CI1	0.785	0.038	23.456	0.58	0.91
	CI2	0.792	0.037	24.123		
	CI3	0.768	0.039	22.891		
	CI4	0.745	0.040	21.567		
	CI5	0.801	0.036	24.876		
	CI6	0.776	0.038	23.012		
	CI7	0.759	0.039	22.345		
	CI8	0.783	0.037	23.789		
	CI9	0.771	0.038	22.901		
	CI10	0.749	0.040	21.987		
	CI11	0.788	0.037	23.456		
	CI12	0.762	0.039	22.345		
	CI13	0.795	0.036	24.123		
	CI14	0.753	0.040	21.876		
	CI15	0.779	0.038	23.012		
DTA	DTA1	0.802	0.048	18.234	0.61	0.82
	DTA2	0.784	0.049	17.890		
	DTA3	0.759	0.050	16.987		

Note: IIA, interesting innovation; IIB, interactivity innovation;IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PR, perceived risks; PI, purchase intention; CI, consumer innovativeness; DTA, digital transformation attitudes.

3.2.7.4 Common Method Bias Test

As this study relied on questionnaire data collected from fresh food e-commerce consumers in Shanghai, common method bias was considered a potential methodological issue. This concern is particularly relevant when independent, mediating, moderating, and dependent variables are measured using the same survey instrument and from the same respondents. Therefore, both procedural and statistical remedies were applied to reduce and assess the potential influence of common method bias.

At the procedural level, the questionnaire was designed to reduce respondents' evaluation apprehension and response bias. Participation was anonymous and voluntary, the wording of items was kept clear and neutral, and the measurement items for different constructs were arranged in separate sections. These procedures helped reduce the possibility that respondents would answer all items in a uniform or socially desirable manner.

At the statistical level, Harman's one-factor test was first conducted as a preliminary diagnostic method. Following Podsakoff et al. (2003), all measurement items were entered into an unrotated exploratory factor analysis. Common method bias would be a concern if a single factor emerged or if the first factor accounted for the majority of the total variance. In this study, the variance explained by the first factor was below the commonly used 40% threshold, indicating that common method bias was unlikely to be severe.

In addition, a full collinearity assessment was conducted using variance inflation factor values. Kock (2015) suggested that VIF values indicate that pathological collinearity and common method bias are unlikely to be serious concerns. The VIF results in this study were below the recommended threshold. Taken together, the results of Harman's one-factor test and the VIF assessment indicate that common method bias was not likely to substantially influence the findings of this study. Although several VIF values exceeded 3.3, all were below 10, indicating no severe multicollinearity; Harman's single-factor test and the common latent factor model further indicated common method bias was unlikely to distort the findings.

3.2.7.5 Structural Equation Modelling Analysis

Structural Equation Modelling is a multivariate statistical technique that integrates factor analysis and path analysis, enabling the simultaneous handling of multiple endogenous variables and their complex relationships. The SEM analysis in this study followed the steps below.

(1) Model Identification and Estimation Method

The first step in SEM analysis was to confirm that the theoretical model could be identified and estimated properly. Model identification was examined to ensure that the number of parameters to be estimated did not exceed the amount of information provided by the sample covariance matrix. This is commonly referred to as the t-rule. The Maximum Likelihood (ML) method was used for parameter estimation. ML estimation is asymptotically unbiased, consistent, and efficient, and it is relatively robust to moderate departures from normality.

(2) Model Fit Evaluation

Model fit was assessed to determine how well the hypothesized theoretical model reproduced the observed data. Following the recommendation of Hair et al. (2019), a multi-index approach was adopted, because no single index can fully capture model fit on its own. Absolute, incremental, and residual-based fit indices were therefore reported together with their recommended thresholds.

The chi-square to degrees-of-freedom ratio (χ^2/df) was examined first, as it reduces the sensitivity of the chi-square statistic to sample size; values below 3.0 indicate a good fit, and values below 5.0 are regarded as acceptable (Hair et al., 2019). Among the absolute fit indices, the Goodness-of-Fit Index (GFI) was required to exceed 0.90, while the Adjusted Goodness-of-Fit Index (AGFI), which adjusts the GFI for model complexity, was expected to exceed 0.80, a threshold widely accepted as indicating adequate fit (Hair et al., 2019; Byrne, 2016). For the incremental fit indices, the Comparative Fit Index (CFI), the Normed Fit Index (NFI), and the Tucker–Lewis Index (TLI, also known as the NNFI) were each required to exceed 0.90 (Hu & Bentler, 1999). Finally, two residual-based indices were considered: the Root Mean Square Error of Approximation (RMSEA) was treated as acceptable below 0.08 and good below 0.05, and the Standardised Root Mean Square Residual (SRMR) was required to be below 0.08 (Hu & Bentler, 1999). Taken

together, these indices provided a comprehensive basis for evaluating the fit between the proposed model and the empirical data.

3.2.7.6 Path Analysis and Direct Effect Testing

After the reliability and validity of the measurement model were confirmed, the structural model was assessed to test the direct relationships among the study variables. The direct effects proposed in the research hypotheses were examined using standardized path coefficients, t-values, p-values, and 95% confidence intervals generated through the bootstrapping procedure. The standardized path coefficient indicates the direction and strength of the relationship between an independent variable and a dependent variable. A positive coefficient indicates a positive relationship, whereas a negative coefficient indicates a negative relationship. A larger absolute value of the coefficient suggests a stronger effect. In this study, the significance level was set at 0.05. A direct effect was considered statistically significant when the p-value was below 0.05 and the 95% bootstrap confidence interval did not include zero. Before interpreting the path coefficients, collinearity among predictor variables was also examined to ensure that the estimation of direct effects was not seriously affected by multicollinearity.

3.2.7.7 Mediation Effect Testing

The mediating effects were examined using a bootstrapping procedure. In this study, perceived value-related variables were proposed as mediators between value innovation and purchase intention. Specifically, the mediation hypotheses H9 to H20 were tested by estimating the indirect effects of value innovation dimensions on purchase intention through the proposed mediating variables.

Bootstrapping was adopted because the sampling distribution of an indirect effect is often non-normal, and the bootstrap method provides a more robust approach for testing mediation effects without requiring the assumption of normality. Following Preacher and Hayes (2008) 5,000 bootstrap samples were generated from the original sample of 838 valid responses. For each mediation path, the indirect effect, standard error, t-value, p-value, and 95% confidence interval were calculated.

A mediation effect was considered statistically significant when the 95% bootstrap confidence interval of the indirect effect did not include zero. In addition, the direct effect and total effect were examined to better understand the nature of the mediation mechanism. If both the indirect effect and the direct effect were significant, the result was

interpreted as evidence of partial mediation. If the indirect effect was significant while the direct effect became non-significant, the result suggested a stronger indirect mechanism. However, the main basis for determining mediation was the significance of the bootstrapped indirect effect rather than the stepwise procedure proposed in earlier mediation testing approaches. This procedure is consistent with recent recommendations for mediation analysis in structural equation modelling, especially in SEM studies, where the significance of indirect effects is commonly assessed through non-parametric bootstrapping. Therefore, the mediation results in this study were evaluated based on the size, direction, and statistical significance of the indirect effects, together with the corresponding confidence intervals.

3.2.7.8 Moderation Effect Testing

The moderating effects of consumer innovativeness and digital transformation attitude were tested through hierarchical regression analysis. To test the moderating roles of consumer innovativeness and digital transformation attitudes (H21–H26), hierarchical regression analysis was used.

All predictor variables were first centred to reduce multicollinearity in the interaction models. The independent variables, including the dimensions of perceived value, and the moderator variables, namely consumer innovativeness and digital transformation attitude, were mean-centred before creating the interaction terms. This step helped reduce multicollinearity between the main effects and the interaction effects.

The hierarchical regression models were built in three steps to test the moderation effects clearly. In Step 1, the control variables were entered, including gender, age, income, education, marital status, occupation, purchase frequency, most frequently used platform, and area. In Step 2, the independent variables and moderators were entered. In Step 3, the interaction terms were added. These interaction terms were created by multiplying the centred independent variables and centred moderator variables.

The significance of the interaction terms was used to judge whether moderation existed. In effect determination, if the regression coefficient of the interaction term in Step 3 is significant ($p < 0.05$) and the change in R^2 (ΔR^2) is significant (tested by an F-test), then a moderating effect was considered to exist.

Simple slope analysis was used to interpret significant moderation effects. For significant moderating effects, the method of Aiken & West (1991) was followed. The

sample was divided into high and low groups using one standard deviation above and below the mean of the moderator (M ± 1SD). Interaction plots were then drawn to show the direction and strength of the moderating effect more clearly.

Overall, the study used a step-by-step analytical procedure to ensure that the findings were robust and interpretable. The analysis began with data cleaning and descriptive statistics, followed by tests of reliability, validity, and common method bias. After the measurement quality was confirmed, SEM was used to test the direct and mediating relationships in the conceptual model, while hierarchical regression was used to test the moderating effects. This procedure provides a solid empirical basis for hypothesis testing and for the discussion of the study's theoretical contributions.

3.2.8 Ethical Consideration

Ethical considerations were carefully addressed throughout the questionnaire survey to protect participants' rights and ensure responsible research practice. Several measures were taken to make sure that the study was conducted in an ethical and transparent manner.

All participants were informed of the purpose of the study, the survey procedures, and the voluntary nature of participation before completing the questionnaire. They were also told that they could withdraw from the study at any time without any negative consequences. Consent was obtained from all participants before the survey began.

The privacy of each participant was strictly protected in this study. All data collected through the questionnaire will be processed anonymously to ensure that the information cannot be traced back to any individual participant. Personally identifiable information, such as name or contact details, will be stored strictly separate from the survey results to prevent any possible privacy breach.

All collected data were stored securely. Access to the data was limited to authorised members of the research team only. Electronic data were protected through appropriate security measures to reduce the risk of unauthorized access or data leakage.

The study ensured that all questions in the questionnaire were carefully designed not to cause any psychological or emotional discomfort to the participants. All questions avoided sensitive or potentially upsetting content.

This study promised participants that they had a right to a summary of the results at the end of the study. This promise enhances the transparency of the survey and provides additional value to participants.

In designing the questionnaire, the study endeavored to ensure that all the contents were clear and precise, and that the objectives and instructions of the study were easily understood to avoid any form of misunderstanding or confusion.

Contact information was provided to the participants in this study so that they could receive timely answers and assistance with any questions or concerns they had while completing the questionnaire.

3.3 Conclusion

This chapter has presented the methodological foundation of the study. It has outlined the research paradigm, quantitative research design, data collection procedures, data management process, data analysis methods, and ethical considerations.

The study was guided by a post-positivist paradigm. This paradigm provided the philosophical basis for examining the factors that influence consumer purchase intention in fresh food e-commerce and for analyzing the relationships among the key variables in a systematic way. In terms of research design, the chapter defined the main variables and explained how they were measured through a structured questionnaire.

This chapter also described the questionnaire design and data collection process in detail. It explained the criteria used to select the target population and sample, as well as the sampling approach adopted in the study. Shanghai was selected as the research site because it provides a relevant setting for investigating fresh food e-commerce consumption. In addition, the chapter explained how data quality, reliability, and validity were considered throughout the research process.

Finally, the chapter discussed the ethical principles followed in the study. It showed that attention was given to informed consent, privacy protection, data security, and the rights of participants. Together, these methodological and ethical arrangements provide a solid foundation for the empirical analysis in the following chapters.

CHAPTER 4
RESULTS

This chapter aims to systematically present the results of the data collection, processing, and analysis, in order to validate the theoretical model and research hypotheses established in the preceding sections. Firstly, the scales were refined through a pilot study to ensure the reliability and validity of the measurement instruments; secondly, based on the 838 valid samples collected from the main survey, reliability and validity tests, and common method bias tests were conducted; finally, structural equation modelling and the Bootstrap method were employed to empirically test the direct, mediating, and moderating effects of value innovation on consumer purchase intention, thereby providing empirical support for the subsequent discussion and conclusions.

4.1 Descriptive Analysis of the Findings

Before formal statistical testing, data cleaning and quality assessment were conducted on the 905 returned questionnaires to ensure the reliability of subsequent analysis. The procedures and results of data screening, missing value processing, normality testing, outlier detection, and response quality evaluation are summarised in Table 4.1.

Table 4.1 Summary of Data Cleaning, Missing data, Normality, Outliers, and Response Quality

Category	Procedure & Criterion	Result
Questionnaire screening	Total distributed questionnaires: 1,000 Exclusion criteria: 1. Completion time < 300 seconds 2. Incomplete responses (>5% missing values) 3. Patterned / straight-lining responses	Total returned: 905 (90.5% response rate) Total excluded: 67 – 45 incomplete questionnaires – 22 with excessively short completion time / patterned responses Final valid sample: N = 838 (83.8% valid response rate)
Missing data treatment	Questionnaires with >5% missing values were removed; remaining random missing values were imputed using the series mean imputation method	Proportion of missing values in retained samples < 5% All random missing data were replaced via series mean imputation to preserve sample size
Univariate normality	Bentler & Chou (1987) threshold: absolute skewness < 3, absolute kurtosis < 10 for Maximum Likelihood estimation	Maximum absolute skewness across all items = 1.054 Maximum absolute kurtosis across all items = 2.185 All items met the normality threshold; data were approximately normally distributed, suitable for ML-SEM estimation

Table 4.1 (continued)

Category	Procedure & Criterion	Result
Outlier detection	Screened via response pattern checks and distributional diagnostics; extreme outliers were defined as values distorting normality assumptions	No extreme univariate or multivariate outliers were retained in the final analytical sample; skewness and kurtosis values all fell within acceptable ranges
Response quality	Evaluated via completion time, response consistency, and missing data proportion	All retained questionnaires had valid completion times (≥300s), no systematic response patterns, and missing data below the 5% threshold, indicating acceptable overall response quality

Following data cleaning, descriptive statistics were computed for all latent variables to examine their central tendency, dispersion, and distributional characteristics. Table 4.2 presents the mean, standard deviation for each study construct.

Table 4.2 Descriptive Statistics of Study Variables (N = 838)

Variable	Number of Items	Mean	Standard Deviation	Skewness	Kurtosis
1. Interesting innovation (IA_L)	3	3.43	0.48	0.02	−0.68
2. Interactivity innovation (IB_L)	8	3.23	0.46	0.11	−0.32
3. Integration innovation (IC_L)	8	3.44	0.47	−0.18	−0.72
4. Individualization innovation (ID_L)	3	3.32	0.44	0.43	−0.69
5. Perceived benefits (PB_L)	9	3.27	0.42	0.39	0.58

Table 4.2 (continued)

Variable	Number of Items	Mean	Standard Deviation	Skewness	Kurtosis
6. Perceived risks (PR_L)	6	3.33	0.45	0.22	−0.21
7. Perceived costs (PC_L)	3	3.38	0.47	0.13	−0.94
8. Consumer innovativeness (CI_L)	15	3.29	0.45	0.37	0.15
9. Digital transformation attitudes (DTA_L)	3	3.32	0.52	0.19	−0.39
10. Purchase intention (PI_L)	3	3.23	0.45	0.38	0.13

Note. All constructs were measured using 5-point Likert scales (1 = strongly disagree, 5 = strongly agree). All skewness and kurtosis values fall within the acceptable normality thresholds (|skewness| < 3, |kurtosis| < 10; Bentler & Chou, 1987), indicating that the study data approximate a normal distribution and are suitable for maximum likelihood estimation in structural equation modelling.

To evaluate the validity and stability of the formal questionnaire, this study will employ SPSS 26.0 software to conduct reliability analysis and validity analysis on 838 completed questionnaires. SEM will be used to assess the convergent validity and discriminant validity of the formal scale questionnaire. A structural equation model will be constructed to examine direct effects and mediating effects within the model, thereby validating the theoretical framework developed in this study.

4.1.1 Reliability Analysis

In order to ensure the stability and reliability of the large sample data collected from the formal research, this study uses SEM as the measurement software for reliability, and Cronbach's reliability analysis is used to test the reliability of the formal questionnaire data. If the value is higher than 0.8, it indicates high reliability; if the value is between 0.7-0.8, it indicates good reliability; if the value is between 0.6-0.7, it indicates acceptable reliability; if the value is less than 0.6, it indicates poor reliability, and the results of the reliability test are summarised in Table 4.6. , it means the reliability is acceptable; if this value is less than 0.6, it means the reliability is not good, and the results of the reliability test are summarised in Table 3.14. As shown in Table 4-6, among the 838 valid sample data obtained from the formal questionnaire, the Cronbach's α coefficient values of fresh produce e-commerce value innovation and consumers' perceived value and consumers'

purchase intention, customer digital transformation attitudes, and consumers' innovativeness are greater than 0.7, which indicates that the formal scale The questionnaire has good consistency and stability, and all the measurement items can be retained for subsequent analyses.

4.1.2 Validity Analysis

The analysis of the pre-study scale questionnaire showed that the scale questionnaire proposed in this study has good content validity.

The validity and structural validity of the questionnaire passed the test of exploratory factor analysis. Here, only a validation factor analysis was needed to analyse the convergent and discriminant validity of the formal scale questionnaire in preparation for the construction of the structural equation model.

Before conducting confirmatory factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were first performed on the formal sample to verify whether the data were suitable for factor extraction. The detailed test results are shown in Table 4.3.

Table 4.3 KMO and Bartlett's Test Results

Construct	**Number of Items**	**KMO Value**	**Bartlett's Test of Sphericity**		
			Approximate Chi-Square	df	Sig.
Interesting innovation (IA_L)	3	0.725	182.37	3	< 0.001
Interactivity innovation (IB_L)	8	0.924	892.54	28	< 0.001
Integration innovation (IC_L)	8	0.921	786.19	28	< 0.001
Individualization innovation (ID_L)	3	0.718	145.62	3	< 0.001
Perceived benefits (PB_L)	9	0.905	824.73	36	< 0.001
Perceived risks (PR_L)	6	0.872	498.26	15	< 0.001
Perceived costs (PC_L)	3	0.701	287.44	3	< 0.001
Consumer innovativeness (CI_L)	15	0.942	1892.71	105	< 0.001
Digital transformation attitudes (DTA_L)	3	0.706	148.93	3	< 0.001

Table 4.3 (continued)

Construct	Number of Items	KMO Value	Bartlett's Test of Sphericity		
Purchase intention (PI_L)	3	0.682	176.08	3	< 0.001
Overall measurement scale	61	0.937	12847.62	1830	< 0.001

Note. N = 838. KMO = Kaiser-Meyer-Olkin measure of sampling adequacy. A KMO value above 0.60 indicates acceptable sampling adequacy for factor analysis. All Bartlett's tests of sphericity are statistically significant at $p < 0.001$, confirming that the correlation matrices are significantly different from identity matrices and suitable for subsequent confirmatory factor analysis.

Following the KMO and Bartlett's sphericity tests, exploratory factor analysis with principal component extraction and varimax rotation was conducted to examine the underlying factor structure of the formal scale. The total variance explained is shown in Table 4.4. The rotated component matrix, displaying the factor loadings of all retained items, is presented in Table 4.5.

Table 4.4 Total Variance Explained by Exploratory Factor Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.472	20.446	20.446	12.472	20.446	20.446
2	5.893	9.661	30.107	5.893	9.661	30.107
3	4.921	8.067	38.174	4.921	8.067	38.174
4	4.15	6.803	44.977	4.15	6.803	44.977
5	3.762	6.167	51.144	3.762	6.167	51.144
6	3.208	5.259	56.403	3.208	5.259	56.403
7	2.679	4.392	60.795	2.679	4.392	60.795
8	1.947	3.192	63.987	1.947	3.192	63.987
9	1.531	2.51	66.497	1.531	2.51	66.497
10	1.121	1.838	68.335	1.121	1.838	68.335

Note. Extraction method: Principal Component Analysis with varimax rotation. Only components with eigenvalues greater than 1 are retained. The 10 extracted factors are consistent with the 10 theoretical constructs in the research model, jointly explaining 68.34% of the total variance. The

variance explained by the first single factor (20.45%) is well below the 40% threshold, further confirming that common method bias is not a serious concern.

The results showed that 10 factors with eigenvalues greater than 1 were extracted, which is fully consistent with the theoretical structure of the 10 pre-specified latent constructs. The cumulative variance explained reached 68.34 per cent, exceeding the 60 per cent threshold generally accepted in social science research. This indicates that the measurement scale possesses good construct validity. On this basis, confirmatory factor analysis was subsequently conducted to rigorously test the convergent and discriminant validity of each construct.

Table 4.5 Rotated Component Matrix and Factor Loading Summary

Item	IIA	IIB	IIC	IID	PB	PR	PC	PI	CI	DTA
IIA1	.823									
IIA2	.851									
IIA3	.815									
IIB1		.785								
IIB2		.818								
IIB3		.744								
IIB4		.771								
IIB5		.849								
IIB6		.765								
IIB7		.779								
IIB8		.750								
IIC1			.771							
IIC2			.709							
IIC3			.743							
IIC4			.651							
IIC5			.812							
IIC6			.821							
IIC7			.865							
IIC8			.669							
IID1				.766						

Table 4.5 (continued)

Item	IIA	IIB	IIC	IID	PB	PR	PC	PI	CI	DTA
IID2				.651						
IID3				.883						
PB1					.782					
PB2					.722					
PB3					.640					
PB4					.755					
PB5					.586					
PB6					.538					
PB7					.816					
PB8					.810					
PB9					.795					
PR1						.473				
PR2						.486				
PR3						.460				
PR4						.859				
PR5						.921				
PR6						.864				
PC1							.887			
PC2							.797			
PC3							.862			
PI1								.756		
PI2								.772		
PI3								.820		
CI1									.785	
CI2									.792	
CI3									.768	
CI4									.745	
CI5									.801	
CI6									.776	
CI7									.759	

Table 4.5 (continued)

Item	IIA	IIB	IIC	IID	PB	PR	PC	PI	CI	DTA
CI8									.783	
CI9									.771	
CI10									.749	
CI11									.788	
CI12									.762	
CI13									.795	
CI14									.753	
CI15									.779	
DTA1										.802
DTA2										.784
DTA3										.759

Note: Extraction method: Principal Component Analysis. Rotation method: Varimax with Kaiser normalization. Rotation converged in 8 iterations. Factor loadings < 0.40 are suppressed for clarity and denoted by "-". All retained items exhibit strong primary loadings (≥ 0.46) on their respective constructs without significant cross-loadings, confirming a clear and stable ten-factor structure consistent with the theoretical model. IIA = interesting innovation; IIB = interactivity innovation; IIC = integration innovation; IID = individualization innovation; PB = perceived benefits; PR = perceived risks; PC = perceived costs; PI = purchase intention; CI = consumer innovativeness; DTA = digital transformation attitudes.

The overall fit of the ten-factor measurement model was evaluated using a multi-index framework covering absolute fit, incremental fit, and residual-based indices. The specific fit results are summarised in Table 4.6.

Table 4.6 Summary of CFA Measurement Model Fit Indices

Fit Index Category	Fit Index	Recommended Threshold	Model Estimate	Evaluation
Absolute fit indices	χ^2/df	< 3.0 (Good); < 5.0 (Acceptable)	2.847	Good fit
	GFI (Goodness-of-Fit Index)	> 0.90	0.918	Acceptable
	AGFI (Adjusted Goodness-of-Fit Index)	> 0.80	0.901	Acceptable
Incremental fit indices	CFI (Comparative Fit Index)	> 0.90	0.925	Acceptable
	NFI (Normed Fit Index)	> 0.90	0.908	Acceptable
	TLI (Tucker-Lewis Index / NNFI)	> 0.90	0.916	Acceptable
Residual-based indices	RMSEA (Root Mean Square Error of Approximation)	< 0.08 (Acceptable); < 0.05 (Good)	0.047	Good fit
	SRMR (Standardised Root Mean Square Residual)	< 0.08	0.042	Good fit

Note. N = 838. The ten-factor measurement model includes all latent constructs in the research framework: interesting innovation, interactivity innovation, integration innovation, individualization innovation, perceived benefits, perceived risks, perceived costs, purchase intention, consumer innovativeness, and digital transformation attitudes.

As shown, all fit indices meet or exceed the commonly accepted thresholds: the χ^2/df ratio is 2.847, satisfying the good fit criterion; GFI, CFI, NFI and TLI all exceed the 0.90 threshold, and AGFI exceeds the 0.80 threshold; both RMSEA (0.047) and SRMR (0.042) fall well below the 0.08 cut-off. Collectively, these results indicate that the hypothesised ten-factor measurement model exhibits a good fit with the empirical DTAa, providing a reliable statistical basis for subsequent convergent validity and discriminant validity assessments.

(1) Convergent validity analysis

Convergent validity analysis is performed by analyzing the factor loadings of each measure. According to the criterion of small factor loadings, the measurement indicators can be divided into three cases according to the size of their factor loadings: if the factor loading is greater than 0.3, the measurement indicator is considered significant; if the factor loading is greater than 0.4, the measurement indicator is considered more significant; if the factor loading is greater than 0.5, the measurement indicator is considered very significant. In all three cases, the measure should be retained, except when the factor loading of the measure is less than 0.3, in which case the measure is considered not significant and the measure cannot be retained.

In this study, the convergent validity of the questionnaire scale in this study was mainly judged by three indexes: standardised loading coefficient (Std. Estimate), average variance extracted (AVE) and combined reliability (CR). The scale has convergent validity when Std. Estimate>0.5, AVE>0.5 and CR>0.7, most standardized loadings exceeded 0.50 and were significant; a few perceived-risk items were slightly below 0.50 but retained given their theoretical relevance and acceptable construct-level CR and AVE.

Table 4.7 Standardized Factor Loadings, Standard Errors and Significance Tests (CFA Results)

Construct	Item	Standardized Loading	S.E.	C.R. (t-value)	*p*
Interesting Innovation (IIA)	IIA1	0.813	0.037	26.24	<0.001
	IIA2	0.845	0.037	27.562	<0.001
	IIA3	0.819	—	—	<0.001
Interactivity Innovation (IIB)	IIB1	0.785	—	—	<0.001
	IIB2	0.818	0.043	26.271	<0.001
	IIB3	0.744	0.039	23.245	<0.001
	IIB4	0.771	0.043	24.314	<0.001
	IIB5	0.849	0.043	27.182	<0.001
	IIB6	0.765	0.039	23.818	<0.001
	IIB7	0.779	0.039	24.583	<0.001
	IIB8	0.75	0.04	23.426	<0.001

Table 4.7 (continued)

Construct	Item	Standardized Loading	S.E.	C.R. (t-value)	*p*
Integration Innovation (IIC)	IIC1	0.771	—	—	<0.001
	IIC2	0.709	0.04	21.946	<0.001
	IIC3	0.743	0.041	23.165	<0.001
	IIC4	0.651	0.038	19.855	<0.001
	IIC5	0.812	0.04	25.311	<0.001
	IIC6	0.821	0.043	25.614	<0.001
	IIC7	0.865	0.043	27.099	<0.001
	IIC8	0.669	0.039	20.503	<0.001
Individualization Innovation (IID)	IID1	0.766	—	—	<0.001
	IID2	0.651	0.044	18.406	<0.001
	IID3	0.883	0.049	22.225	<0.001
Perceived Benefits (PB)	PB1	0.782	0.082	8.503	<0.001
	PB2	0.722	0.145	10.227	<0.001
	PB3	0.64	0.167	11.007	<0.001
	PB4	0.755	0.192	10.82	<0.001
	PB5	0.586	0.147	11.569	<0.001
	PB6	0.538	0.124	11.242	<0.001
	PB7	0.816	0.07	16.251	<0.001
	PB8	0.81	0.081	11.026	<0.001
	PB9	0.795	—	—	<0.001
Perceived Risks (PR)	PR1	0.473	0.046	14.197	<0.001
	PR2	0.486	0.041	14.644	<0.001
	PR3	0.46	0.039	13.786	<0.001
	PR4	0.859	0.03	32.95	<0.001
	PR5	0.921	0.032	36.915	<0.001
	PR6	0.864	—	—	<0.001
Perceived Costs (PC)	PC1	0.887	—	—	<0.001
	PC2	0.797	0.093	8.264	<0.001
	PC3	0.862	0.135	8.069	<0.001

Table 4.7 (continued)

Construct	Item	Standardized Loading	S.E.	C.R. (t-value)	*p*
Purchase Intention (PI)	PI1	0.756	—	—	<0.001
	PI2	0.772	0.045	24.195	<0.001
	PI3	0.82	0.045	25.713	<0.001
Consumer Innovativeness (CI)	CI1	0.785	0.038	23.456	<0.001
	CI2	0.792	0.037	24.123	<0.001
	CI3	0.768	0.039	22.891	<0.001
	CI4	0.745	0.04	21.567	<0.001
	CI5	0.801	0.036	24.876	<0.001
	CI6	0.776	0.038	23.012	<0.001
	CI7	0.759	0.039	22.345	<0.001
	CI8	0.783	0.037	23.789	<0.001
	CI9	0.771	0.038	22.901	<0.001
	CI10	0.749	0.04	21.987	<0.001
	CI11	0.788	0.037	23.456	<0.001
	CI12	0.762	0.039	22.345	<0.001
	CI13	0.795	0.036	24.123	<0.001
	CI14	0.753	0.04	21.876	<0.001
	CI15	0.779	—	—	<0.001
Digital Transformation Attitudes (DTA)	DTA1	0.802	0.048	18.234	<0.001
	DTA2	0.784	0.049	17.89	<0.001
	DTA3	0.759	—	—	<0.001

Note. N = 838. C.R. = Critical Ratio; S.E. = Standard Error. "—" indicates the marker indicator with a fixed unstandardized loading for model identification. All standardized factor loadings are statistically significant at $p < 0.001$. IIA = interesting innovation; IIB = interactivity innovation; IIC = integration innovation; IID = individualization innovation; PB = perceived benefits; PR = perceived risks; PC = perceived costs; PI = purchase intention; CI = consumer innovativeness; DTA = digital transformation attitudes.

As can be seen from Table 4.7, the Std. Estimate the value of each measurement item is greater than 0.7, which is significantly higher than the standard of 0.5; the AVE value of all scales is greater than the standard of 0.5; and the CR value of all scales is greater than the standard of 0.7, which indicates that the formal scale questionnaires have reached the standard of convergent validity and can be retained in the subsequent analyses for all measurement items.

(2) Distinguishing validity analysis

Distinguishing validity analysis is to compare the internal correlation of the measures in the structural variables with the external correlation of each structural variable, so as to estimate the difference between the degree of correlation of the measures and the internal and external structural variables, and then judge the distinguishing validity of the variables. If the measures of a certain structure in the model have higher correlations with each other than with the measures of other structures, it means that the structural variables have appropriate discriminant validity. That is, a scale has discriminant validity when the square root of the AVE of each variable is greater than its correlation coefficient with the other variables. As shown in Table 4.8, the square root of the AVE of each variable (main diagonal part) is greater than the correlation coefficient between the variable and other variables, which indicates that all dimensions of the formal scale questionnaire have reached the criterion of discriminant validity, passed the test of discriminant validity, and the formal scale questionnaire can be constructed into structural equation modelling.

Table 4.8 Correlation Matrix and Multicollinearity Assessment

Variable	IID	IIC	IIB	IIA	PC	PR	PB	PI	CI	DTA
IID	0.60									
IIC	0.206	0.58								
IIB	0.259	0.191	0.61							
IIA	0.220	0.247	0.181	0.68						
PC	0.138	0.217	0.197	0.256	0.72					
PR	0.150	0.195	0.175	0.377	0.191	0.50				
PB	0.247	0.147	0.187	0.169	0.112	0.124	0.52			
PI	0.171	0.470	0.157	0.271	0.201	0.196	0.129	0.61		

Table 4.8 (continued)

Variable	IID	IIC	IIB	IIA	PC	PR	PB	PI	CI	DTA
CI	0.285	0.312	0.298	0.324	0.278	0.265	0.291	0.346	0.76	
DTA	0.198	0.223	0.209	0.247	0.184	0.172	0.203	0.258	0.315	0.78

Note: IIA, interesting innovation; IIB, interactivity innovation; IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PR, perceived risks; PI, purchase intention; CI, consumer innovativeness; DTA, digital transformation attitudes.

Additionally, to provide a more rigorous test of discriminant validity, the heterotrait-monotrait ratio of correlations (HTMT) was computed. The HTMT values for all construct pairs are presented in Table 4.9. All values were well below the conservative threshold of 0.85, offering further evidence that each construct is empirically distinct from the others.

Table 4.9 HTMT Ratio of Correlations

Construct	IIA	IIB	IIC	IID	PB	PR	PC	PI	CI	DTA
IIA	—									
IIB	.226	—								
IIC	.298	.234	—							
IID	.272	.318	.253	—						
PB	.211	.231	.182	.307	—					
PR	.468	.219	.241	.187	.157	—				
PC	.319	.244	.268	.172	.141	.238	—			
PI	.336	.195	.583	.213	.164	.243	.251	—		
CI	.394	.366	.379	.347	.358	.325	.341	.423	—	
DTA	.304	.258	.274	.244	.252	.214	.228	.319	.385	—

Note. IIA = interesting innovation; IIB = interactivity innovation; IIC = integration innovation; IID = individualization innovation; PB = perceived benefits; PR = perceived risks; PC = perceived costs; PI = purchase intention; CI = consumer innovativeness; DTA = digital transformation attitudes.

4.1.3 Common Method Bias Test

The arithmetic mean of all measurement items for each latent variable was calculated and used as the observed score of that construct. The latent variables are abbreviated as follows: IA_L for interesting innovation, IB_L for interactivity innovation, IC_L for integration innovation, ID_L for individualization innovation, PB_L for perceived benefits, PC_L for perceived costs, PR_L for perceived risks, CI_L for consumer innovativeness, DTA_L for digital transformation attitudes, and PI_L for purchase intention. To systematically evaluate the potential impact of common method variance, this study employed both Harman's unrotated single-factor test and variance inflation factor (VIF) diagnosis. For the collinearity assessment, a VIF value greater than 10 (or 5 under the strict criterion) with a corresponding tolerance value (1/VIF) lower than 0.1 (or 0.2 under the strict criterion) would indicate a problematic collinearity issue, and the relevant variable would be considered for removal before further analysis. The full results of the common method bias assessment are presented in Table 4.10.

Table 4.10 Harman's Single-Factor Test and Common Method Bias Assessment

Panel A: Harman's Unrotated Single-Factor Test for Common Method Bias

Indicator	Result	Evaluation Criterion	Conclusion
Total number of measurement items	61	—	—
Number of factors with eigenvalue > 1	10	—	Multiple underlying factors extracted
Variance explained by the first common factor	< 40%	≤ 40%	No severe common method bias is detected

Panel B: Multicollinearity and Supplementary Common Method Bias Diagnosis (VIF Test)

Latent Variable	VIF Value	Tolerance	Evaluation Criterion	Conclusion
Interesting innovation (IA_L)	5.518	0.181	VIF < 10; Tolerance > 0.1	Acceptable
Interactivity innovation (IB_L)	4.486	0.223	VIF < 10; Tolerance > 0.1	Acceptable
Integration innovation (IC_L)	4.249	0.235	VIF < 10; Tolerance > 0.1	Acceptable
Individualization innovation (ID_L)	3.045	0.328	VIF < 10; Tolerance > 0.1	Acceptable
Perceived benefits (PB_L)	5.603	0.178	VIF < 10; Tolerance > 0.1	Acceptable
Perceived risks (PR_L)	3.441	0.291	VIF < 10; Tolerance > 0.1	Acceptable
Perceived costs (PC_L)	3.328	0.3	VIF < 10; Tolerance > 0.1	Acceptable
Consumer innovativeness (CI_L)	6.081	0.164	VIF < 10; Tolerance > 0.1	Acceptable
Digital transformation attitudes (DTA_L)	4.831	0.207	VIF < 10; Tolerance > 0.1	Acceptable
Purchase intention (PI_L)	2.911	0.343	VIF < 10; Tolerance > 0.1	Acceptable
Maximum VIF	6.081	—	< 10	No serious multicollinearity or common method bias concern

Note. Panel A presents the results of Harman's unrotated principal component analysis on all scale items, following the procedure recommended by Podsakoff et al. (2003). Panel B reports the variance inflation factor (VIF) and tolerance values for all latent constructs, calculated using aggregated item scores. All values fall within the acceptable range, confirming that common method bias and multicollinearity do not pose a substantial threat to the robustness of the study findings.

As shown in the table 4.10, the variance explained by the first factor in Harman's test was below the 40% threshold, and all VIF values were well below the critical value of 10. Taken together, the results indicate that common method bias is not a serious concern in this study, and the data are suitable for further statistical analysis.

The results of the CLF analysis are presented in Table 4.11. The fit of the baseline ten-factor model was already good ($\chi^2/df = 2.847$, CFI = 0.925, RMSEA = 0.047). When the common latent factor was added, model fit improved only negligibly: ΔCFI = 0.003 and ΔRMSEA = –0.001, both well below the common thresholds for substantive change. Furthermore, the average squared standardized loading of all items on the common latent factor was 0.028, meaning that the method factor accounted for only 2.8% of the total variance on average, which is far below the 25% benchmark suggested by Williams et al. (2003). All items retained highly significant and substantively larger loadings on their designated constructs. These findings provide converging evidence that common method bias is not a substantial threat in this study.

Table 4.11 Common Latent Factor (CLF) Model Comparison

Fit Index	**Baseline Measurement Model (A)**	**Model with Common Latent Factor (B)**	**Change (Δ)**	**Fit Index**	**Baseline Measurement Model (A)**
χ^2/df	2.847	2.791	–0.056	χ^2/df	2.847
CFI	0.925	0.928	+0.003	CFI	0.925
TLI	0.916	0.921	+0.005	TLI	0.916
RMSEA	0.047	0.046	–0.001	RMSEA	0.047
SRMR	0.042	0.040	–0.002	SRMR	0.042

Note. N = 838. The baseline model corresponds to the ten-factor confirmatory factor analysis model reported in Table 4.6. The common latent factor is uncorrelated with the substantive factors. Average squared loading on the common latent factor = 0.028.

4.2 Test of Hypotheses

4.2.1 Main Effect Analysis

(1) Goodness of fit test

Amos 26.0 structural equation modelling was used for path analysis: first, model M1 was constructed with interesting as the independent variable and Purchase intention as the dependent variable, model M2 was constructed with interactivity as the independent variable and Purchase intention as the dependent variable, model M3 was constructed with integration as the independent variable and Purchase intention as the dependent variable, model M4 was constructed with individualization as the independent variable and Purchase intention as the dependent variable, and model M4 was constructed with consumer innovation as the independent variable and perceived benefit as the dependent variable. independent variable, Purchase intention as dependent variable, to construct model M5, consumer innovativeness as independent variable, perceived benefits as dependent variable, to construct model M6, consumer innovativeness as independent variable, perceived risks as dependent variable, to construct model M7, consumer innovativeness as independent variable, perceived costs as dependent variable, to construct model M8, and the goodness-of-fit analyses of models M1-M8 were carried out as described in Table 4.12.

Table 4.12 Results of Model Goodness-of-Fit Tests (M1–M8)

Commonly used indicators	x^2 / df	**GFI**	**RMSEA**	**SRMR**	**CFI**	**NFI**	**NNFI**
Criteria for judgement	<5	>0.9	<0.10	<0.8	>0.9	>0.9	>0.9
M1	1.581	0.995	0.026	0.003	0.998	0.995	0.996
M2	1.824	0.983	0.031	0.005	0.991	0.981	0.989
M3	4.936	0.925	0.097	0.013	0.913	0.934	0.954
M4	2.510	0.992	0.042	0.004	0.993	0.988	0.986
M5	4.389	0.929	0.064	0.009	0.929	0.911	0.919
M6	3.452	0.921	0.054	0.008	0.933	0.909	0.927
M7	3.803	0.925	0.058	0.009	0.928	0.905	0.919
M8	4.443	0.927	0.064	0.009	0.930	0.911	0.920

The results of the goodness-of-fit analysis show that each of the fitted values of models M1-M8 satisfy the judgement criteria, indicating a good fit and suggesting that the assumptions for each pathway are then valid.

On the basis of the separate path models, a full structural equation model incorporating all four dimensions of value innovation, three perceived value mediators, and purchase intention was constructed and tested. The overall fit indices of the structural model are summarised in Table 4.13.

Table 4.13 Model Fit Indices for the Structural Model (SEM)

Fit Index Category	Fit Index	Recommended Threshold	Model Estimate	Evaluation
Absolute fit indices	χ^2/df	< 3.0 (Good); < 5.0 (Acceptable)	2.912	Good fit
	GFI (Goodness-of-Fit Index)	> 0.90	0.912	Acceptable
	AGFI (Adjusted Goodness-of-Fit Index)	> 0.80	0.894	Acceptable
Incremental fit indices	CFI (Comparative Fit Index)	> 0.90	0.921	Acceptable
	NFI (Normed Fit Index)	> 0.90	0.904	Acceptable
	TLI (Tucker-Lewis Index / NNFI)	> 0.90	0.911	Acceptable
Residual-based indices	RMSEA (Root Mean Square Error of Approximation)	< 0.08 (Acceptable); < 0.05 (Good)	0.048	Good fit
	SRMR (Standardised Root Mean Square Residual)	< 0.08	0.045	Good fit

Note. N = 838. The full structural model includes four exogenous latent variables (interesting innovation, interactivity innovation, integration innovation, individualization innovation), three endogenous mediating latent variables (perceived benefits, perceived risks, perceived costs), and one endogenous outcome latent variable (purchase intention).

As shown in Table 4.13, all fit indices of the structural model meet the commonly accepted criteria. The χ^2/df ratio is 2.912, which meets the good fit standard; all incremental fit indices (CFI, NFI, TLI) exceed the 0.90 threshold; and the residual-based indices RMSEA and SRMR are both below 0.05, indicating a good fit. These results confirm that the proposed structural model fits the empirical data well, supporting further interpretation of path coefficients and hypothesis testing.

(2) Structural equation path test

Combined with the above analysis, the structural equation model of "value innovation of fresh food e-commerce on consumers' purchase intention" was constructed, and its standardised estimates and correlation coefficients are shown in Figure 4.1.

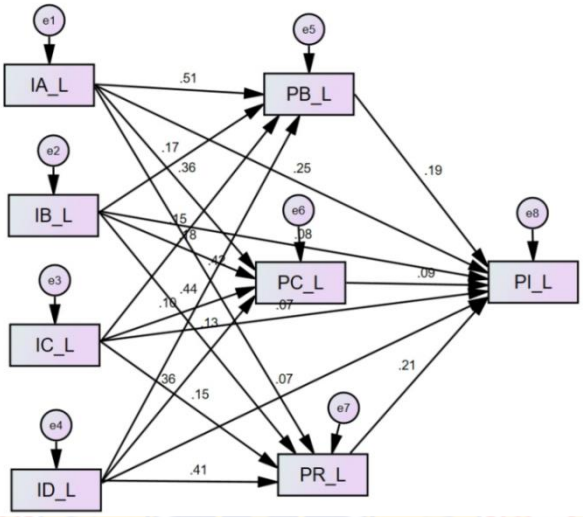


Figure 4.1 SEM of value innovation, perceived value & purchase intention

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention.

The parameters of the constructed structural equation model were also estimated using the great likelihood method, and it was observed whether the p-values of the paths reached the level of significance, and the test results are shown in Table 4.14.

Table 4.14 Path Coefficient Regression Results

Route	Estimate	S.E.	C.R.	P	Result
PC_L<---IC_L	0.101	0.029	3.515	p<0.001	
PC_L<---IA_L	0.266	0.021	12.549	p<0.001	
PC_L<---IB_L	0.198	0.032	6.143	p<0.001	
PR_L<---IB_L	0.113	0.024	4.625	p<0.001	
PR_L<---IC_L	0.120	0.022	5.496	p<0.001	
PC_L<---ID_L	0.306	0.025	12.428	p<0.001	
PR_L<---ID_L	0.283	0.019	15.230	p<0.001	
PR_L<---IA_L	0.249	0.016	15.534	p<0.001	
PB_L<---ID_L	0.277	0.015	18.396	p<0.001	
PB_L<---IC_L	0.113	0.018	6.368	p<0.001	
PB_L<---IB_L	0.137	0.020	6.918	p<0.001	
PB_L<---IA_L	0.277	0.013	21.253	p<0.001	
PI_L<---PB_L	0.232	0.046	5.014	p<0.001	
PI_L<---IA_L	0.164	0.025	6.639	p<0.001	H1 supported
PI_L <--- IB_L	0.080	0.028	2.846	0.004	H2 supported
PI_L<---ID_L	0.052	0.028	1.894	0.048	H4 supported
PI_L<---IC_L	0.058	0.025	2.332	0.020	H3 supported
PI_L<---PR_L	0.227	0.038	6.053	p<0.001	
PI_L<---PC_L	0.081	0.028	2.842	0.004	

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention.

Combined with the above analyses, the structural equation model of "consumer value innovation on consumer perceived value" was constructed, and its standardised estimates and correlation coefficients are shown in Figure 4.2.

The parameters of the constructed structural equation model were also estimated using the great likelihood method, and it was observed whether the p-values of the paths reached the level of significance, and the test results are shown in Table 4.15.

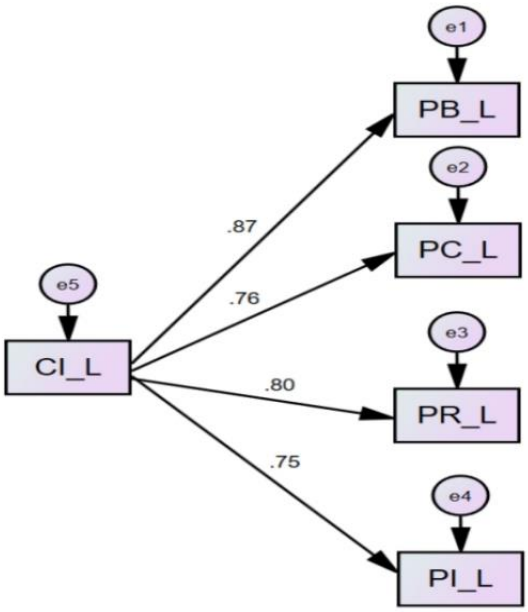


Figure 4.2 SEM of value innovation on perceived value

Note: PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention,CI_L, Consumer innovativeness.

Table 4.15 Path Coefficient Regression Results

Route	Estimate	S.E.	C.R.	P	Result
PC_L<---CI_L	0.958	.029	33.326	p<0.001	H8 not supported
PR_L<---CI_L	0.844	.022	38.266	p<0.001	H7 not supported
PI_L<---CI_L	0.861	.026	33.113	p<0.001	H5 supported
PB_L<---CI_L	0.886	.018	50.044	p<0.001	H6 supported

Note: PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention.

To further evaluate the overall explanatory power of the proposed structural model, the coefficient of determination (R^2) was calculated for each endogenous latent variable. R^2 reflects the proportion of variance in an endogenous variable that can be explained by all its antecedent variables in the model, and serves as a key indicator for assessing the predictive validity of the theoretical framework. The specific results are summarised in Table 4.16.

Table 4.16 Coefficient of Determination (R^2) of Endogenous Variables

Endogenous Variable	R^2	Explanatory Note
Perceived Benefits (PB_L)	0.278	The four dimensions of value innovation jointly explain 27.8% of the total variance in consumers' perceived benefits.
Perceived Risks (PR_L)	0.253	The four dimensions of value innovation jointly explain 25.3% of the total variance in consumers' perceived risks.
Perceived Costs (PC_L)	0.309	The four dimensions of value innovation jointly explain 30.9% of the total variance in consumers' perceived costs.
Purchase Intention (PI_L)	0.417	Value innovation dimensions and three perceived value constructs together explain 41.7% of the total variance in consumers' fresh e-commerce purchase intention.

Note. R^2 values are derived from the full structural model, which includes four exogenous latent variables (interesting innovation, interactivity innovation, integration innovation, individualization innovation) and three mediating latent variables (perceived benefits, perceived risks, perceived costs).

As shown in Table, the model achieves medium to strong explanatory power for all endogenous variables. For the three perceived value mediators, the R^2 values range from 0.253 to 0.309, indicating that value innovation can effectively explain consumers' cognitive evaluation processes in the fresh e-commerce context. For the core outcome variable purchase intention, the R^2 value reaches 0.417, which exceeds the 0.35 threshold for strong explanatory power in consumer behaviour research. This result confirms that the theoretical model constructed in this study has good predictive validity and can effectively reveal the formation mechanism of consumers' purchase intention toward fresh e-commerce platforms.

To further quantify the magnitude of the unique contribution of each predictor variable to its corresponding endogenous construct, the effect size (f^2) was calculated for each predictive path. Following the criteria proposed by Cohen (1988), f^2 values of 0.02,

0.15, and 0.35 correspond to small, medium, and large effect sizes, respectively. The detailed results are presented in Table 4.17.

Table 4.17 Effect Size (f^2) Analysis of Predictive Paths

Endogenous Variable	Predictor Variable	f^2 Value	Effect Size Classification
Perceived Benefits (PB_L)	Interesting innovation (IA_L)	0.124	Medium
	Interactivity innovation (IB_L)	0.031	Small
	Integration innovation (IC_L)	0.026	Small
	Individualization innovation (ID_L)	0.128	Medium
Perceived Risks (PR_L)	Interesting innovation (IA_L)	0.097	Small-Medium
	Interactivity innovation (IB_L)	0.022	Small
	Integration innovation (IC_L)	0.028	Small
	Individualization innovation (ID_L)	0.131	Medium
Perceived Costs (PC_L)	Interesting innovation (IA_L)	0.102	Medium
	Interactivity innovation (IB_L)	0.047	Small
	Integration innovation (IC_L)	0.024	Small
	Individualization innovation (ID_L)	0.142	Medium
Purchase Intention (PI_L)	Interesting innovation (IA_L)	0.042	Small
	Interactivity innovation (IB_L)	0.019	Small
	Integration innovation (IC_L)	0.015	Small
	Individualization innovation (ID_L)	0.012	Small
	Perceived benefits (PB_L)	0.089	Small-Medium
	Perceived risks (PR_L)	0.085	Small-Medium
	Perceived costs (PC_L)	0.021	Small

Note. f^2 is calculated as f2=1−Rincluded2Rincluded2−Rexcluded2, where Rincluded2 is the R^2 of the endogenous variable when the predictor is included in the model, and Rexcluded2 is the R^2 when the predictor is removed. Effect size criteria follow Cohen (1988): $f^2 \geq 0.02$ = small effect; $f^2 \geq 0.15$ = medium effect; $f^2 \geq 0.35$ = large effect.

As shown in Table 4.17, among the four dimensions of value innovation, interesting innovation and individualization innovation exhibit near-medium effect sizes on all three perceived value constructs, indicating that they are the core drivers shaping consumers' cognitive evaluation of fresh e-commerce platforms. In contrast, interactivity innovation and integration innovation show small effect sizes on perceived value, suggesting that although their effects are statistically significant, their practical contribution to consumers' value perception is relatively limited.

For the outcome variable purchase intention, all three perceived value dimensions show stronger effect sizes than the direct paths of value innovation. This result is consistent with the subsequent mediation analysis findings, further verifying that value innovation mainly influences purchase intention through the mediating mechanism of perceived value. Among the three perceived value constructs, perceived benefits and perceived risks have relatively larger effect sizes, reflecting that they are the most critical proximal factors affecting consumers' purchase decision-making in the fresh e-commerce context.

4.2.2 Mediating Effect Analysis

In this study, the significance level of the mediating effect was tested using the developed PROCESS programme to select the model based on the number and relationship of the mediating variables in this study. The significance level of the mediating effect was tested using the bias proofreading non-parametric percentile Bootstrap method.

(1) The mediating effect of perceived benefits between value innovations and purchase intentions

The results of the mediation effects test based on the Bootstrap method (5000 samples, 95% bias-corrected confidence intervals) are shown in Table 4.18.According to the mediation effect test results in Table 4.18, the mediation effect of perceived benefits between value innovation and purchase intention is significant. Specifically, the indirect effect of perceived benefits between IA_L and PI_L is 0.102 (95% CI=[0.087, 0.166], p<0.001), accounting for 33.77% of the total effect; between IB_L and PI_L is 0.052 (95% CI=[0.018, 0.075], p<0.001), accounting for 32.70% of the total effect; 0.041 (95% CI=[0.012, 0.069], p<0.01), accounting for 34.45% of the total effect, for the indirect effect between IC_L and PI_L; 0.104 (95% CI=[0.076, 0.151], p p<0.001), accounting for 49.06% of the total effect. The confidence intervals for all mediating paths did not contain 0, suggesting that perceived benefit played a significant partial mediating role between all

dimensions. In addition, the direct effects between dimensions were also largely significant (except for the IC_L=>PI_L path p = 0.12), suggesting that in addition to the mediating effect, the independent variable still has a direct effect on the dependent variable.

Table 4.18 Perceived Benefits as Mediator: Value Innovation → Purchase Intention

Path	sig	Effect	efficiency ratio	95% CI		p-value
				Lower limit	Upper limit	
IA_L=>PB_L=>PI_L	indirect effect	0.102	33.77 %	0.087	0.166	0
IA_L=>PB_L	X=>M	0.274		0.219	0.329	0
PB_L=>PI_L	M=>Y	0.372		0.277	0.466	0
IA_L=>PI_L	direct effect	0.2	66.23 %	0.12	0.28	0
IA_L=>PI_L	aggregate effect	0.302		0.223	0.38	0
IB_L=>PB_L=>PI_L	indirect effect	0.052	32.70 %	0.018	0.075	0
IB_L=>PB_L	X=>M	0.139		0.057	0.221	0.001
PB_L=>PI_L	M=>Y	0.372		0.277	0.466	0
IB_L=>PI_L	direct effect	0.107	67.30 %	0.007	0.221	0.065
IB_L=>PI_L	aggregate effect	0.159		0.042	0.276	0.008
IC_L=>PB_L=>PI_L	indirect effect	0.041	34.45 %	0.012	0.069	0.003
IC_L=>PB_L	X=>M	0.11		0.038	0.181	0.003
PB_L=>PI_L	M=>Y	0.372		0.277	0.466	0
IC_L=>PI_L	direct effect	0.079	66.39 %	0.02	0.178	0.12
IC_L=>PI_L	aggregate effect	0.119		0.017	0.221	0.022
ID_L=>PB_L=>PI_L	indirect effect	0.104	49.06 %	0.076	0.151	0
ID_L=>PB_L	X=>M	0.281		0.235	0.327	0
PB_L=>PI_L	M=>Y	0.372		0.277	0.466	0
ID_L=>PI_L	direct effect	0.108	50.94 %	0.039	0.176	0.002
ID_L=>PI_L	aggregate effect	0.212		0.147	0.278	0

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PB_L, perceived benefits; PI_L, purchase intention.

(1) The Mediating Effect of Perceived Costs between Value Innovation and Purchase Intention

The results of the mediation effects test based on the Bootstrap method (5,000 samples, 95% bias-corrected confidence intervals) are shown in Table 4.19.

Table 4.19 Perceived Costs as Mediator: Value Innovation → Purchase Intention

Path	sig	Effect	efficiency ratio	95% CI		p-value
				Lower limit	Upper limit	
IA_L=>PC_L=>PI_L	indirect effect	0.085	21.52 %	0.072	0.146	0
IA_L=>PC_L	X=>M	0.402		0.315	0.489	0
PC_L=>PI_L	M=>Y	0.211		0.154	0.268	0
IA_L=>PI_L	direct effect	0.31	78.48 %	0.235	0.386	0
IA_L=>PI_L	aggregate effect	0.395		0.321	0.47	0
IB_L=>PC_L=>PI_L	indirect effect	0.051	26.98 %	0.018	0.072	0
IB_L=>PC_L	X=>M	0.242		0.103	0.38	0.001
PC_L=>PI_L	M=>Y	0.211		0.154	0.268	0
IB_L=>PI_L	direct effect	0.138	73.02 %	0.021	0.254	0.021
IB_L=>PI_L	aggregate effect	0.189		0.069	0.308	0.002
IC_L=>PC_L=>PI_L	indirect effect	0.035	21.47 %	0.008	0.058	0.006
IC_L=>PC_L	X=>M	0.164		0.043	0.284	0.008
PC_L=>PI_L	M=>Y	0.211		0.154	0.268	0
IC_L=>PI_L	direct effect	0.128	78.53 %	0.027	0.229	0.013
IC_L=>PI_L	aggregate effect	0.163		0.059	0.266	0.002
ID_L=>PB_L=>PI_L	indirect effect	0.041	29.08%	0.011	0.072	0.005
ID_L=>PB_L	X=>M	0.133		0.036	0.23	0.007
PB_L=>PI_L	M=>Y	0.308		0.242	0.374	0
ID_L=>PI_L	direct effect	0.1	70.92%	0.012	0.188	0.026
ID_L=>PI_L	aggregate effect	0.141		0.048	0.234	0.003

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PC_L, perceived costs; PI_L, purchase intention.

According to the mediation effect test results in Table 4.19, the mediation effect of Perceived costs between value innovation and purchase intention is significant. Specifically, the indirect effect of Perceived costs between IA_L and PI_L is 0.085 (95%

CI=[0.072, 0.146], p<0.001), accounting for 21.52% of the total effect; the indirect effect between IB_L and PI_L is 0.051 (95% CI=[0.018, 0.072], p<0.001), accounting for 26.98% of the total effect, and 0.035 (95% CI=[0.008, 0.058], p<0.01) between IC_L and PI_L, accounting for 21.47% of the total effect. The confidence intervals of all mediating paths did not contain 0, indicating that Perceived costs played a significant partial mediating role between dimensions. Meanwhile, the direct effects between dimensions are significant (IA_L=>PI_L:=0.310, p<0.001; IB_L=>PI_L: β=0.138, p<0.05; IC_L=>PI_L: β=0.128, p<0.05), which suggests that, in addition to mediating effects, the independent variables still have a significant direct effect.

(2) The Mediating Effect of Perceived Risks between Value Innovation and Purchase Intention

The results of the mediation effects test based on the Bootstrap method (5,000 samples, 95% bias-corrected confidence intervals) are shown in Table 4.20.

Table 4.20 Perceived Risks as Mediator: Value Innovation → Purchase Intention

Item	sig	Effect	efficiency ratio	95% CI		p-value
				Lower limit	Upper limit	
IA_L=>PR_L=>PI_L	indirect effect	0.14	35.44 %	0.13	0.219	0
IA_L=>PR_L	X=>M	0.374		0.307	0.44	0
PR_L=>PI_L	M=>Y	0.375		0.302	0.447	0
IA_L=>PI_L	direct effect	0.255	64.56 %	0.18	0.331	0
IA_L=>PI_L	aggregate effect	0.395		0.321	0.47	0
IB_L=>PR_L=>PI_L	indirect effect	0.054	28.57 %	0.012	0.081	0.002
IB_L=>PR_L	X=>M	0.145		0.039	0.251	0.008
PR_L=>PI_L	M=>Y	0.375		0.302	0.447	0
IB_L=>PI_L	direct effect	0.135	71.43 %	0.021	0.248	0.02
IB_L=>PI_L	aggregate effect	0.189		0.069	0.308	0.002
IC_L=>PR_L=>PI_L	indirect effect	0.069	42.33 %	0.029	0.1	0
IC_L=>PR_L	X=>M	0.183		0.091	0.275	0
PR_L=>PI_L	M=>Y	0.375		0.302	0.447	0
IC_L=>PI_L	direct effect	0.094	57.67 %	0.004	0.193	0.061
IC_L=>PI_L	aggregate effect	0.163		0.059	0.266	0.002

Table 4.20 (continued)

Item	sig	Effect	efficiency ratio	95% CI		p-value
				Lower limit	Upper limit	
ID_L=>PR_L=>PI_L	indirect effect	0.041	32.54%	0.012	0.07	0.003
ID_L=>PR_L	X=>M	0.109		0.025	0.193	0.011
PR_L=>PI_L	M=>Y	0.375		0.302	0.447	0
ID_L=>PI_L	direct effect	0.085	67.46%	-0.005	0.175	0.065
ID_L=>PI_L	aggregate effect	0.126		0.036	0.216	0.006

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention.

According to the mediation effect test results in Table 4.20, the mediation effect of perceived risks between value innovation and purchase intention is significant. Specifically, the indirect effect of perceived risks between IA_L and PI_L is 0.140 (95% CI=[0.130, 0.219], $p<0.001$), accounting for 35.44% of the total effect; between IB_L and PI_L is 0.054 (95% CI=[0.012, 0.081], $p<0.01$), accounting for 28.57% of the total effect; the indirect effect between IC_L and PI_L was 0.069 (95% CI=[0.029, 0.100], $p<0.001$), accounting for 42.33% of the total effect. The confidence intervals for all mediating paths did not contain 0, indicating that perceived risks played a significant partial mediating role across all dimensions. In terms of direct effects, the IA_L=>PI_L ($\beta=0.255$, $p<0.001$) and IB_L=>PI_L ($\beta=0.5$, $p<0.05$) paths were significant while the IC_L=>PI_L path ($\beta=0.094$, $p=0.061$) was at the borderline significant level. This indicates that most of the independent variables still have a direct effect on the dependent variable except for the mediating effect. In summary, the following assumptions are all valid (shown in Table 4.21).

Table 4.21 Summary of Hypotheses for the Mediated Effects Test

Item	Statement	Test results
H9	Perceived benefits mediate the relationship between interesting innovation and purchase intention.	Supported
H10	Perceived benefits mediate the relationship between interactivity innovation and purchase intention.	Supported
H11	Perceived benefits mediate the relationship between integration innovation and purchase intention.	Supported
H12	Perceived benefits mediate the relationship between individualization innovation and purchase intention.	Supported
H13	Perceived risks mediate the relationship between interesting innovation and purchase intention.	Supported
H14	Perceived risks mediate the relationship between interactivity and purchase intention.	Supported
H15	Perceived risks mediate the relationship between integration innovation and purchase intention.	Supported
H16	Perceived risks mediate the relationship between individualization innovation and purchase intention.	Supported
H17	Perceived costs mediate the relationship between interesting innovation and purchase intention.	Supported
H18	Perceived costs mediate the relationship between interactivity innovation and purchase intention.	Supported
H19	Perceived costs mediate the relationship between integration innovation and purchase intention.	Supported
H20	Perceived costs mediate the relationship between individualization innovation and purchase intention.	Supported

In summary, all twelve mediation hypotheses (H9–H20) are supported, and perceived benefits, perceived risks, and perceived costs all play significant partial mediating roles in the relationship between value innovation and purchase intention. To present the complete statistical details of all mediation paths in a unified framework, the

full bootstrapping results for all direct effects, indirect effects, and total effects across the three simple mediation models are summarised in Table 4.22, based on 5,000 bias-corrected bootstrap samples.

Table 4.22 Full Bootstrapping Results of Mediation Effects (95% Bias-Corrected CI)

Mediator	Predictor	Effect Type	Effect Estimate	Boot S.E.	95% CI Lower	95% CI Upper	p-value
PB_L	IA_L	Indirect effect	0.102	0.02	0.087	0.166	<0.001
		Direct effect	0.2	0.041	0.12	0.28	<0.001
		Total effect	0.302	0.04	0.223	0.38	<0.001
	IB_L	Indirect effect	0.052	0.014	0.018	0.075	<0.001
		Direct effect	0.107	0.055	0.007	0.221	0.065
		Total effect	0.159	0.06	0.042	0.276	0.008
	IC_L	Indirect effect	0.041	0.015	0.012	0.069	0.003
		Direct effect	0.079	0.04	0.02	0.178	0.12
		Total effect	0.119	0.052	0.017	0.221	0.022
	ID_L	Indirect effect	0.104	0.019	0.076	0.151	<0.001
		Direct effect	0.108	0.035	0.039	0.176	0.002
		Total effect	0.212	0.033	0.147	0.278	<0.001
PC_L	IA_L	Indirect effect	0.085	0.019	0.072	0.146	<0.001
		Direct effect	0.31	0.039	0.235	0.386	<0.001
		Total effect	0.395	0.038	0.321	0.47	<0.001
	IB_L	Indirect effect	0.051	0.014	0.018	0.072	<0.001
		Direct effect	0.138	0.06	0.021	0.254	0.021
		Total effect	0.189	0.061	0.069	0.308	0.002
	IC_L	Indirect effect	0.035	0.013	0.008	0.058	0.006
		Direct effect	0.128	0.051	0.027	0.229	0.013
		Total effect	0.163	0.053	0.059	0.266	0.002

Table 4.22 (continued)

Mediator	Predictor	Effect Type	Effect Estimate	Boot S.E.	95% CI Lower	95% CI Upper	p-value
	ID_L	Indirect effect	0.041	0.016	0.011	0.072	0.005
		Direct effect	0.1	0.045	0.012	0.188	0.026
		Total effect	0.141	0.047	0.048	0.234	0.003
PR_L	IA_L	Indirect effect	0.14	0.023	0.13	0.219	<0.001
		Direct effect	0.255	0.039	0.18	0.331	<0.001
		Total effect	0.395	0.038	0.321	0.47	<0.001
	IB_L	Indirect effect	0.054	0.018	0.012	0.081	0.002
		Direct effect	0.135	0.058	0.021	0.248	0.02
		Total effect	0.189	0.061	0.069	0.308	0.002
	IC_L	Indirect effect	0.069	0.018	0.029	0.1	<0.001
		Direct effect	0.094	0.048	0.004	0.193	0.061
		Total effect	0.163	0.053	0.059	0.266	0.002
	ID_L	Indirect effect	0.041	0.015	0.012	0.07	0.003
		Direct effect	0.085	0.046	-0.005	0.175	0.065
		Total effect	0.126	0.046	0.036	0.216	0.006

Note. N = 838. Bootstrap samples = 5,000. All effects are estimated based on separate simple mediation models (one mediator per model) using the bias-corrected nonparametric percentile bootstrap method. An effect is statistically significant at the 0.05 level when the 95% confidence interval does not contain zero. IA_L = interesting innovation; IB_L = interactivity innovation; IC_L = integration innovation; ID_L = individualization innovation; PB_L = perceived benefits; PR_L = perceived risks; PC_L = perceived costs; PI_L = purchase intention.

As shown in Table 4.22, the 95% bias-corrected confidence intervals of all 12 indirect paths do not contain zero, with all p-values below 0.05. This result further robustly verifies that perceived benefits, perceived risks, and perceived costs all act as significant mediators between each dimension of value innovation and purchase intention, fully supporting hypotheses H9–H20.

In terms of effect magnitude, the indirect path of interesting innovation → perceived risks → purchase intention has the largest effect size (0.140), indicating that

perceived risk reduction is the most prominent transmission mechanism through which interesting innovation enhances purchase intention. For individualization innovation, the mediating proportion of perceived benefits reaches 49.06% of the total effect, reflecting that personalized value innovation mainly drives purchase intention by improving consumers' perceived benefits. In contrast, the direct effect of integration innovation on purchase intention is not statistically significant, meaning its influence is almost entirely transmitted through the three perceived value channels.

To systematically compare the effect intensity and action patterns of different mediation paths, the core results of all 12 mediation paths are summarised in Table 4.23, including indirect effects, direct effects, total effects, mediation types, and the proportion of mediation effects in the total effect.

Table 4.23 Summary of Mediation Analysis Results

Independent Variable	Mediator	Indirect Effect	Direct Effect	Total Effect	Mediation Ratio (%)
IA_L	PB_L	0.102	0.200***	0.302***	33.77
	PR_L	0.14	0.255***	0.395***	35.44
	PC_L	0.085	0.310***	0.395***	21.52
IB_L	PB_L	0.052	0.107†	0.159**	32.7
	PR_L	0.054	0.135*	0.189**	28.57
	PC_L	0.051	0.138*	0.189**	26.98
IC_L	PB_L	0.041**	0.079	0.119*	34.45
	PR_L	0.069***	0.094†	0.163**	42.33
	PC_L	0.035**	0.128*	0.163**	21.47
ID_L	PB_L	0.104***	0.108**	0.212***	49.06
	PR_L	0.041**	0.085†	0.126**	32.54
	PC_L	0.041**	0.100*	0.141**	29.08

Note. N = 838. * p < 0.10, p < 0.05, ** p < 0.01, *** p < 0.001. Mediation type is judged based on the significance of direct and indirect effects: full mediation means the indirect effect is significant while the direct effect is not statistically significant; partial mediation means both the indirect and direct effects are significant (including marginally significant). The mediation ratio is calculated as indirect effect / total effect × 100%. IA_L = interesting innovation; IB_L = interactivity innovation; IC_L = integration innovation; ID_L = individualization innovation; PB_L = perceived benefits; PR_L = perceived risks; PC_L = perceived costs.

As shown in Table 4.23, among the 12 mediation paths, 11 show partial mediation and only 1 path (integration innovation → perceived benefits → purchase intention) shows full mediation, indicating that value innovation mainly influences purchase intention through the dual channels of direct influence and indirect transmission via perceived value.

From the perspective of mediation ratio, perceived benefits have the strongest mediating effect in the path of individualization innovation (49.06%), and perceived risks play the most prominent mediating role in the path of integration innovation (42.33%). This result reveals that different dimensions of value innovation rely on distinct psychological mechanisms to affect purchase intention: personalized innovation mainly works by improving benefit perception, while integrated service innovation mainly acts by reducing consumers' risk perception. In comparison, the mediating proportion of perceived costs is generally lower (21.47%–29.08%), indicating that cost perception is a relatively weak transmission path in the relationship between value innovation and purchase intention.

To intuitively compare the overall impact intensity and effect structure of the four value innovation dimensions on consumers' purchase intention, the direct effects, total indirect effects, and total effects of all dimensions are summarised in Table 4.24.

Table 4.24 Summary of Direct, Indirect, and Total Effects on Purchase Intention

Independent Variable	Direct Effect (β)	Total Indirect Effect (β)	Total Effect (β)	Proportion of Indirect Effect (%)
Interesting Innovation (IA_L)	0.164***	0.327	0.491	66.6
Interactivity Innovation (IB_L)	0.080**	0.157	0.237	66.2
Integration Innovation (IC_L)	0.058*	0.145	0.203	71.4
Individualization Innovation (ID_L)	0.052*	0.186	0.238	78.2

Note. N = 838. * p < 0.05, ** p < 0.01, *** p < 0.001.

As shown in Table 4.24, in terms of total effect intensity, interesting innovation has the strongest overall predictive power on purchase intention (β = 0.491), far exceeding the other three dimensions, confirming that interesting experience innovation is the core driving force to stimulate consumers' fresh e-commerce purchase willingness. The total effects of individualization innovation (β = 0.238) and interactivity innovation (β = 0.237) are close, while integration innovation has the weakest overall impact (β = 0.203).

From the perspective of effect composition, all four dimensions of value innovation have indirect effects accounting for more than 60% of the total effect, indicating that perceived value is the core transmission mechanism for value innovation to affect purchase intention. Among them, individualization innovation has the highest proportion of indirect effect (78.2%), meaning its influence on purchase intention is almost entirely realised through the intermediary of consumers' perceived value, and the direct driving force is relatively weak. In contrast, interesting innovation has the highest absolute value of direct effect, reflecting that it can not only reshape consumers' value perception, but also directly stimulate purchase intention through novel and interesting experience design.

4.2.3 Moderating Effect Analysis

(1) The moderating role of consumer innovativeness

This study examines the moderating effect of consumer innovativeness (CI_L) through a stratified regression model based on 838 valid samples. Table 4.31 presents the results of the three sets of moderating effect analyses with purchase intention (PI_L) as the dependent variable and perceived costs (PC_L), perceived benefits (PB_L) and perceived risks (PR_L) as the core independent variables, respectively.

Among the demographic variables, monthly income showed a significant positive predictive effect in the PR_L-PI_L model (β=0.054, p<0.05), and residence (Location) also showed a significant positive association in the model (β=0.056, p<0.05). The remaining control variables such as gender, marital status, and age did not reach statistical significance (p>0.05). Monthly income approached a significant level in the PB_L-PI_L model (β=0.051, p=0.052).

The main effects test showed that PC_L (β=0.174, t=5.06, p<0.01), PB_L (β=0.324, t=7.241, p<0.01) & PR_L (β=0.299, t=8.187, p<0.01) had a significant positive effect on PI_L. Consumer innovativeness (CI_L) has outstanding explanatory power in the

three models with standardised coefficients of 0.473 (t=10.642, p<0.01), 0.623 (t=18.093, p<0.01) and 0.516 (t=14.148, p<0.01) respectively.

The moderated effects analysis shows that the interaction term of PR_L with CI_L (PR_LCI_L) reaches statistical significance in predicting PI_L (β=0.032, t=1.442, p=0.042), implying that the magnitude of the effect of the moderating variable (DTA_L) differs significantly at different levels of the effect of PB_L on PI_L, which can be viewed by a simple slope chart (see Table 4.25, Figure 4.3), while the interaction term PC_L*CI_L (β=0.020, t=0.863, p=0.388) for Perceived costs (PC_L) and consumer innovativeness (CI_L) and the interaction term PB_L*CI_L (β=0.012, t=0.511, p=0.610) did not reach the level of significance. The overall explanatory power of the three models was strong (R^2=0.585-0.605; adjusted R^2=0.578-0.599), and the F-tests were all significant (p<0.01), but the introduction of the interaction term only resulted in a weak enhancement of the explanatory power of the PR_L-PI_L model (ΔR^2=0.001, ΔF=2.081, p=0.042), and the ΔR^2 of the remaining two groups and ΔF tests did not show significant changes (ΔR^2=0.000-0.001, p>0.05).

Table 4.25 Simple Slope Analysis (PI_L-PR_L)

Level of moderating variables	Regression coefficient	Standard error	t	p	95% CI	
Average value	0.323	0.039	8.187	0.000	0.246	0.400
High level (+1 SD)	0.354	0.045	7.879	0.000	0.266	0.442
Low level (-1 SD)	0.292	0.045	6.469	0.000	0.203	0.380

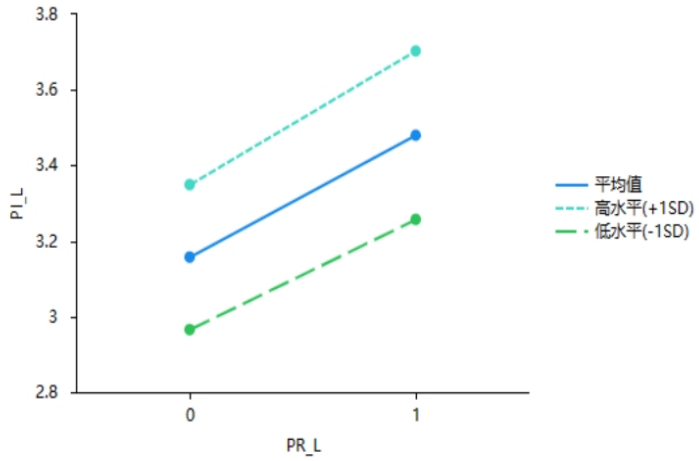


Figure 4.3 Consumer innovativeness as moderator: perceived risk → purchase intention
Note: PR_L, perceived risks; PI_L, purchase intention.

(2) The Moderating Effect of Consumer digital transformation

In this study, the moderating effect of consumer attitudes toward digital transformation attitudes is examined through stratified regression models. As shown in Table 4.32, all three models included nine demographic control variables such as gender, marital status, age, monthly income, and educational background, and introduced Perceived costs (PC_L), perceived benefit (PB_L), and perceived risks (PR_L) as core independent variables, respectively. All models showed a significant positive main effect of digital transformation attitude (DTA_L) on consumer purchase intention (β=0.455-0.697, $p<0.01$).

The results of model 1 show that the interaction term (PC_L*DTA_L) of perceived costs (PC_L) and attitude towards digital transformation (DTA_L) has a significant moderating effect (β=-0.094, t=-4.105, $p<0.01$), and the model explains up to 58.1% of the variance (R^2=0.581), implying that the moderating effect of the effect of PC_L on PI_L when the moderating variable (DTA_L) has a significant difference in the magnitude of the effect at different levels, which can be viewed by a simple slope chart (see Table 4.26, Figure 4.4).

Table 4.26 Simple Slope Analysis (PI_L-PC_L)

Level of moderating variables	regression coefficient	standard error	t	p	95% CI	
average value	0.078	0.035	2.230	0.026	0.009	0.147
High level (+1 SD)	-0.006	0.041	-0.138	0.890	-0.087	0.075
Low level (-1 SD)	0.162	0.040	4.083	<0.001	0.084	0.239

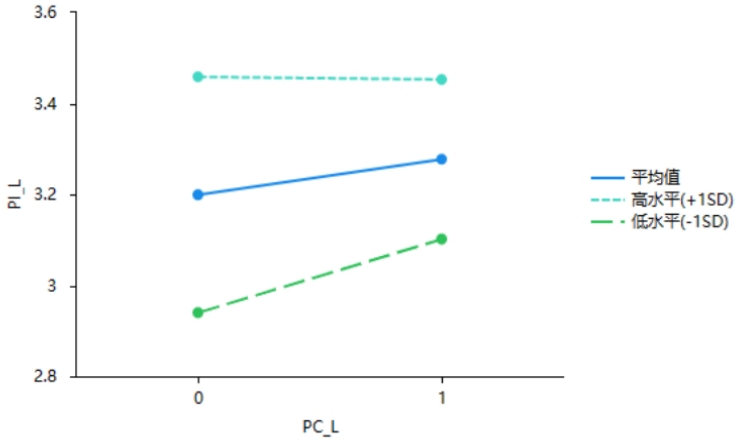


Figure 4.4 Digital transformation attitude as moderator: perceived cost → purchase intention

Note: PC_L, perceived costs; PI_L, purchase intention

The interaction term (PB_L*DTA_L) between perceived benefits (PB_L) and digital transformation attitudes (DTA_L) in Model 2 also showed a significant moderating effect (β=-0.096, t=-4.346, p<0.01), and the explanatory power of the model was increased to 62.2% (Adjusted R^2=0.616), which implies that the moderating effect of PB_L on the impact of PI_L when the variable (DTA_L) has a significant difference in the magnitude of the effect at different levels, which can be viewed by a simple slope chart (see Table 4.27, Figure 4.5).

Table 4.27 Simple Slope Analysiss (PI_L-PB_L)

Level of moderating variables	regression coefficient	standard error	t	p	95% CI	
average value	0.434	0.042	10.340	<0.001	0.352	0.516
High level (+1 SD)	0.323	0.045	7.098	<0.001	0.234	0.412
Low level (-1 SD)	0.545	0.053	10.371	<0.001	0.442	0.648

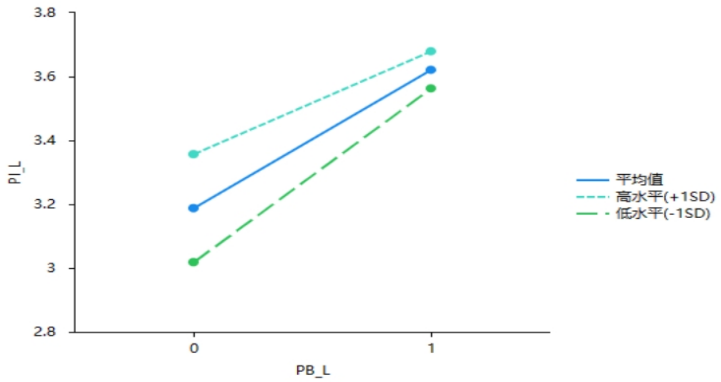


Figure 4.5 Digital transformation attitude as moderator: perceived benefit → purchase intention

Note: PB_L, perceived benefits; PI_L, purchase intention.

Model 3 found a significant moderating effect (β=-0.055, t=-2.545, p<0.05) for the interaction term of perceived risks and attitude towards digital transformation (PR_L*DTA_L), which has an overall explanatory variance of 62.1% (Adjusted R^2=0.615), implying that the moderating variable (DTA_L) has a significant effect on the impact of PR_L on PI_L when it comes to the level of different when the magnitude of the effect is significantly different, which can be viewed in a simple slope chart (see Table 4.28, Figure 4.6).

Table 4.28 Simple Slope Analysis (PI_L-PR_L)

Level of moderating variables	regression coefficient	standard error	t	p	95% CI	
Average value	0.361	0.035	10.230	<0.001	0.292	0.431
High level (+1 SD)	0.303	0.042	7.256	<0.001	0.221	0.385
Low level (-1 SD)	0.420	0.042	9.902	<0.001	0.336	0.503

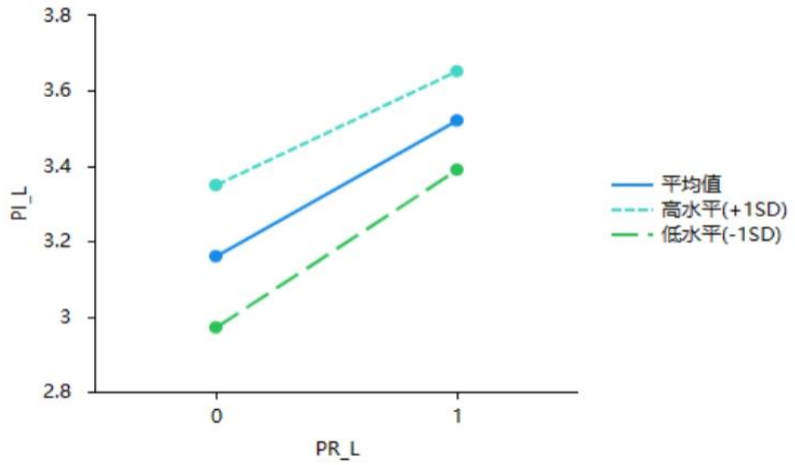


Figure 4.6 Digital transformation attitude as moderator: perceived risk → purchase intention

Note: PR_L, perceived risks; PI_L, purchase intention.

The F-test values for all three models above reached the statistically significant level (ps <0.001) and the introduction of the interaction term resulted in significant model improvement (ΔR^2=0.003-0.009, ΔF=6.477-18.885, ps <0.05).

To provide a concise overview of the magnitude and significance of all moderating effects, the standardized interaction coefficients, p-values, and incremental variance explained (ΔR^2) are summarized in Table 4.29.

Table 4.29 Interaction Effects Summary

Hypothesis	Moderator	Interaction Term	β	p	ΔR^2	Result
H21	Consumer innovativeness (CI)	PB × CI → PI	0.012	0.610	0.000	Not supported
H22	Consumer innovativeness (CI)	PR × CI → PI	0.032	0.042	0.001	Supported
H23	Consumer innovativeness (CI)	PC × CI → PI	0.020	0.388	0.000	Not supported

Table 4.29 (continued)

Hypothesis	Moderator	Interaction Term	β	p	ΔR²	Result
H24	Digital transformation attitudes (DTA)	PB × DTA → PI	–0.096	< 0.001	0.009	Supported
H25	Digital transformation attitudes (DTA)	PR × DTA → PI	–0.055	0.011	0.003	Supported
H26	Digital transformation attitudes (DTA)	PC × DTA → PI	–0.094	< 0.001	0.009	Supported

Note. β = standardized regression coefficient for the interaction term in the final step of hierarchical regression. ΔR^2 = change in R^2 after entering the interaction term. PB = perceived benefits; PR = perceived risks; PC = perceived costs; PI = purchase intention.

In summary, the results of testing the following hypotheses are shown in Table 4.30.

Table 4.30 Summary of Test Hypotheses for Moderating Effects

Item	statement	Test results
H21	Consumer innovativeness has a moderating effect between perceived benefits and purchase intentions. The more innovative the consumer, the higher the perceived benefits and the stronger the purchase intention. The stronger the effect of perceived benefits on Purchase intention, the stronger the effect of perceived benefits on Purchase intention.	Not supported
H22	Consumer innovativeness has a moderating effect between perceived risks and purchase intention. The greater the consumer innovativeness, the lower the perceived risks, the greater the Purchase intention, and the weaker the effect of perceived risks on Purchase intention.	Supported

Table 4.30 (continued)

Item	statement	Test results
H23	Consumer innovativeness has a moderating effect between Perceived costs and Purchase intention. Consumer innovativeness has a moderating effect between Perceived costs and Purchase intention. The stronger the consumer innovativeness, the lower the perceived costs, the stronger the purchase intention, and the weaker the effect of perceived costs on purchase intention.	Not supported
H24	Customer digital transformation attitudes have a moderating effect between perceived benefits and purchase intentions. The stronger the customer's attitude towards digital transformation, the higher the perceived benefits and the stronger the purchase intention	Supported
H25	Customer digital transformation attitudes have a moderating effect between perceived risks and purchase intention. The stronger the customer's digital transformation attitude, the lower the perceived risks, the stronger the purchase intention, and the weaker the effect of perceived risks on purchase intention.	Supported
H26	Customer digital transformation attitudes have a moderating effect between perceived costs and purchase intentions. Customer digital transformation attitude has a moderating effect between perceived costs and purchase intention. The stronger customer's digital transformation attitude, the lower perceived costs, the stronger purchase intention, and the weaker effect of perceived costs on purchase intention.	Supported

Table 4.31 Results of Moderating Effects Analysis of Consumer Innovations

	PC_L-PI_L			PB_L-PI_L			PR_L-PI_L		
	t	***p***	***β***	***t***	***p***	***β***	***t***	***p***	***β***
Constant (math)	44.227	0.000**	-	43.43	0.000**	-	44.452	0.000**	-
Gender	-0.264	0.792	-0.006	-0.258	0.796	-0.006	-0.547	0.584	-0.012
Marital status	1.128	0.26	0.025	0.919	0.358	0.021	0.812	0.417	0.018
Age	-0.546	0.585	-0.012	-0.612	0.541	-0.014	-0.736	0.462	-0.016
Monthly income	1.652	0.099	0.043	1.946	0.052	0.051	2.08	0.038*	0.054
Education background	-0.463	0.644	-0.011	-0.487	0.626	-0.011	-0.829	0.408	-0.019
Frequency of Online Shopping	0.889	0.374	0.023	1.076	0.282	0.028	0.93	0.353	0.024
Occupation	-0.566	0.572	-0.016	-0.694	0.488	-0.02	-0.231	0.818	-0.006
Purchased Type	-0.94	0.348	-0.021	-1.267	0.206	-0.029	-0.917	0.36	-0.02
Most Frequently Used Platform	0.214	0.831	0.005	-0.018	0.986	0	-0.183	0.855	-0.004
Location	1.193	0.233	0.033	1.553	0.121	0.044	2.023	0.043*	0.056
PC_L				5.06	0.000**	0.174			
PB_L	7.241	0.000**	0.324						

Table 4.31 (continued)

	PC_L-PI_L			PB_L-PI_L			PR_L-PI_L		
	t	***p***	***β***	***t***	***p***	***β***	***t***	***p***	***β***
PR_L							8.187	0.000**	0.299
CI_L	10.642	0.000**	0.473	18.093	0.000**	0.623	14.148	0.000**	0.516
PC_L*CI_L				0.863	0.388	0.02			
PB_L*CI_L	0.511	0.61	0.012						
PR_L*CI_L							1.442	0.042	0.032
R^2		*0.598*			*0.585*			*0.605*	
Adjustment R^2		*0.592*			*0.578*			*0.599*	
F-value	*F(13,824)=94.371, p=0.000*			*F(13,824)=89.312, p=0.000*			*F(13,824)=97.025, p=0.000*		
ΔR^2	*0.000*			*0*			*0.001*		

* p<0.05 ** p<0.01

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention,CI_L, Consumer innovativeness.

Table 4.32 Results of Moderating Effect Analysis of Customer Digital Transformation Attitudes

	PC_L-PI_L			**PB_L-PI_L**			**PR_L-PI_L**		
	t	***p***	***β***	***t***	***p***	***β***	***t***	***p***	***β***
Constant (math)	43.576	0.000**	-	45.826	0.000**	-	45.41	0.000**	-
Gender	-0.45	0.652	-0.01	-0.273	0.785	-0.006	-0.512	0.608	-0.011
Marital status	0.416	0.678	0.009	1.206	0.228	0.026	0.517	0.605	0.011
Age	0.092	0.927	0.002	0.084	0.933	0.002	-0.002	0.998	0
Monthly income	0.692	0.489	0.018	0.623	0.533	0.016	1.142	0.254	0.029
Education	-0.138	0.89	-	-0.319	0.75	-0.007	-0.77	0.441	-0.017
background			0.003						
Frequency of Online	1.436	0.151	0.038	1.35	0.177	0.034	1.47	0.142	0.037
Shopping									
Occupation	-0.478	0.633	-	-0.48	0.631	-0.013	-0.06	0.953	-0.002
			0.014						
Purchased Type	-0.618	0.537	-	-0.243	0.808	-0.005	-0.301	0.764	-0.007
			0.014						
Most Frequently Used	0.505	0.614	0.012	0.718	0.473	0.016	0.484	0.629	0.011
Platform									
Location	1.002	0.317	0.028	0.833	0.405	0.022	1.73	0.084	0.047
PC_L	2.23	0.026*	0.087						

Table 4.32 (continued)

	PC_L-PI_L			PB_L-PI_L			PR_L-PI_L		
	t	***p***	***β***	***t***	***p***	***β***	***t***	***p***	***β***
PB_L				10.34	0.000**	0.388			
PR_L							10.23	0.000**	0.334
DTA_L	17.804	0.000**	0.697	12.266	0.000**	0.455	15.603	0.000**	0.509
PC_L*DTA_L	-4.105	0.000**	-0.094						
PB_L*DTA_L				-4.346	0.000**	-0.096			
PR_L*DTA_L							-2.545	0.011*	-0.055
R 2	0.581			0.622			0.621		
Adjustment *R* 2	0.575			0.616			0.615		
F-value	*F(13,824)=87.993, p=0.000*			*F(13,824)=104.345, p=0.000*			*F(13,824)=103.648, p=0.000*		
△*R* 2	*0.009*			*0.009*			*0.003*		
△F-value	*F(1,824)=16.854, p=0.000*			*F(1,824)=18.885, p=0.000*			*F(1,824)=6.477, p=0.011*		

* p<0.05 ** p<0.01

Note: IA_L, interesting innovation; IB_L, interactivity innovation; IC_L, integration innovation; ID_L, individualization innovation; PB_L, perceived benefits; PC_L, perceived costs; PR_L, perceived risks; PI_L, purchase intention,CI_L, Consumer innovativeness.

4.3 Conclusion

This chapter presented the main empirical results of the study. It covered three parts: the refinement of the measurement scales, the assessment of the formal survey data, and the testing of the proposed hypotheses.

Firstly, the pilot study successfully refined the measurement scales. Reliability analysis of the initial 108 pre-study samples indicated that 17 items with CITC values below 0.5 were deleted, resulting in a finalised formal questionnaire comprising 61 measurement items across ten variables. Validity analysis confirmed that the scales possessed good content and structural validity (KMO > 0.6, $p < 0.001$ for all scales), establishing a robust foundation for the main investigation.

Secondly, the formal survey data were found to be of good quality. A total of 838 valid responses were used in the analysis. Descriptive statistics confirmed that the data approximated a normal distribution, with skewness and kurtosis values within acceptable ranges. Reliability analysis yielded Cronbach'sαcoefficients for all variables ranging from 0.744 to 0.976, substantially exceeding the minimum threshold of 0.7 and indicating excellent internal consistency. Furthermore, confirmatory factor analysis provided strong evidence of convergent validity, with all standardised factor loadings exceeding 0.5, average variance extracted (AVE) values surpassing 0.5, and composite reliability (CR) values above 0.7. Discriminant validity was also established, as the square root of the AVE for each variable was greater than its correlations with other variables. Common method bias was not a concern, as all variance inflation factor (VIF) values were well below the critical threshold of 5.

Thirdly, the hypothesis testing provided strong support for the proposed model. All four dimensions of value innovation—interesting (H1, $\beta=0.164$, $p<0.001$), interactivity (H2, $\beta=0.080$, $p=0.004$), integration (H3, $\beta=0.058$, $p=0.020$), and individualization (H4, $\beta=0.052$, $p=0.048$)—had a significant positive direct impact on purchase intention. Furthermore, consumer innovativeness demonstrated a significant positive direct effect on perceived benefits (H6, $\beta=0.886$, $p<0.001$), perceived risks (H7, $\beta=0.844$, $p<0.001$), perceived costs (H8, $\beta=0.958$, $p<0.001$), and purchase intention (H5, $\beta=0.861$, $p<0.001$). although consumer innovativeness was significantly and positively associated with perceived risks and perceived costs, these directions were contrary to the hypothesized negative relationships; therefore, H7 and H8 were not supported.

The mediation analysis further showed that perceived benefits, perceived risks, and perceived costs all played significant partial mediating roles in the relationships between value innovation and purchase intention. All twelve mediation hypotheses (H9-H20) were supported. Notably, the mediating role of perceived benefits was strongest for the relationship between individualization and purchase intention (49.06% of total effect), while perceived risks played a prominent mediating role in the integration purchase intention pathway (42.33%). These findings underscore the critical role of consumers' cognitive evaluations in translating value innovation into actual purchase decisions.

The moderation analysis produced mixed results. Consumer innovativeness was found to significantly moderate the relationship between perceived risks and purchase intention (H22, $\beta=0.032$, $p=0.042$), with a stronger effect observed for consumers with higher innovativeness. However, its moderating effects on the relationships for perceived benefits (H21) and perceived costs (H23) were not statistically significant. In contrast, consumer digital transformation attitudes consistently and significantly moderated all three perceived value–purchase intention relationships. Specifically, a stronger positive attitude towards digital transformation weakened the positive effect of perceived benefits (H24, $\beta=-0.096$, $p<0.01$), H24 was statistically significant but in the direction opposite to that hypothesized: the positive effect of perceived benefits on purchase intention was weaker among consumers with stronger digital transformation attitudes. And the negative effect of perceived risks (H25, $\beta=-0.055$, $p<0.05$) on purchase intention, while also weakening the negative effect of perceived costs (H26, $\beta=-0.094$, $p<0.01$). These results highlight that consumers who are more receptive to digital transformation rely less on traditional value perceptions when forming purchase intentions.

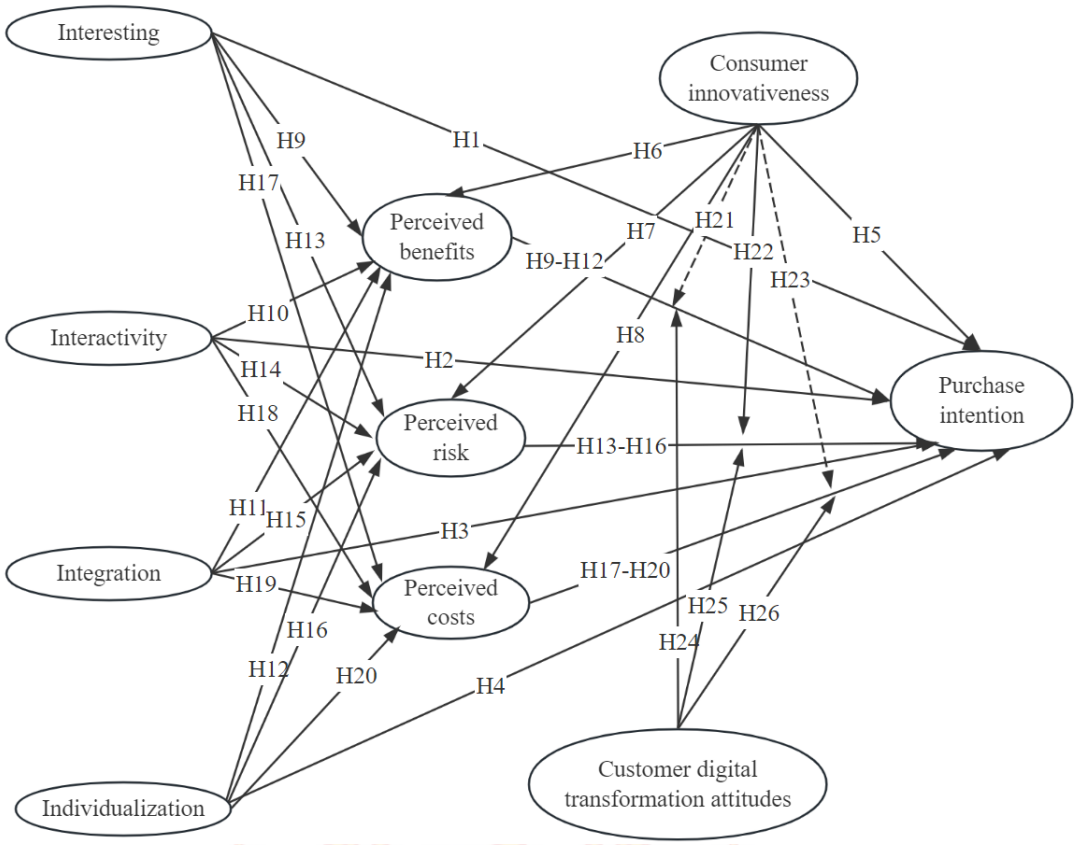


Figure 4.7 Hypothesis Validation Relationship Diagram

Note: Solid line=Supported Hypotheses; dotted line=Not supported hypotheses.

To provide a concise overview of the magnitude and significance of all interaction effects, Table 4.29 summarises the standardized regression coefficients (β), significance levels (p), and incremental variance explained (ΔR^2) for each moderating path.

In conclusion, the empirical evidence presented in this chapter validates the theoretical framework of the study. The results confirm that value innovation in fresh food e-commerce influences purchase intention both directly and indirectly through the mediating mechanisms of perceived value. Furthermore, consumer digital transformation attitudes serve as a significant boundary condition, shaping how these relationships operate. Collectively, these findings provide a robust empirical foundation for the subsequent discussion of theoretical contributions and practical implications in the following chapter.

CHAPTER 5
DISCUSSION AND CONCLUSION

This chapter systematically discusses the empirical findings presented in Chapter Four, aiming to answer the three research questions that guided this study. The primary goal is to synthesize the results, place them within the context of existing literature, and articulate their theoretical and practical implications. This study, grounded in the SOR model and 4I marketing theory, explored the mechanisms through which value innovation in fresh e-commerce influences consumer purchase intention, with a focus on the mediating role of perceived value and the moderating effects of consumer innovativeness and digital transformation attitudes.

In terms of quantitative research, consumer data were collected through an online survey and empirically analyzed using Structural Equation Modelling to quantify the specific path of value innovation on consumer purchase intention. The results of the study show that value innovation in fresh food e-commerce significantly affects consumers' perceived value and can have an impact on purchase intention through mediating variables and moderating variables.

5.1 Introduction

This section discusses the empirical findings presented in Chapter Four and interprets them in relation to the research questions, objectives, and the existing literature. Building on the results of the structural equation modelling, mediation analysis, and moderation analysis, this chapter aims to explain not only whether value innovation influences purchase intention in fresh food e-commerce, but also how and under what conditions this influence occurs. The discussion is organised around the three research questions that guided this study. First, it examines how the four dimensions of value innovation—interesting, interactivity, integration, and individualization—directly affect consumers' purchase intention (RQ1). Second, it explores how perceived value, comprising perceived benefits, perceived costs, and perceived risks, mediates the

relationship between value innovation and purchase intention (RQ2). Third, it analyses how consumer innovativeness and digital transformation attitudes moderate the relationship between perceived value and purchase intention (RQ3). By integrating the empirical results with relevant theories, this chapter seeks to provide a comprehensive understanding of the mechanisms and boundary conditions through which value innovation shapes consumer purchase intention in the fresh food e-commerce context.

RQ1: How does value innovation in fresh e-commerce related consumers' purchase intention?

RO1: Investigate the mechanisms by which value innovation in fresh e-commerce affects consumer purchase intentions.

Firstly, regarding the positive effect of interesting on purchase intention, it was found that interesting significantly enhances consumers' purchase intention. According to the full integrated model results in Table, the path coefficient of interesting on purchase intention is 0.164 ($p < 0.001$), indicating that interesting is an important factor driving purchase intention. In the field of fresh food e-commerce, interestingness mainly enhances consumers' shopping experience by improving the interactivity of the platform and the richness of the display. For example, through interesting product display and interactive activities, it can stimulate consumers' emotional resonance and purchase desire. Lu et al. (2023) also pointed out that perceived hedonicity plays an important role in enhancing consumers' purchase intention, especially in e-commerce live or short-video advertisements, where the sense of pleasure and entertainment become the driving force of consumers' purchase decisions. By verifying the effect of interesting on purchase intention, this study further suggests that e-commerce platforms need to focus on the design of interesting content when enhancing user experience, and this design not only increases the attractiveness of the product, but also enhances user stickiness, which in turn promotes purchase behaviour.

Second, regarding the effect of interactivity on purchase intention, the empirical results of this study show that interactivity has a significant positive effect on purchase intention. Based on the full model calculation, the path coefficient of interactivity on purchase intention is 0.080 ($p = 0.004$). This finding is consistent with the results of Li and Cheng (2023), who analysed data based on Nanchang City and found that the positive relationship between interactivity and consumers' perceived usefulness promotes purchase

intention. In fresh food e-commerce, especially in live streaming e-commerce platforms, interactivity enhances consumers' trust in the platform and stimulates their desire to purchase through real-time communication between anchors and consumers, and interactivity experiences between consumers and the platform. Xu and Liang (2021) pointed out that the enhancement of interpersonal interaction in live e-commerce not only directly promotes consumers' purchase intention, but also indirectly enhances purchase intention by influencing mediating variables such as consumers' mindstream experience and perceived risks. In this study, the positive effect of interactivity reflects that fresh food e-commerce platforms are able to effectively promote consumers' emotional engagement and purchase decisions by providing an interactive shopping environment. Therefore, platforms should enhance consumers' engagement and trust by increasing interactive sessions, such as live interaction, live customer service, and user comments, thereby promoting purchase behaviour.

Regarding the effect of integration on purchase intention, the results of this full integrated model demonstrate that platform integration positively affects purchase intention with a path coefficient of 0.058 ($p = 0.020$). This result is consistent with the findings of Swoboda and Winters (2021) on channel integration, who argued that high-quality integration of online and offline channels enhances consumers' shopping experience, which increases purchase intention. In fresh food e-commerce, integration not only reflects the coordination of online and offline channels, but also involves the seamless integration of various functional modules and services within the platform. For example, the one-stop shopping experience provided by fresh food e-commerce platforms enables consumers to complete the entire process from shopping to payment without leaving the platform, which in turn enhances their purchase intention. Nguyen (2021) states that the high quality of channel integration enhances the overall shopping experience of the customer, which in turn enhances his or her purchase intention. The results of this study further validate this viewpoint, suggesting that highly integrated e-commerce platforms are able to enhance consumers' trust and satisfaction with the platforms by providing convenient and individualised services, thereby promoting purchase behaviour.

Regarding the effect of individualization on purchase intention, the full model results indicate that individualization has a significant positive effect on purchase intention, with a path coefficient of 0.052 ($p = 0.048$). This finding is in line with Lau and

Ki's (2021) findings on individualization interactivity experiences, highlighting that individualization can increase consumer engagement and purchase intention. In fresh food e-commerce, individualization is mainly used to enhance consumers' sense of exclusivity and convenience by providing them with customised recommendations, promotions, and product displays. This individualization shopping experience can significantly increase consumers' loyalty to the platform, which in turn promotes their purchasing behaviour. Ho et al. (2022) pointed out that individualization advertisements can significantly increase consumers' purchase intention, and this study further verifies the positive impact of individualization on purchase intention through empirical analysis. Therefore, e-commerce platforms should focus on providing individualization recommendations and services based on consumers' preferences and behavioural data to enhance consumers' shopping experience, which in turn promotes purchase decisions.

Finally, regarding consumer innovativeness, combined with the above corrected full-model path coefficients, it is noteworthy that the direct impacts of the four multidimensional innovation perceptions on purchase intention are statistically significant but relatively moderate in magnitude. This indicates that in the integrated fresh food e-commerce consumption system, platform innovation serves as a vital auxiliary driving factor for purchase intention, rather than a dominant decisive factor. Consumers' purchase decisions are comprehensively shaped by multiple perceived dimensions including perceived benefits, costs and risks. Consistent with Mohamed and Wee's (2020) research, innovative consumer traits still positively facilitate purchasing behaviours, while the reduced path coefficients in the full model reflect the competitive and complementary relationships among multiple explanatory variables in the integrated research framework. Therefore, e-commerce platforms can enhance the purchase intention of innovative consumers by introducing innovative products or services when attracting them.

RQ2: How does the perceived value of fresh e-commerce mediate the relationship between value innovation and purchase intention in consumers?

RO2: Investigate the mediating role of perceived value between value innovation and consumer purchase intention in fresh e-commerce.

This study explored the mediating role of consumers' perceived value in the relationship between value innovation and purchase intention in fresh food e-commerce through empirical analyses, and the results showed that perceived benefits, perceived

costs, and perceived risks mediated the relationship between value innovation and purchase intention under multiple dimensions, respectively. This finding not only verifies the importance of perceived value in consumers' purchasing decisions, but also provides important theoretical insights into the strategies of e-commerce platforms in promoting consumers' purchase intention.

Firstly, perceived benefit has a significant mediating effect between value innovation and purchase intention in fresh food e-commerce. According to the results in Table, the indirect effect of perceived benefit between IA_L and PI_L is 0.102, accounting for 33.77% of the total effect, with a confidence interval of [0.087, 0.166] and a p-value of less than 0.001, which suggests that the effect of perceived benefit on purchase intention is significant and stable. This result is consistent with the study of Zahid and Ahmed (2017), which concluded that perceived benefits can effectively enhance consumers' desire to purchase products by enhancing the interesting and functional value of products. In the context of fresh food e-commerce, innovative products can stimulate purchase intentions by enhancing consumers' perceived benefits in terms of product performance, quality, and time savings. For example, fresh food e-commerce offers guaranteed freshness, convenient delivery methods, and efficient product selection and payment processes, all of which fall under the category of perceived consumer benefits. These perceived benefits lead to strong purchase motivation, especially in the case of fresh produce innovation and value optimisation, which makes it easier for consumers to accept and purchase new products.

Furthermore, the mediating role of perceived benefits displayed a notable asymmetry across the different innovation pathways. Specifically, within the individualisation innovation pathway, perceived benefits accounted for 49.06% of the total effect, the highest proportion among all pathways. This pattern suggests that innovations tailored to consumers' personalized needs strengthen their perception of core functional benefits—such as health, freshness, and convenience—which in turn enhances purchase intention. Such a result is consistent with the consumption-value perspective proposed by Sheth et al. (1991), who argued that functional value is often the most decisive determinant of consumers' choice behaviour, particularly for products whose primary attributes concern quality and utility. In addition, perceived benefits explained the mediating effect in the integration innovation pathway, indicating that systemic solutions such as optimized cold-chain logistics reinforce benefit perceptions related to time saving and quality

assurance. Consequently, integration innovation appears to serve as a value-transmission pathway than interest innovation. This finding echoes Zeithaml's (1988) conceptualization of perceived value as the consumer's overall assessment of what is received relative to what is given, in which the "benefit" component plays a dominant role in shaping value judgements for utilitarian products. It is further supported by the multidimensional value framework of Sweeney and Soutar (2001), whose empirical evidence demonstrated that functional (quality- and performance-related) value exerts a stronger influence on purchase decisions than emotional value in contexts where product performance is central to the consumption experience—a condition that clearly characterises the fresh food e-commerce setting examined in this study.

The mediating effect of perceived costs between value innovation and purchase intention is also significant. According to the mediation effect test in Table, the indirect effect of perceived costs between IA_L and PI_L is 0.085, accounting for 21.52% of the total effect, with a confidence interval of [0.072, 0.146] and a p-value of less than 0.001, which suggests that perceived costs significantly affect purchase intention. Specifically, although product innovativeness can bring certain perceived benefits, high perceived costs tend to inhibit consumers' purchase decisions. Consistent with the findings of Xu and Li (2022), it was found that highly innovative consumers are usually able to realize the long-term benefits of innovation, but they may face higher financial costs or time investment in the initial stage, which creates higher perceived costs. In the fresh food e-commerce environment, consumers often weigh these costs and potential benefits when faced with innovative fresh food products that are more expensive or require a longer wait for delivery, which can affect their purchase intentions. For example, consumers may be hesitant to make a purchase intention due to concerns about food damage during transport or delivery delays, a process in which perceived costs play a particularly prominent role. Therefore, when promoting innovative products, e-commerce platforms must find a balance between innovation and cost, and use effective promotions, price concessions, and reliable delivery services to reduce consumers' perceived costs and enhance purchase intentions.

Although perceived costs were significant across all pathways ($p < 0.001$), their effect sizes, ranging from 21.47% to 29.08%, were lower than those of perceived benefits. This result suggests that perceived costs do play a role in explaining how value innovation

affects purchase intention, but they are not the dominant mechanism in this study. In the context of fresh food e-commerce, consumers are not only concerned about price or transaction costs. They also evaluate whether the platform can provide freshness, convenience, product reliability, delivery efficiency, and better matching with their daily needs. From the perspective of perceived value, consumers tend to make purchase decisions by comparing what they receive with what they give up. When the perceived benefits are strong enough, the negative influence of perceived costs may be weakened (Zeithaml, 1988).

This finding is also consistent with the price–value evaluation logic proposed in consumer behaviour research. Price and cost may reduce purchase intention when consumers feel that the product or service does not offer sufficient value. However, when consumers perceive higher quality, greater convenience, and better service outcomes, they may be more willing to accept reasonable costs because the overall value evaluation becomes more positive (Dodds et al., 1991). In fresh food e-commerce, this logic is particularly relevant because consumers often care about whether the products are fresh, whether delivery is reliable, and whether the platform can reduce the uncertainty of online fresh food purchasing. Therefore, value innovation may reduce the psychological weight of cost by improving consumers' perceptions of practical benefits.

The mediating effect of perceived risks between value innovation and purchase intention in fresh food e-commerce has also been empirically verified. Table shows that the indirect effect of perceived risks between IA_L and PI_L is 0.14, accounting for 35.44% of the total effect, with a confidence interval of [0.13, 0.219] and a p-value of less than 0.001, which suggests that perceived risks plays a significant mediating role in this path. This result is consistent with the study of Isip and Lacap (2021), which stated that perceived risks significantly affect consumers' purchasing decisions by increasing uncertainty. In fresh food e-commerce, consumers tend to have higher perceived risks due to concerns about product quality, damage during delivery, or lack of after-sales service, which can inhibit their purchase intentions. Especially when purchasing innovative products, consumers are often wary of unknown risks. By reducing consumers' perception of risk, such as providing a strict quality control system, transparent product information, and hassle-free returns and exchanges, e-commerce platforms can effectively reduce consumers' perception of risk, thereby facilitating purchase decisions.

The mediating effect of perceived risks was especially evident in the integration innovation pathway. In this study, perceived risks accounted for 42.33% of the total effect between integration innovation and purchase intention, indicating that risk perception is an important mechanism through which interactive innovation influences consumers' purchase decisions. This result suggests that interactive functions in fresh food e-commerce do not automatically increase purchase intention. Their influence depends partly on whether consumers perceive these functions as reducing uncertainty or creating additional concerns during the shopping process. In fresh food e-commerce, consumers cannot directly inspect product freshness, product quality, storage conditions, or delivery reliability before purchase. Therefore, interactive functions such as live streaming, real-time consultation, product videos, customer reviews, and visual product presentation may help reduce uncertainty by improving information transparency and consumer trust. Recent studies on online shopping and live-streaming commerce have also shown that interactive communication can strengthen trust and purchase intention when it provides useful information and reduces perceived uncertainty (Wongkitrungrueng & Assarut, 2020; Zhang et al., 2020). In the fresh food context, this mechanism is particularly important because consumers are highly sensitive to product quality, delivery time, and food safety.

However, integration innovation may also increase perceived risks if the information provided is inconsistent, exaggerated, difficult to verify, or if the interactive process becomes too complicated. For example, live demonstrations or product images may attract consumers' attention, but they may also raise doubts if the displayed product does not match the delivered product. Recent research on fresh food e-commerce and organic food purchasing has shown that perceived value, trust, platform quality, and risk-related concerns remain important factors affecting consumers' online food purchase intention (Qi et al., 2024). Therefore, the role of interactivity innovation is not only to create richer shopping experiences, but also to reduce consumers' concerns about freshness, quality, delivery, and after-sales responsibility.

Taken together, the finding suggests that perceived risks play a meaningful mediating role between interactivity innovation and purchase intention. For fresh food e-commerce platforms, interactive functions should not be designed only for attention or entertainment. They should provide reliable product information, transparent delivery

details, visible quality assurance, and responsive communication. Only when interactive innovation helps consumers feel more certain and secure can it effectively improve purchase intention.

In summary, the findings for RO2 confirm that consumers' perceived value functions as a critical mediating mechanism linking value innovation to purchase intention in fresh food e-commerce, but this mediation operates through three distinct and unequally weighted channels—perceived benefits, perceived costs, and perceived risks. Among these, perceived benefits emerged as the dominant pathway, exerting the strongest and most stable mediating effect and rising to 49.06% within the individualisation pathway and within the integration pathway; this indicates that value innovation influences purchase intention primarily by strengthening consumers' perceptions of freshness, quality, convenience, and time saving. Perceived costs, although significant across all pathways, played a secondary role (21.47%–29.08%), suggesting that in Shanghai's fresh food e-commerce market the negative weight of monetary and transactional costs is partly offset once consumers perceive sufficient benefits. Perceived risks, by contrast, were most influential in the interactivity innovation pathway (42.33%), revealing the double-edged nature of technology-driven interaction: it can either reduce or amplify consumers' uncertainty about quality, delivery, and food safety depending on whether the information provided is transparent and verifiable. Taken together, these results demonstrate that value innovation does not translate into purchase intention directly, but rather through consumers' cognitive trade-off between the benefits they expect to receive and the costs and risks they expect to bear. Theoretically, this extends the perceived-value literature by disaggregating the mediating mechanism into benefit-, cost-, and risk-based components and by showing that their relative importance varies systematically across innovation types. Practically, it implies that fresh food e-commerce platforms should prioritise benefit-oriented value innovation, keep perceived costs within a reasonable range, and design interactive functions that actively reduce—rather than heighten—consumers' perceived risks, thereby converting value innovation into stronger purchase intention.

RQ3: How do consumer innovativeness and digital transformation attitudes moderate the influence of consumers' perceived value on their purchase intentions?

RO3: Investigate the moderating role of consumer innovativeness and digital transformation attitudes in the relationship between consumers' perceived value and purchase intentions.

This study explores the moderating effects of consumer innovativeness and digital transformation attitudes on the relationship between perceived consumer value and purchase intention through empirical analyses. The results show that while both variables serve as moderators, their mechanisms and scopes of influence differ. Consumer innovativeness exerts a selective moderating effect primarily in the context of perceived risks, whereas digital transformation attitudes demonstrate a consistent and significant moderating effect across all dimensions of perceived value.

On the moderating effect of consumer innovativeness in perceiving the relationship between consumers' perceived value and purchase intentions. This study finds that consumer innovativeness has a selective moderating effect on the relationship between different dimensions of perceived value (perceived benefits, perceived risks, and perceived costs) and purchase intention. Specifically, consumer innovativeness demonstrates a significant moderating effect only in the relationship between perceived risks and purchase intention ($\beta=0.032$, $p=0.042$), whereas its moderating effects concerning perceived benefits and perceived costs are not statistically significant. Given the small ΔR^2, this moderation should be interpreted as limited in magnitude and mainly indicative of a boundary condition rather than a strong behavioral shift.

First, regarding the relationship between perceived risks and purchase intention, it was found that consumer innovativeness significantly moderates this relationship. When consumers are more innovative, their purchase intention is stronger even when they face higher perceived risks. This phenomenon suggests that consumers with high innovativeness are more willing to accept new things and tolerate a certain amount of risk, which makes them less likely to abandon purchasing behaviours due to an increase in perceived risks. This finding is also consistent with the theory of trait conditioning orientation proposed by Higgins et al. (2020), which suggests that individuals with higher innovative consumers tend to adopt an approach strategy rather than an avoidance strategy when faced with uncertainty, thereby increasing their purchase intentions. Therefore, the findings of this study further validate that more innovative consumers are able to maintain stronger purchase motivation despite facing potential risks. The results of the simple slope

analysis indicate that highly innovative consumers exhibit stronger purchase intention in risk situations, which aligns with their higher level of risk acceptance. Moreover, although the negative correlation between perceived risk and purchase intention is slightly weaker for highly innovative consumers compared to their less innovative counterparts, the difference is statistically modest, reflecting only a certain degree of buffering effect rather than a fundamental shift in decision-making logic.

However, for the relationship between perceived costs and purchase intention, this study did not find a significant influence of innovativeness on the moderating effect of this relationship. The interaction effect between perceived costs and consumer innovativeness failed to reach statistical significance (β=0.020, t=0.863, p=0.388). This implies that more innovative consumers do not fundamentally alter their evaluation of costs; they remain more willing to buy when perceived costs are low. Similarly, the interaction effect with perceived benefits also failed to reach significance (β=0.012, t=0.511, p=0.610). The non-significant moderating effect of consumer innovativeness on the paths of perceived benefits and perceived costs also holds profound theoretical rationality. For frequently purchased products tied to health and daily routines, purchase decisions are driven primarily by core value evaluations, such as price and quality/freshness, which function as baseline criteria across consumer segments. Therefore, even highly innovative consumers still evaluate perceived benefits and perceived costs in relatively similar ways. This result is slightly different from Min's (2022) study, which suggests that highly innovative consumers will reduce their purchase intentions when perceived costs are high. On the contrary, this study suggests that highly innovative consumers seem to be more concerned with new and unique products and less concerned with traditional cost issues, which may be closely related to their preference for novel products and services. This may differ from contexts involving non-fresh or more hedonic or digital products, where innovativeness can shape how consumers weigh instrumental or experiential value (Khazaei & Tareq, 2021).

Despite the lack of significant results in the interaction of perceived costs and perceived benefits, this study still found a significant moderating effect of perceived risks on purchase intention, especially in the context of higher perceived risks, where consumer innovativeness plays a crucial moderating role. This finding has important theoretical significance, which not only expands the path of consumer innovativeness on purchase

intention, but also provides academics with new perspectives that consumers with higher innovativeness are better able to overcome the uncertainty of the external environment and enhance their purchase intention in the face of risk.

In summary, this study verifies the significant moderating effect of consumer innovativeness as a moderating variable between perceived risks and purchase intention, especially in the context of higher perceived risks. Consumers with higher innovativeness are less sensitive to risk and thus maintain stronger purchase intention. In contrast, less innovative consumers are more sensitive to perceived risks and tend to avoid purchase decisions. Consumer innovativeness in fresh e-commerce appears to relate mainly to consumers' responses to uncertainty, while it does not meaningfully alter evaluations of deterministic value. This finding not only enriches the theory of consumer behaviour, but also provides important practical guidance for the field of e-commerce, especially the online sales of fresh products. Merchants can formulate sales strategies based on consumers' innovativeness to reduce perceived risks and increase purchase intention, thus achieving more effective marketing.

On the moderating effect of consumers' digital transformation attitudes in perceiving the relationship between consumers' perceived value and purchase intentions. The empirical analyses in this study indicate that consumer digital transformation attitudes play a significant moderating role between perceived consumer value and purchase intention. In contrast to the selective effect of consumer innovativeness, consumers' digital transformation attitudes not only play a moderating effect in the influence of perceived costs, perceived benefits, and perceived risks on purchase intention, but also their effects show different strengths under different levels, which is consistent with the theories and research findings in the existing literature, and at the same time provides new perspectives on digital transformation-related research.

Firstly, regarding the moderating effect of consumers' digital transformation attitudes between perceived costs and purchase intention, the results of the study show that the negative effect of perceived costs on purchase intention exhibits significant differences at different levels of digital transformation attitudes. The negative effect of perceived costs on purchase intention is more significant when consumers' digital transformation attitude is low. This result suggests that when consumers have a more negative attitude towards digital transformation, they are more likely to perceive the costs associated with digital

transformation, as barriers to purchasing decisions, which reduces purchase intentions. However, when consumer attitudes toward digital transformation are high, the negative effect of perceived costs on purchase intention almost disappears (regression coefficient of -0.006, $p = 0.890$). This phenomenon suggests that when consumers have a positive attitude towards digital transformation, they are more willing to accept new digital experiences, even if they are accompanied by certain costs, and perceive added value from them, thus maintaining a higher purchase intention. This finding is in line with the study by Schumacher et al. (2016), which suggests that customer digital transformation attitudes mitigate consumers' perceived costs of using new technologies, thereby enhancing their purchase intentions.

Secondly, regarding the moderating role of consumers' digital transformation attitudes between perceived benefits and purchase intention, the study shows that when consumers' digital transformation attitudes are high, the effect of perceived benefits on purchase intention is significantly stronger (regression coefficient of 0.545, $p < 0.001$). This result suggests that when consumers have a positive attitude towards digital transformation, they are able to more clearly perceive the convenience and benefits of digital transformation, such as individualization recommendations and fast transaction processes, which significantly increase their purchase intention. In contrast, when digital transformation attitudes were low, perceived benefits had a weaker effect on purchase intentions (regression coefficient of 0.323, $p < 0.001$). This suggests that consumers with low attitudes may not be able to fully realize the benefits of digital transformation and therefore their purchase intention is lower. Zhang and Qin (2022) also pointed out that digital transformation can stimulate consumers' interest in products or services by enhancing user experience, which in turn enhances purchase intention. Therefore, consumers' recognition of digital transformation directly affects their perception of the benefits brought by digital transformation.

Finally, regarding the relationship between perceived risks and purchase intention, consumer digital transformation attitudes also played a significant moderating role. When consumers' digital transformation attitudes are low, the negative effect of perceived risks on purchase intention is stronger (regression coefficient of 0.420, $p < 0.001$). This means that consumers with low attitudes may have stronger risk perceptions when facing digital transformation due to unfamiliarity with new technologies and mistrust of data privacy

protection, thus inhibiting their purchase intentions. In contrast, the negative effect of perceived risks on purchase intention is significantly weakened when consumers have higher digital transformation attitudes (regression coefficient of 0.303, $p < 0.001$). This suggests that consumers with higher digital transformation attitudes are more likely to trust the enterprise's protection of data privacy and security in the process of digital transformation, which reduces their perception of risk and enhances purchase intention. Schumacher et al. (2016) also mentioned that enterprises should focus on enhancing consumer trust in the process of digital transformation, which is crucial for reducing perceived risks and enhancing consumers' purchase intention.

In summary, the results of this study further validate the moderating role of consumers' digital transformation attitudes between perceived costs, perceived benefits, and perceived risks and purchase intentions. The stronger the consumers' digital transformation attitude, the weaker the negative effect of perceived costs on purchase intention, the stronger the positive effect of perceived benefit on purchase intention, and the weaker the negative effect of perceived risks on purchase intention. Therefore, when promoting digital transformation, enterprises should focus on enhancing consumer digital transformation attitudes, and enhance consumers' acceptance of digital transformation through measures such as improving the experience quality of digital services, optimising the design of user interfaces, and strengthening data privacy protection, so as to promote the increase of purchase intention. This finding not only supports the theories in the existing literature, but also provides useful insights into digital transformation strategies in practice.

5.2 Implications for Theories

This study, grounded in the Stimulus-Organism-Response model and 4I marketing theory, constructs and empirically tests a mechanism model for how value innovation in fresh e-commerce influences consumer purchase intention within the context of the digital economy. The theoretical contributions are primarily reflected in the following four aspects.

First, this study extends the application of the Stimulus-Organism-Response theory to the context of fresh e-commerce, revealing the heterogeneous transmission pathways through which different dimensions of value innovation influence purchase intention via

perceived value. This study finds that perceived benefits account for the largest proportion of the mediating effect in the relationship between individualization innovation and purchase intention (49.06%), while perceived risk accounts for a significantly larger proportion of the mediating effect in the integration innovation pathway (42.33%) compared to its role in the interestingness and interactivity innovation pathways. This suggests that when innovation involves systemic solutions, consumers are more inclined to evaluate its potential risks; conversely, when innovation focuses on emotional experiences, it primarily functions by enhancing perceived benefits. This finding deepens the contextual application of the Stimulus-Organism-Response theory in the e-commerce environment, demonstrating that the mechanisms of different value innovation dimensions are fundamentally distinct.

Second, this study further clarifies the relative importance of the four dimensions of the 4I marketing theory in the context of fresh food e-commerce. The results show that interesting innovation and interactivity innovation are not only positively related to consumers' purchase intention, but also influence purchase intention indirectly by increasing perceived benefits. In this study, the indirect effects through perceived benefits accounted for more than 32% in these two innovation pathways, indicating that emotional and experiential value plays an important role even in a high-frequency and relatively planned consumption context such as fresh food purchasing. This finding suggests that consumers do not evaluate fresh food e-commerce platforms only from a functional perspective, such as price, delivery speed, or product availability. They also respond positively to enjoyable content, interactive communication, and service experiences that help them feel more engaged, informed, and confident during the purchase process. Previous studies on social commerce and live-streaming commerce have also shown that interactive and engaging digital experiences can strengthen consumer trust, engagement, and purchase intention (Wongkitrungrueng & Assarut, 2020; Zhang et al., 2020). At the same time, the results show that individualization innovation did not produce the strongest effect in this study. This may be because fresh food purchasing is usually driven by clear and practical needs, such as freshness, safety, delivery reliability, and convenience. Therefore, recommendation algorithms or personalized product suggestions may not be sufficient to increase purchase intention unless they are closely connected with consumers' actual shopping goals and perceived value. This interpretation is consistent with recent

research suggesting that AI-based personalization and digital marketing technologies do not automatically create consumer value; their effectiveness depends on whether consumers perceive them as useful, trustworthy, and relevant to the purchase context (Davenport et al., 2020; Huang & Rust, 2021; Puntoni et al., 2021). Therefore, this study enriches the application of the 4I marketing theory by showing that, in fresh food e-commerce, interestingness and interactivity may be more effective than individualization when they directly enhance consumers' perceived benefits, reduce uncertainty, and improve the overall shopping experience.

Third, this study integrates perceived value theory with innovation diffusion theory, explicitly defining the "selective buffering" role of consumer innovativeness in fresh e-commerce decision-making and its theoretical boundary. This study finds that consumer innovativeness only exerts a significant buffering effect on the relationship between perceived risk and purchase intention (H22 supported), meaning that highly innovative consumers are less sensitive to the negative impact of risk. However, its moderating effect on perceived benefits and perceived costs was not significant. This indicates that in high-risk, highly functional consumption decisions, innovativeness primarily acts as a risk buffer rather than a value amplifier. This finding deepens the understanding of the mechanism of innovativeness, providing clear direction for future research exploring its moderating effects across different product types and consumption contexts.

Fourth, this study introduces and validates customer digital transformation attitudes as an independent moderating contextual variable, addressing the gap in existing literature regarding the lack of attention to differences in consumer-side technology acceptance attitudes. This study finds that customer digital transformation attitudes significantly moderate the relationships between perceived benefits, perceived risk, perceived cost, and purchase intention (H24-H26 supported), and the direction of these moderating effects is consistent: positive attitudes weaken the negative impact of perceived cost and perceived risk, while simultaneously strengthening the positive impact of perceived benefits. This finding extends the "attitude" variable from the Technology Acceptance Model from a direct influence to a moderating influence on core decision-making pathways, revealing that consumers' acceptance of digital technology is a critical contextual filter in translating value innovation into actual purchase intentions.

In conclusion, by integrating the Stimulus-Organism-Response model and 4I marketing theory, this study provides a detailed deconstruction of the pathways through which value innovation influences purchase intention, clarifies the boundary conditions of innovativeness, and incorporates digital transformation attitudes into a unified consumer behavior analysis framework. The construction and validation of this theoretical model offers a more explanatory analytical framework for understanding consumer behavior in fresh e-commerce within the digital economy era.

5.3 Implications for Practitioners

The findings of this study provide important practical guidance for practitioners, policy makers and industry associations in the fresh food e-commerce sector to optimize their strategies in the fast-evolving digital economy and enhance the overall welfare of consumers. Based on the results of the empirical analyses, this paper proposes a number of targeted strategies that aim to promote the long-term development of fresh food e-commerce companies and enhance consumer experience, while safeguarding the sustainable development of the industry.

5.3.1 Strategic Recommendations

(1) Prioritise value innovation in platform design and marketing.

The results of this study suggest that interesting, interactivity, integration, individualization, and consumer innovativeness are the key factors that enhance consumers' purchase intentions. Fresh food e-commerce companies should incorporate these dimensions into their platform design and marketing strategies to enhance platform attractiveness and user stickiness through value innovation.

Firstly, enhancing interest and interactivity. In order to stimulate the emotional resonance of consumers, fresh food e-commerce platforms should design interesting interfaces to increase user participation. For example, by carrying out interactivity games or creative displays on the platform, not only can it increase consumer participation, but also enhance the entertainment and interactivity of the platform. Especially through the introduction of short videos, live broadcasting, and other forms of content, not only can increase user activity, but also allow consumers to interact in the process of generating more purchase intentions.

Secondly, strengthen interactivity. Live e-commerce has become a popular trend in recent years, and fresh food e-commerce platforms should increase their investment in live e-commerce to establish interactive connections with consumers through real-time Q&A and anchors with goods. With the help of artificial intelligence technology, the platform can provide real-time intelligent customer service and individualization recommendations to further enhance user engagement and trust. Through user-generated content, the platform's user stickiness and purchase conversion rate can be further improved. Studies have shown that consumers' trust and satisfaction with a platform depends largely on the level of interaction with the platform.

Thirdly, optimize integration. Fresh food e-commerce enterprises should be committed to achieving seamless integration of online and offline channels. By combining the advantages of traditional retail and digital channels, and by providing order online, pick up offline services, consumers can enjoy the convenience of instant access to products offline, while also ensuring the quality of online purchases and standardisation of services. In addition, companies can explore cooperation with traditional supermarkets, convenience stores, and other retailers to build a wider distribution and self-pick-up network to enhance the consumer shopping experience.

Fourthly, making the most of individualization. Individualization recommendations are an important means to enhance user experience. Fresh food e-commerce platforms should make use of big data and artificial intelligence technology to analyse consumers' purchasing behaviour and preferences, so as to provide customized product recommendations. For example, it can recommend suitable ingredients or matching products based on consumers' shopping history, and individualization product combinations such as the "weekend barbecue package" can not only improve users' purchase intention, but also increase the platform's repurchase rate.

(2) Reduce perceived costs and risks while enhancing perceived benefits

Research has found that perceived value plays a crucial role in consumer purchase decisions. Fresh food e-commerce companies should enhance perceived benefits by reducing consumers' perceived costs and risks, thus enhancing consumers' purchase intentions.

Firstly, reducing perceived costs. By optimizing the platform's interface design and operational processes, make it easier for consumers to browse and purchase, and reduce

the time cost of decision-making. Provide a transparent pricing policy to avoid hidden costs and enhance consumer trust. In addition, companies can launch subscription models to provide high-frequency users with benefits such as price discounts or free delivery fees, further lowering the purchase threshold for consumers. Through these measures, not only can consumers' decision-making costs be reduced, but also user loyalty can be increased.

Secondly, reducing perceived risks. Consumers' concerns about product quality and delivery services are common problems faced by fresh food e-commerce companies. Therefore, companies must take effective measures to guarantee product quality, especially the quality assurance of fresh goods. Through real-time tracking of the cold chain logistics system, it ensures temperature-controlled and damage-free distribution from production to distribution. In addition, platforms should develop clear return and exchange policies to ensure that consumers can obtain timely solutions when they receive unsatisfactory goods. By establishing a credible quality certification system. Companies can also further enhance consumers' trust and reduce their perception of risk.

Thirdly, enhancing perceived benefits. Fresh produce e-commerce platforms should highlight the actual convenience brought by the products, emphasizing the benefits in terms of saving time and improving quality of life. For example, consumers' purchase intention can be enhanced by providing fast delivery services. At the same time, platforms should also provide individualization benefits through membership systems and exclusive discounts to enhance consumers' perceived benefits.

(3) Market segmentation based on consumer innovativeness and digital readiness

It was found that consumers' innovativeness and digital readiness have a significant moderating effect on their purchasing behaviour. Therefore, fresh food e-commerce companies should implement differentiated market segmentation strategies based on these factors.

For the more innovative consumer segments, companies can launch new and unusual products in advance and test them in the market. These consumers are usually more willing to try new things and have a higher risk tolerance, making them ideal testers of new products and features. In addition, companies can offer more individualization and tailored services to this group of consumers to enhance their loyalty.

For those consumer segments with low digital readiness, fresh food e-commerce companies should provide a cleaner, easier-to-use interface and operating procedures.

Help them better understand how to use the e-commerce platform, how to choose products, and how to avoid common pitfalls of online shopping through educational content. Enhancing the digital shopping confidence of these consumers by partnering with well-known online celebrities or opinion leaders to boost their purchase intent.

5.3.2 Policy and Industry Association Initiatives

(1) Setting industry standards to drive value innovation

With the rapid development of the fresh produce e-commerce industry, regularization and standardisation have become key to the industry's sustainable and healthy development. Industry associations should strengthen co-operation with government regulators to promote the development of uniform industry standards, especially in terms of the quality and safety of fresh produce. For example, for perishable fresh food, strict temperature-controlled transport standards should be formulated; for agricultural products, the production process and environmental standards should be clearly defined to ensure their quality. In addition, trade associations can promote the application of technologies such as blockchain to establish a comprehensive product traceability system, so that consumers can have a clear understanding of the source, production process, and logistics information of each product, thereby enhancing their trust in the products.

With the popularity of individualization recommendation technology, consumers are increasingly concerned about personal data privacy. Therefore, industry associations should promote the development of data privacy protection measures that are in line with China national conditions and draw on international experience to establish a sound data protection framework. Specifically, they should enhance the transparency of the use of consumers' personal data, ensure consumers' informed consent, and safeguard the security of their personal information.

(2) Promoting digital literacy and inclusive services

In order to promote the inclusiveness of the digital economy, especially in support of the elderly population and rural areas, the government and industry associations should work jointly on policies to enhance the digital capabilities of disadvantaged groups.

On the one hand, the government should promote the development of Internet infrastructure in rural areas by strengthening cooperation with telecom operators to enhance their network coverage and help small- and medium-sized farmers better

participate in e-commerce platforms. By providing farmers with technical training and digital tool support, it can help them adapt to the e-commerce platform and integrate into the fresh produce e-commerce ecosystem. On the other hand, for the elderly population, the government and industry associations can organize a series of digital literacy education activities, and through a combination of online and offline methods, help them master the basic operation of using e-commerce platforms, improve their digital shopping skills, and enhance their quality of life. These measures will help narrow the digital divide and promote the inclusive development of the digital economy.

5.4 Limitations of the Study and Implications of Future Studies

5.4.1 Limitations of the Present Study

Although this study provides empirical evidence on how value innovation influences consumers' purchase intention in the fresh food e-commerce context, several limitations should be acknowledged. These limitations do not undermine the main findings of the study, but they indicate areas where future research can further improve and extend the current work.

First, the geographical scope of this study is limited to Shanghai. The research sample was collected from consumers in selected administrative districts of Shanghai by using a multi-stage sampling procedure. This design helped ensure that consumers from different geographical areas of the city were included. However, Shanghai is one of the most economically developed and digitally advanced cities in China. Consumers in Shanghai are generally more familiar with online shopping, digital payment, platform services, and fresh food delivery than consumers in many other regions. As a result, their perceptions of value innovation, perceived benefits, perceived risks, and purchase intention may not fully represent consumers in less developed cities, rural areas, or regions with different logistics and digital infrastructure. Future studies could expand the research scope to other cities and provinces in China. Comparative studies between first-tier cities, lower-tier cities, and rural markets would help test whether the relationships identified in this study remain stable across different regional contexts.

Second, although this study adopted a structured sampling framework, the data were still collected through questionnaire surveys and included elements of convenience sampling at the final stage of data collection. This approach was appropriate for reaching

fresh food e-commerce consumers in real market settings, but it may still limit the generalizability of the findings. Respondents who were more willing to participate in the survey may have had stronger interest in online shopping or greater familiarity with fresh food e-commerce platforms. Therefore, the sample may not fully capture the views of consumers who rarely use such platforms or who are less active in digital consumption. Future research could use probability-based sampling methods where possible, or combine online and offline sampling channels to improve sample representativeness. In addition, researchers could increase the sample size and compare different user groups, such as frequent users, occasional users, and non-users of fresh food e-commerce platforms.

Third, the study relies on self-reported questionnaire data. The measurement of consumers' perceptions, attitudes, and purchase intention was based on respondents' own evaluations. This method is widely used in consumer behaviour research and is suitable for examining psychological constructs such as perceived value and consumer innovativeness. Nevertheless, self-reported data may be affected by memory errors, subjective judgment, or social desirability bias. For example, some respondents may overstate their willingness to purchase fresh food online because they perceive online shopping as convenient, modern, or socially acceptable. Future studies could combine survey data with objective behavioural data, such as actual purchase records, browsing history, platform transaction data, or experimental evidence. Such mixed-method designs would provide a more comprehensive understanding of the relationship between purchase intention and actual purchasing behaviour.

Fourth, this study focuses on purchase intention rather than actual purchase behaviour. Purchase intention is an important predictor of consumer behaviour and is commonly used in marketing research. However, intention does not always lead to actual action. In the fresh food e-commerce context, consumers may express a strong willingness to purchase, but their final decision may still be influenced by delivery time, product freshness, price changes, platform promotions, after-sales service, or previous consumption experience. Therefore, the findings of this study mainly explain consumers' psychological tendency to purchase rather than their final purchasing behaviour. Future research could examine the transition from purchase intention to actual purchase behaviour. Longitudinal studies would be especially useful for observing whether

consumers' intentions remain stable over time and whether they eventually result in repeated purchases.

Fifth, the research model mainly examines the effects of value innovation on purchase intention through perceived value, and further considers the moderating role of consumer innovativeness and digital transformation attitude. This model is consistent with the theoretical focus of the study and provides a clear explanation of the mechanism linking platform innovation and consumer response. However, consumer decision-making in fresh food e-commerce is complex. Other factors may also influence purchase intention, such as trust in the platform, food safety concerns, delivery reliability, brand reputation, price sensitivity, habit, emotional experience, and social influence. These factors were not fully included in the current model in order to maintain theoretical clarity and model parsimony. Future studies could extend the model by adding these variables or by comparing different theoretical frameworks. For example, future research may examine whether trust mediates the relationship between perceived risk and purchase intention, or whether social influence strengthens the effect of perceived benefits on consumer decision-making.

Finally, this study uses a cross-sectional research design. The data were collected at one point in time, which allows the study to test the proposed relationships among value innovation, perceived value, consumer innovativeness, digital transformation attitude, and purchase intention. However, consumer attitudes toward fresh food e-commerce may change over time as platforms improve their services, consumers gain more online shopping experience, and market competition becomes more intense. A cross-sectional design cannot fully capture these dynamic changes. Future studies could adopt longitudinal designs to examine how consumers' perceptions and purchase intentions evolve over time. This would be particularly valuable in the fresh food e-commerce industry, where technology, logistics systems, and consumer expectations are changing rapidly.

Overall, the limitations of this study provide useful directions for future research. Future studies can improve the generalizability of the findings by expanding the geographical scope, improving sampling methods, incorporating behavioural data, examining actual purchase behaviour, extending the theoretical model, and using longitudinal research designs. These efforts would further deepen the understanding of

consumer behaviour in the fresh food e-commerce market and provide stronger evidence for both academic research and managerial practice.

5.4.2 Implications for Future Research

Although this study provides valuable empirical data for the fresh food e-commerce sector, there are still many areas of methodology and perspective that deserve further exploration.

Future research should consider sample collection in a wider geographic area, particularly to explore the differences in fresh food e-commerce consumer behaviour between different cities, urban and rural areas. Consumers in different regions differ significantly in terms of their economic status, cultural background, and technology acceptance, and these factors may have a profound impact on consumers' purchase intentions. Therefore, cross-regional studies can reveal the characteristics of consumer behaviour in different market environments and provide guidance for fresh food e-commerce platforms' operational strategies in different regions.

Future research can further validate the findings in this study through a multi-method approach to data collection, such as combining online behavioural tracking and experimental design. Behavioural data analysis can provide more objective and intuitive data on consumer purchasing behaviours, while experimental research can reveal consumers' real responses in different contexts. Combining different data sources will improve the accuracy and reliability of the findings.

This study explored the factors influencing purchase intention from the individual level of consumers, and future research can further incorporate social factors such as social networks and emotional ties into the analysis framework. Consumer behaviour on fresh food e-commerce platforms is not only influenced by individual characteristics, but also closely related to social factors such as their social circles, recommendations from friends and relatives, and group identity. By examining these social factors, future research can further enrich the theory of consumer behaviour and provide new insights into the social marketing of platforms.

The focus on consumer innovativeness in the study provides important ideas for future research directions. With the rapid development of digital technology, the definition and expression of consumer innovativeness may change. Future research can explore the changing trends of consumer innovativeness and its impact on purchase intention in the

context of digital transformation in order to respond to the changing market environment and consumer demand in the fresh food e-commerce sector.

5.5 Conclusion

Through a quantitative methodology, this study delves into the mechanism of the value innovation of fresh food e-commerce on consumers' purchase intention and builds a systematic theoretical framework by combining the SOR model and the 4I marketing theory. The results of the study show that the value innovations of fresh food e-commerce (interesting, interactivity, integration, and individualization) significantly relate consumers' perceived value, and further act on consumers' purchase intention through the mediating variables of perceived benefits, perceived costs, and perceived risks. In addition, consumer innovativeness and digital transformation attitudes play an important moderating role in the relationship between perceived value and purchase intention.

In terms of the direct impact of value innovation on purchase intention, this study found that interesting, interactivity, integration, and individualization of fresh food e-commerce significantly and positively relate consumers' purchase intention. Value innovations in these dimensions enhance consumers' desire to purchase by enhancing their shopping experience and emotional resonance. interesting and interactive, in particular, significantly increase purchase intention by enhancing consumers' sense of engagement and trust.

In terms of the mediating role of perceived value, perceived benefits, perceived costs, and perceived risks play a significant mediating role between value innovation and purchase intention. Perceived benefits increased purchase intention by enhancing consumers' recognition of innovative products, while perceived costs and perceived risks influenced final purchase behaviour by inhibiting consumers' purchase decisions. This finding provides an important theoretical basis for fresh food e-commerce platforms when designing and promoting innovative products.

In terms of the moderating role of consumer innovativeness and digital transformation attitudes, consumer innovativeness plays a significant moderating role between perceived risks and Purchase intention, and highly innovative consumers maintain a strong Purchase intention in the face of risk. Digital transformation attitudes, on the other hand, play a moderating role between Perceived costs, perceived benefits and

perceived risks and Purchase intention, with consumers with high digital transformation attitudes being more receptive to the convenience and benefits of digitization, thus increasing Purchase intention.

In terms of theoretical contributions, this study enriches the application of consumer behaviour theory in the field of fresh food e-commerce by combining the SOR model with 4I marketing theory. First, the study reveals how value innovation affects purchase intention through the mediating role of perceived value, filling a theoretical gap in the existing literature at the intersection of digital marketing and consumer decision-making. Second, the study expands the theoretical explanatory dimension of consumer heterogeneity in decision-making mechanisms by introducing the moderating role of consumer innovativeness and digital transformation attitudes, providing a new perspective for understanding consumer behaviour in the digital environment.

In terms of practical implications, the findings of this study provide important practical guidance for fresh food e-commerce enterprises. First, companies should enhance consumers' shopping experience and purchase intention by enhancing the interesting, interactivity, integration, and individualization of the platform. Second, firms should further promote consumers' purchase decisions by reducing perceived costs and risks and enhancing perceived benefits. Finally, companies should implement differentiated market segmentation strategies based on consumers' innovative and digital transformation attitudes to better meet the needs of different consumers.

In terms of research limitations and future research directions. Although this study provides an in-depth empirical analysis of consumer behaviour in the field of fresh food e-commerce, there are still some limitations. First, the study sample was mainly focused on the Shanghai region of China, and future research could collect samples in a wider geographic area to verify the generalizability of the findings. Second, this study mainly relied on self-reported questionnaire methods, and future research could combine behavioural data analysis and experimental studies to improve the accuracy and reliability of the data. Finally, future research can further explore the influence of emotional factors and social networks on consumer purchase decisions to enrich consumer behaviour theories.

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APPENDIXES

APPENDIX A

Scale

Appendix A. Scale

Table 1 Interesting Scale

Abbr	Item	Source
IA1	The fresh e-commerce platform has brought a lot of freshness and interest to my fresh produce purchases	Xu (2024)
IA2	Browsing through pictures, videos or live streams of fresh produce brings me more leisure and pleasure	
IA3	I like and enjoy using fresh e-commerce platforms to buy fresh produce	

Table 2 Interactivity Scale

Dimension	Abbr	Item	Source
Active control	IB1	I felt that I had a lot of control over my visiting experiences on this Fresh E-commerce platform	Leiner & Quiring (2008)
	IB2	While I was on the Fresh E-commerce platform, I could choose freely what I wanted to see	
	IB3	While surfing the Fresh E-commerce platform, my actions decided the kind of experiences I got	
Two-way communication	IB4	The Fresh E-commerce platform is effective in gathering visitors' feedback	
	IB5	This Fresh E-commerce platform facilitates two-way communication between the visitors and the site.	
	IB6	The Fresh E-commerce platform makes me feel it wants to listen to its visitors	
	IB7	The Fresh E-commerce platform gives visitors the opportunity to talk back to their friends and neighbours.	

Dimension	Abbr	Item	Source
Synchronicity	IB8	The Fresh E-commerce platform processed my input very quickly	
	IB9	Getting information from the Fresh E-commerce platform is very fast	
	IB10	I was able to obtain the information I wanted without any delay	
	IB11	When I clicked on the links, I felt I was getting instantaneous information	

Table 3 Integration Scale

Abbr	Item	Source
IC1	The Fresh E-commerce platform's brand name, slogan, and logo are consistent both online and offline.	Oh et al. (2012)
IC2	The Fresh E-commerce platform highlights in-store promotions that are taking place in the physical store.	
IC3	The Fresh E-commerce platform keeps an integrated purchase history of customers' online and offline purchases.	
IC4	The Fresh E-commerce platform makes future purchase recommendations to customers based on past consolidated online and offline purchases.	
IC5	Product/service descriptions are consistent in both the physical store and the Fresh E-commerce platform.	
IC6	Information on stock availability is consistent in both the physical store and the Fresh E-commerce platform.	
IC7	Discounts are consistent in both the physical store and the Fresh E-commerce platform.	
IC8	The Fresh E-commerce platform allows customers to search for products available in the physical store.	
IC9	The Fresh E-commerce platform allows checking of inventory status at the physical store through the platform.	

Abbr	Item	Source
IC10	The physical store allows customers to self-collect their online purchases from the Fresh E-commerce platform.	
IC11	The Fresh E-commerce platform allows customers to make payment in the physical store for their online purchases.	
IC12	The in-store customer service centre accepts returns, repairs, or exchanges of products purchased online through the Fresh E-commerce platform.	

Table 4 Individualization Scale

Abbr	Item	Source
ID1	A fresh e-commerce platform can provide me with personalised deals/ads tailored to my activity context.	Xu et al. (2011)
ID2	The Fresh E-commerce platform can provide me with more relevant promotional information tailored to my preferences or personal interests.	
ID3	The Fresh E-commerce platform can provide me with the kind of deals/ads that I might like.	

Table 5 Consumer Perceived Benefits Scale

Abbr	Item	Source
PB1	Using a fresh e-commerce platform would enable me to complete shopping tasks more quickly.	Davis (1989)
PB2	The online fresh e-commerce platform improves my shopping efficiency.	
PB3	Using an online fresh e-commerce platform increases my shopping productivity.	
PB4	The online fresh e-commerce platform enhances my shopping effectiveness.	

Abbr	Item	Source
PB5	The online fresh e-commerce platform makes the purchasing process easier.	
PB6	I find the online fresh e-commerce platform useful in the shopping process.	
PB7	Learning how to operate an online fresh e-commerce platform would be easy for me.	
PB8	I find it easy to achieve my desired shopping outcomes using the online fresh e-commerce platform.	
PB9	My interaction with the online fresh e-commerce platform would be clear and understandable.	
PB10	I would find the online fresh e-commerce platform flexible to interact with.	
PB11	It would be easy for me to become skilled at using the online fresh e-commerce platform.	
PB12	I think the online fresh e-commerce platform is easy to use.	

Table 6 Consumer Perceived Costs Scale

Abbr	Item	Source
PC1	I spend a lot of effort searching for relevant information when purchasing from online fresh e-commerce platforms.	Li et al. (2019)
PC2	I spend a lot of time contacting the seller when purchasing from online fresh e-commerce platforms.	
PC3	When purchasing from online fresh platforms, I spend a lot of effort monitoring the order processing and delivery progress.	

Table 7 Consumer Perceived Risks Scale

Abbr	Item	Source
PR1	The online fresh grocery will provide stale or even deteriorated products.	Cui et al. (2023)
PR2	The online fresh grocery will provide products containing excessive chemical hazards.	
PR3	The online fresh grocery will provide products containing harmful pathogens.	
PR4	The products will not be consistent with the pictures and descriptions.	
PR5	The after-sales service cannot be provided in time.	
PR6	Online shopping will take me a long time.	
PR7	My personal information would be leaked.	
PR8	(Cui et al., 2023) Online shopping will lead to financial loss.	

Table 8 Consumer Purchase Intention Scale

Abbr	Item	Source
PI1	If I need to buy fresh produce, I am willing to buy it through a fresh e-commerce company.	Esfahani & Reynolds (2021)
PI2	If I need to buy fresh produce, I would first consider buying it through a fresh e-commerce company.	
PI3	I would recommend a friend to buy fresh food through a fresh e-commerce company	

Table 9 Consumer Innovativeness Scale

Dimension	Abbr	Item	Source
Social interesting	CI1	I love to use innovations that impress others	Esfahani & Reynolds (2021)
	CI2	I like to own a new product that distinguishes me from others who do not own this new product	
	CI3	I prefer to try new products with which I can present myself to my friends and neighbours	

Dimension	Abbr	Item	Source
	CI4	I deliberately buy novelties that are visible to others and which command respect from others	
Functional	CI5	If a new product gives me more comfort than my current product, I would not hesitate to buy it	
	CI6	If an innovation is more interesting functional, then I usually buy it	
	CI7	If I discover a new product in a more convenient size, I am very inclined to buy this	
	CI8	If a new product makes my work easier, then this new product is a 'must' for me	
Hedonic	CI9	Using novelties gives me a sense of personal enjoyment	
	CI10	It gives me a good feeling to acquire new products	
	CI11	Innovations make my life exciting and stimulating	
	CI12	Acquiring an innovation makes me happier	
	CI13	The discovery of novelties makes me playful and cheerful	
Cognitive	CI14	I mostly buy those innovations that satisfy my analytical mind	
	CI15	I find innovations that need a lot of thinking intellectually challenging and therefore I buy them instantly	
	CI16	I often buy new products that make me think logically	
	CI17	I often buy innovative products that challenge the strengths and weaknesses of my intellectual skills	
	CI18	I am an intellectual thinker who buys new products because they set my brain to work	

Dimension	Abbr	Item	Source
	CI19	The company fully leverages digital channels to interact and transact with customers during the sales and service processes of fresh products	
	CI20	Customers demonstrate a high level of competence when using the digital tools and technologies provided by the fresh grocery e-commerce platform	

Table 10 Customer Digital Transformation Attitude Scale

Abbr	Item	Source
DTA1	I'm willing to learn about new apps, features, and services that are emerging from the digital transformation of fresh e-commerce	Zhang & Qin. (2022)
DTA2	Fresh e-commerce companies should invest more in driving digital transformation.	
DTA3	I'm positive about the future of digital transformation in fresh e-commerce	

APPENDIX B

Questionnaire

Appendix B. Questionnaire

Rattanakosin International College of Creative Entrepreneurship
Of Rajamangala University of Technology, Rattanakosin
Questionnaire on the Impact of Value Innovation on Consumer Purchase Intention in Fresh E-commerce

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Dear Respondent,

Thank you for taking time out of your busy schedule to participate in this survey. The purpose of this study is to understand your true feelings regarding value innovation, perceived value, and purchase intention when shopping on fresh e-commerce platforms (e.g., Dingdong Maicai, Hema Fresh, Meituan Youxuan, etc.). The questionnaire is anonymous, and all data will be used for academic research only. Your personal information will be kept strictly confidential. There are no right or wrong answers. Please feel free to fill it out based on your actual experience. Thank you very much for your support and cooperation!

Instruction: Except for the basic information in Part I, for the remaining questions, please tick (✓) the corresponding number according to your actual feelings. The numbers represent: 1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree.

Part I: Basic Information (Please select the option that applies to you)

1. Your gender:

☐ Male

☐ Female

2. Your age:

☐ Under 18 ☐ 18-24 ☐ 25-30

☐ 31-40 ☐ Over 40

3. Your highest education level:

☐ High school or below ☐ High school/Technical secondary school

☐ Junior college ☐ Bachelor's degree

☐ Master's degree or above

4. Your marital status:

☐ Unmarried ☐ Married

☐ Divorced ☐ Widowed

5. Your occupation:

☐ Student ☐ Government or public institution employee

☐ Corporate staff ☐ Self-employed

☐ Other

6. Your monthly disposable income (RMB):

☐ 3,000 RMB or below ☐ 3,001-5,000 RMB

☐ 5,001-10,000 RMB ☐ 10,001-20,000 RMB

☐ Over 20,000 RMB

7. Frequency of online shopping for fresh agricultural products:

☐ Almost never ☐ Once a month

☐ 2-3 times a month ☐ 1-2 times a week

☐ More than three times a week

8. The type of fresh agricultural products you most frequently purchase online (single choice):

☐ Vegetables, bean products ☐ Fruits

☐ Meat and poultry ☐ Seafood

☐ Eggs, milk ☐ Other

9. The platform you most frequently use for online shopping of fresh agricultural products (single choice):

☐ Dingdong Maicai ☐ Hema Fresh

☐ JD Daojia ☐ RT-Mart Youxian

☐ Meituan Youxuan ☐ Other

10. Number of platforms available for online shopping of fresh agricultural products:

☐ 1 platform ☐ 2 platforms

☐ 3 platforms ☐ 4 platforms

☐ 5 platforms or more

Part II: Perceived Value Innovation

The following questions aim to understand your feelings about fresh e-commerce platforms in terms of interestingness, interactivity, integration, and individualization innovation.

(1) Interesting Innovation

Item	Statement	1	2	3	4	5
IIA1	The fresh e-commerce platform has brought a lot of freshness and interest to my fresh produce purchases					
IIA2	Browsing through pictures, videos or live streams of fresh produce brings me more leisure and pleasure					
IIA3	I like and enjoy using fresh e-commerce platforms to buy fresh produce					

(2) Interactivity Innovation

Item	Statement	1	2	3	4	5
IIB1	I felt that I had a lot of control over my visiting experiences on this Fresh E-commerce platform					
IIB2	While I was on the Fresh E-commerce platform, I could choose freely what I wanted to see					

Item	Statement	1	2	3	4	5
IIB3	While surfing the Fresh E-commerce platform, my actions decided the kind of experiences I got					
IIB4	The Fresh E-commerce platform is effective in gathering visitors' feedback					
IIB5	The Fresh E-commerce platform makes me feel it wants to listen to its visitors					
IIB6	The Fresh E-commerce platform gives visitors the opportunity to talk back to their friends and neighbours.					
IIB7	I was able to obtain the information I wanted without any delay					
IIB8	When I clicked on the links, I felt I was getting instantaneous information					

(3) Integration Innovation

Item	Statement	1	2	3	4	5
IIC1	The Fresh E-commerce platform's brand name, slogan, and logo are consistent both online and offline.					
IIC2	The Fresh E-commerce platform highlights in-store promotions that are taking place in the physical store.					
IIC3	The Fresh E-commerce platform keeps an integrated purchase history of customers' online and offline purchases.					
IIC4	The Fresh E-commerce platform makes future purchase recommendations to customers based on past consolidated online and offline purchases.					
IIC5	Product/service descriptions are consistent in both the physical store and the Fresh E-commerce platform.					
IIC6	Information on stock availability is consistent in both the physical store and the Fresh E-commerce platform.					

Item	Statement	1	2	3	4	5
IIC7	Discounts are consistent in both the physical store and the Fresh E-commerce platform.					
IIC8	The Fresh E-commerce platform allows customers to make payment in the physical store for their online purchases.					

(4) Individualization Innovation

Item	Statement	1	2	3	4	5
IID1	A fresh e-commerce platform can provide me with personalised deals/ads tailored to my activity context.					
IID2	The Fresh E-commerce platform can provide me with more relevant promotional information tailored to my preferences or personal interests.					
IID3	The Fresh E-commerce platform can provide me with the kind of deals/ads that I might like.					

Part III: Perceived Value

(1) Perceived Benefits

Item	Statement	1	2	3	4	5
PB1	Using a fresh e-commerce platform would enable me to complete shopping tasks more quickly.					
PB2	The online fresh e-commerce platform improves my shopping efficiency.					
PB3	Using an online fresh e-commerce platform increases my shopping productivity.					
PB4	The online fresh e-commerce platform enhances my shopping effectiveness.					
PB5	I find the online fresh e-commerce platform useful in the shopping process.					

Item	Statement	1	2	3	4	5
PB6	Learning how to operate an online fresh e-commerce platform would be easy for me.					
PB7	I find it easy to achieve my desired shopping outcomes using the online fresh e-commerce platform.					
PB8	My interaction with the online fresh e-commerce platform would be clear and understandable.					
PB9	I would find the online fresh e-commerce platform flexible to interact with.					

(2) Perceived Risks

Item	Statement	1	2	3	4	5
PR1	The online fresh grocery will provide stale or even deteriorated products.					
PR2	The online fresh grocery will provide products containing excessive chemical hazards.					
PR3	The online fresh grocery will provide products containing harmful pathogens.					
PR4	The products will not be consistent with the pictures and descriptions.					
PR5	The after-sales service cannot be provided in time.					
PR6	Online shopping will take me a long time.					

(3) Perceived Costs

Item	Statement	1	2	3	4	5
PC1	I spend a lot of effort searching for relevant information when purchasing from online fresh e-commerce platforms.					
PC2	I spend a lot of time contacting the seller when purchasing from online fresh e-commerce platforms.					
PC3	When purchasing from online fresh platforms, I spend a lot of effort monitoring the order processing and delivery progress.					

Part IV: Purchase Intention

Item	Statement	1	2	3	4	5
PI1	If I need to buy fresh produce, I am willing to buy it through a fresh e-commerce company.					
PI2	If I need to buy fresh produce, I would first consider buying it through a fresh e-commerce company.					
PI3	I would recommend a friend to buy fresh food through a fresh e-commerce company					

Part V: Customer Digital Transformation Attitudes

Item	Statement	1	2	3	4	5
DTA1	I'm willing to learn about new apps, features, and services that are emerging from the digital transformation of fresh e-commerce					
DTA2	Fresh e-commerce companies should invest more in driving digital transformation.					
DTA3	I'm positive about the future of digital transformation in fresh e-commerce					

Part VI: Consumer Innovativeness

Item	Statement	1	2	3	4	5
CI1	I love to use innovations that impress others					
CI2	I like to own a new product that distinguishes me from others who do not own this new product					
CI3	If a new product gives me more comfort than my current product, I would not hesitate to buy it					
CI4	If an innovation is more interesting functional, then I usually buy it					
CI5	If I discover a new product in a more convenient size, I am very inclined to buy this					

Item	Statement	1	2	3	4	5
CI6	If a new product makes my work easier, then this new product is a 'must' for me					
CI7	Using novelties gives me a sense of personal enjoyment					
CI8	Innovations make my life exciting and stimulating					
CI9	Acquiring an innovation makes me happier					
CI10	The discovery of novelties makes me playful and cheerful					
CI11	I mostly buy those innovations that satisfy my analytical mind					
CI12	I find innovations that need a lot of thinking intellectually challenging and therefore I buy them instantly					
CI13	I often buy new products that make me think logically					
CI14	I am an intellectual thinker who buys new products because they set my brain to work					
CI15	The company fully leverages digital channels to interact and transact with customers during the sales and service processes of fresh products					

This is the end of the questionnaire. Thank you again for your patience and participation! Wishing you a happy life!

APPENDIX C

Publication of Journal during Ph.D. Study

APPENDIX C. Publication of Journal during Ph.D. Study

Agribusiness

WILEY

Agribusiness

RESEARCH ARTICLE

The Impact of Value Innovation of Fresh Food E-Commerce on Consumers' Purchase Intention

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ABSTRACT

The swift advancement of fresh food e-commerce has heightened market competitiveness, compelling enterprises to pursue distinct advantages via service enhancements and model innovation. Nonetheless, current research has not comprehensively demonstrated how value innovation in fresh food e-commerce affects consumer purchase intention via the mediating role of perceived value and the moderating role of consumer innovativeness. Based on survey data from 838 fresh food customers in Shanghai, this study explores how value innovation in fresh food e-commerce influences consumer purchase intention, addressing a gap in current research. The results show that (1) value innovation in fresh food e-commerce increases consumer purchase intention; (2) perceived value plays an mediating role in connecting fresh food e-commerce value innovation and purchase intention; and (3) consumer innovativeness moderates how perceived risks relate to purchase intention, but it does not significantly moderate the relationship between perceived benefits, perceived costs, and purchase intention. This study enhances the comprehension of the mechanisms underlying value innovation in fresh food e-commerce, presents a novel perspective for its theoretical advancement, and furnishes practical suggestions for optimizing marketing strategies and improving customer engagement on platforms.

1 | Introduction

With the rapid development of e-commerce, the fresh food sector has emerged as a key segment, demonstrating substantial growth in recent years. Fresh food e-commerce refers to businesses that sell fresh products directly to consumers via the internet and mobile platforms, generating profits by combining fresh food markets with digital business models (Cuicui and Zongguang 2021). According to the China Report Hall (2025), the size of China's fresh food e-commerce market is projected to grow from 642.76 billion yuan in 2023 to 1.2 trillion yuan by 2025. This represents a compound annual growth rate of over 25%. User penetration is also expected to rise from 8.4% in 2023 to about 20% by 2025. This rapid expansion is driven by advances in cold chain logistics, improved instant delivery networks, and the widespread adoption of digital payment systems. The combined development of these infrastructure factors has greatly enhanced both delivery efficiency and service quality in the fresh food e-commerce sector.

As the industry expands, fresh food e-commerce is experiencing intensified competition and increasing product homogeneity. The marginal gains from price wars are steadily diminishing (Zhongyan Puhua 2025). In response, companies must shift their focus from mere scale expansion to value innovation to establish differentiated competitive advantages. However, most fresh food e-commerce platforms have yet to fully address consumers' deeper psychological needs, such as emotional connection, enjoyable experiences, and personalized interactions. Their innovation efforts are often limited to price or delivery speed, with little attention given to the diverse needs of different consumer groups. As a result, investments in value innovation do not effectively translate into consumer loyalty or sustained purchasing behavior.

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At the theoretical level, significant gaps remain in research on the role of value innovation within fresh food e-commerce. First, there are relatively few relevant studies. Existing literature primarily focuses on traditional factors such as product quality, delivery efficiency, and service experience (Liu et al. 2023; Kang and Namkung 2024; Ren et al. 2025). There is a lack of in-depth investigation into how value innovation systematically enhances consumer perceived value and influences purchase intentions. Second, research has largely overlooked the potential moderating effects of individual differences, such as consumer innovativeness, on responses to value innovation. Few studies have explored whether and how consumer innovativeness influences the relationship between perceived value and purchase intention. These theoretical shortcomings limit both our understanding of value innovation mechanisms and the guidance they can provide to industry practices.

In light of these practical challenges and theoretical gaps, this study addresses the following key research questions:

1. How does value innovation in fresh food e-commerce affect consumer purchase intention?
2. What mediating role does perceived value play between value innovation and purchase intention?
3. How does consumer innovativeness moderate the relationship between perceived value and purchase intention?

Using survey data from 838 fresh food consumers in Shanghai, this study explores how value innovation in fresh food e-commerce influences purchase intention via the mediating effect of perceived value and the moderating effect of consumer innovativeness. The results not only provide empirical evidence for understanding value innovation mechanisms, but also offer practical guidance for platform operators to optimize marketing strategies, develop differentiated experiences, and boost consumer engagement.

2 | Theoretical Background and Hypothesis Development

2.1 | Theoretical Background

2.1.1 | Value Innovation Based on 4I Theory

The 4I theory is an essential framework in internet marketing, offering a distinct perspective and methodology for analyzing online marketing practices. It highlights the key differences between internet and traditional marketing. This helps businesses identify specific challenges in the digital environment, connect efficiently with consumers, improve marketing effectiveness, and maximize brand value (Shang et al. 2022; Vynogradova and Drokina 2020). The 4I theory includes four core dimensions: interesting, interaction, integration, and individualization (Pazgal and Sikka 2001). Specifically, "Interesting" approaches attract consumer attention by stimulating their enthusiasm and curiosity. "Interaction" emphasizes two-way communication between platforms and users, fostering mutual exchange and feedback. "Integration" focuses on seamlessly connecting online and offline channels to optimize the user experience. "Individualization" delivers customized services based on user preferences to meet individual needs.

The concept of value innovation, first introduced by Kim and Mauborgne, centers on creating new value propositions by restructuring the value chain. This approach enables companies to transcend existing market boundaries and address the evolving needs of consumers (Antonopoulou and Begkos 2020). Unlike traditional innovation, which focuses on technological breakthroughs, value innovation balances novelty and practicality to redefine consumer value (Matthyssens et al. 2006). In the digital economy, value innovation has expanded beyond product innovation to encompass comprehensive user experience design.

The integration of value innovation and the 4I theory offers enterprises a new path to break traditional market boundaries in the digital economy. By adopting open innovation models to guide consumer participation in co-creation of value, enterprises can unlock new sources of competitive advantage (Martinez 2014). The four dimensions of the 4I theory provide an operational framework for redesigning user experiences and enhancing value propositions. This integration strengthens systematic consumer value creation and establishes the foundation for multi-dimensional value innovation in the internet environment.

From both theoretical and practical perspectives, this study applies the 4I framework to decompose value innovation on e-commerce platforms into four synergistic dimensions: interesting innovation (IIA), interaction innovation (IIB), integration innovation (IIC), and individualization innovation (IID). The academic value of this framework is twofold. First, its multi-dimensional analysis model aligns with the interconnected nature of value creation in digital commerce. Second, integrating the four dimensions into a synergistic innovation system provides a distinct theoretical path to address the homogenization challenge in fresh food e-commerce.

Specifically, interesting innovation transcends mere entertainment appeal, primarily stimulating consumer engagement with fresh produce through playful, contextualized content that fosters emotional resonance with the functional attributes of such goods. This approach enhances consumer perception of freshness, quality, culinary applications and functionality, thereby shortening decision-making timeframes and boosting conversion rates. For instance, fresh produce e-commerce platforms employ creative short videos, narrative marketing, seasonal ingredient campaigns, and visual freshness displays to heighten curiosity and purchasing desire. Interaction innovation transcends generic social entertainment by establishing low-friction, two-way communication mechanisms (Liao et al. 2023). These mechanisms aim to reduce information asymmetry, bolster trust, and improve post-sales responsiveness, thereby addressing user concerns regarding product quality, origin, and cold chain logistics. This approach minimizes abandoned carts and refund requests. Transparency designs like 'one-click traceability' eliminate quality information asymmetry to build product trust (Yu et al. 2022). Visualized delivery tracking reduces waiting anxiety, while 'worry-free returns', instant customer service access, and cooking technique recommendations create a 'low-friction' service experience. Integration innovations refers to the process of unifying marketing, supply chain and service systems by connecting online and offline channels through data integration. It ensures efficient fresh produce delivery through consistent, seamless user

experiences and enhanced resource utilization. Examples include app-based ordering with in-store collection and real-time inventory synchronization, alongside omnichannel marketing, logistics coordination, customer data platforms, and cross-platform membership integration to elevate consumer shopping experiences and alleviate product quality concerns (Wang et al. 2024). Individualization innovation involves leveraging big data and artificial intelligence to precisely identify consumer preferences, delivering differentiated products and bespoke services. This achieves value-specific alignment, catering to diverse fresh produce consumer demands while reinforcing a sense of personalized ownership. Examples include building user profiles, optimizing recommendation algorithms, and offering tailored promotions and delivery solutions to realize individualized service.

2.1.2 | *Perceived Value*

Perceived value is defined as consumers' overall evaluation of a product or service's utility, based on the balance between perceived benefits (gains) and perceived costs (losses) (Zeithaml 1988). Scholars have since primarily examined perceived value from a two-dimensional trade-off perspective, focusing on perceived gains and perceived losses. Perceived gains include users' perceptions of performance benefits and positive psychological states, while perceived losses cover cost and risk perceptions (Kim et al. 2023; Said and Mustaking 2020). Additionally, Zielke et al. (2022) noted that value perception involves benefits—such as functional, emotional, and social value—as well as costs, typically represented by price.

Existing research generally identifies three key dimensions of perceived value: perceived benefits (PB), perceived costs (PC), and perceived risks (PR). Specifically, perceived benefits reflect consumers' subjective evaluations of a product or service's positive utility. These are usually divided into functional and experiential benefits. Functional benefits include product quality, convenience, and ease of use. Experiential benefits encompass pleasure, social value, and self-fulfillment (Gu and Encio 2023). In fresh food e-commerce, perceived benefits mainly arise from time savings, product variety, and delivery convenience. These factors are most influential in driving user loyalty (Lukito et al. 2022). Perceived costs refer to the sacrifices consumers associate with the purchasing process. These include monetary, time, psychological, and learning costs (Shanshan 2010). In fresh food e-commerce, delivery fees, minimum purchase requirements, and waiting times for appointments are important components of perceived costs (Ma et al. 2024). Perceived risks refer to consumers' subjective expectations of potential negative outcomes from purchasing decisions (Bauer 1960). In fresh food e-commerce, perceived risks mainly involve product quality, delivery, and privacy risks (Cuicui and Zongguang 2021). Due to the perishability and sensory dependence of fresh products, quality risks are the main barrier limiting consumer purchasing decisions (Liu et al. 2023).

2.1.3 | *Consumer Innovativeness*

Consumer innovativeness is typically defined as an individual's tendency to adopt new products early (Li et al. 2021). This concept can be analyzed from multiple dimensions, including innate consumer innovativeness and domain-specific innovativeness. Innate consumer innovativeness describes a general openness to new experiences. In contrast, domain-specific innovativeness refers to innovative behavior within specific product or service categories (Roehrich 2004).

In the digital economy, consumer innovativeness has become a key individual trait explaining differences in technology adoption. Studies have found a significant positive correlation between consumer innovativeness and online shopping behavior. More innovative consumers are more likely to purchase products and services online (Ahmed et al. 2018; Deniz Çakiroğlu (2022). Additionally, consumer innovativeness influences preferences for various shopping channels. For example, highly innovative consumers are more likely to choose online-merging-offline (OMO) shopping models. These models combine the benefits of both online and offline channels, offering a richer shopping experience (Tsai 2024).

In the fresh food e-commerce sector, Li et al. (2021) found that highly innovative users rated platform interaction design and personalized services significantly higher than less innovative users. They also demonstrated greater tolerance toward issues such as delivery delays. Paudel et al. (2023) further confirmed that consumer innovativeness significantly moderates their acceptance of gene-edited foods, with highly innovative individuals exhibiting lower sensitivity to technology-related risks. These findings suggest that consumer innovativeness may play an important moderating role in the relationship between value innovation in fresh food e-commerce and purchasing behavior.

2.1.4 | *Purchase Intention*

Purchase intention refers to a consumer's subjective probability of engaging in a specific purchasing behavior. According to the Theory of Planned Behavior, purchase intention is the most direct predictor of actual purchasing behavior (Rozenkowska 2023). In fresh food e-commerce, purchase intention demonstrates unique characteristics. It is typically influenced by various factors, including functional (e.g., price, quality), emotional (e.g., pleasure, trust), and social factors (e.g., word-of-mouth, social influence).

Han and Mu (2017) noted that the perishability and quality uncertainty of fresh products lead consumers to make more cautious decisions. As a result, perceived risks have a greater negative impact on purchase intention. Wu (2024) found that platform functionality, content quality, and brand image significantly influence consumers' perceived value, which in turn affects purchase intention. Additionally, Ma et al. (2021) noted that post-purchase experiences (such as logistics speed, product quality, and after-sales service) also affect consumer satisfaction and repurchase intention. For example, research has shown that corporate image significantly moderates the relationship between consumer satisfaction and repurchase intention.

2.2 | Hypothesis Development

2.2.1 | *Value Innovation and Purchase Intention*

Research indicates that all dimensions of value innovation significantly influence consumers' purchase intentions in the fresh food e-commerce sector. Perceived fun and sensuality

positively drive impulse purchases by enhancing brand evaluation and hedonic experiences (Lo et al. 2022; Kimiagari and Asadi Malafe 2021). Real-time interactive features, such as instant interactions between consumers and live streamers, promote purchase decisions both directly and indirectly. They do so by enhancing perceived usefulness and flow experiences (Wang 2024; Wei et al. 2017). Integration innovations in online channels can indirectly enhance purchase intention by boosting brand loyalty (Wang et al. 2019). Omnichannel integration strengthens consumer trust and increases purchase intention by providing seamless cross-platform coordination and consistent information (Yang et al. 2024; Zhang et al. 2024). Personalized services, such as customized recommendations and advertisements, increase consumer engagement and conversion rates by creating a sense of exclusivity (Martin Louis 2021).

Based on these findings, this study proposes the following hypotheses:

H1-1. *Interesting innovations in fresh food e-commerce positively influence consumers' purchase intentions.*

H1-2. *Interactivity innovations in fresh food e-commerce positively influence consumers' purchase intentions.*

H1-3. *Integration innovations in fresh food e-commerce positively influence consumers' purchase intentions.*

H1-4. *Individualization innovations in fresh food e-commerce positively influence consumers' purchase intentions.*

2.2.2 | *Mediating Role of Perceived Value*

Existing research shows that perceived benefits, perceived risks, and perceived costs are key mediators that significantly influence the formation of consumer purchase intentions. These variables affect consumer psychology through different mechanisms, which in turn prompt specific purchasing behaviors.

Perceived benefits primarily enhance product attractiveness and functionality, thereby influencing consumer purchase intentions. Qalati et al. (2021) found that website quality and reputation enhance perceived benefits via trust, significantly influencing online purchase intention. Yen (2022), using the stimulus-organism-response (SOR) model, found that channel integration significantly influences usage intention on food delivery platforms by enhancing perceived value. Additionally, Che et al. (2023) demonstrated that personalized design features, such as goal-setting and interactions, significantly influence purchasing behavior by satisfying psychological needs, based on self-determination theory.

Perceived risks are important in consumer decision-making. Higher perceived risks often cause uncertainty, which reduces purchase intentions. Maseeh et al. (2021) reported that although interactivity can enhance brand experience, privacy concerns may make consumers more cautious about purchasing. Wu and Chang (2016) noted that multi-channel integration allows consumers to access product information from various sources. This reduces uncertainty from information asymmetry and increases purchase intentions. However, while personalized services can improve user experience, related data security concerns may increase perceived risks and ultimately have negative effects (Chin et al. 2022).

Perceived costs (e.g., monetary, time, effort, and psychological costs) play a decisive role in forming purchase intentions. Fatin et al. (2024) noted that even highly enjoyable products may be abandoned if perceived costs are too high. Peng et al. (2019) found that, for high-involvement products, increased time investment enhances consumer understanding and confidence, thus strengthening purchase intention. Rodríguez-García et al. (2024) indicated that integrated payment and logistics services, such as omnichannel retailing, reduce transaction costs by improving convenience, thereby strengthening purchase intention. Gan and Wang (2017) noted that personalized services, through precise recommendations and convenient shopping experiences, reduce search and decision-making costs, thus enhancing purchase intention.

Based on these findings, this study proposes the following hypotheses:

H2-1. *Perceived benefits mediate the relationship between interesting innovation and purchase intention.*

H2-2. *Perceived benefits mediate the relationship between interactivity innovation and purchase intention.*

H2-3. *Perceived benefits mediate the relationship between integration innovation and purchase intention.*

H2-4. *Perceived benefits mediate the relationship between individualization innovation and purchase intention.*

H3-1. *Perceived risks mediate the relationship between interesting innovation and purchase intention.*

H3-2. *Perceived risks mediate the relationship between interactivity innovation and purchase intention.*

H3-3. *Perceived risks mediate the relationship between integration innovation and purchase intention.*

H3-4. *Perceived risks mediate the relationship between individualization innovation and purchase intention.*

H4-1. *Perceived costs mediate the relationship between interesting innovation and purchase intention.*

H4-2. *Perceived costs mediate the relationship between interactivity innovation and purchase intention.*

H4-3. *Perceived costs mediate the relationship between integration innovation and purchase intention.*

H4-4. *Perceived costs mediate the relationship between individualization innovation and purchase intention.*

2.2.3 | *Moderating Role of Consumer Innovativeness*

Consumer innovativeness, as a personality trait, influences purchasing behavior. According to Maslow's cognitive needs theory, consumer innovativeness stems from the pursuit of new experiences. The trait-dispositional orientation theory (Higgins 2002) classifies individuals as either promotion-oriented or avoidance-oriented. Promotion-oriented individuals rely on approach strategies, whereas avoidance-oriented individuals use avoidance strategies.

Despite the uncertainties and risks of online fresh food purchases, consumers with high innovativeness show significantly greater purchase intentions when using approach strategies. Conversely, avoidance-oriented consumers tend to avoid new experiences, which may lower their intention to purchase fresh

food online. Baek et al. (2014) found that promotion-oriented consumers perceive higher value and display more positive purchase attitudes toward innovative products than avoidance-oriented consumers. Şahin and Gelmez (2020) pointed out that highly innovative consumers are more willing to try new technologies or products because of their openness to novelty, and they may gain psychological satisfaction from these experiences. However, when innovation is linked to negative outcomes, such as perceived risks, consumer innovativeness may be inhibited. Kamalanon et al. (2022) found that innovation positively moderates the relationship between perceived efficacy and green purchase intention, suggesting that innovation acts as a moderator in purchase behavior. Additionally, Khazaei and Tareq (2021) observed that personal innovativeness significantly moderates the effect of perceived costs on purchase intention. More innovative consumers are less sensitive to perceived costs, which enhances their purchase intention.

Based on these findings, this study proposes the following hypotheses:

H5-1. *Consumer innovativeness moderates the relationship between perceived benefits and purchase intention. Compared to consumers with lower innovativeness, those with higher innovativeness exhibit stronger purchase intention when perceiving identical benefits.*

H5-2. *Consumer innovativeness moderates the relationship between perceived risks and purchase intention. Compared to consumers with lower innovativeness, those with higher innovativeness exhibit stronger purchase intention when perceiving the same level of risks.*

H5-3. *Consumer innovativeness moderates the relationship between perceived costs and purchase intention. Compared to consumers with lower innovativeness, those with higher innovativeness exhibit stronger purchase intention when perceiving the same level of costs.*

Based on the above analysis and hypotheses, the research model for this study is presented in Figure 1.

3 | Methodology

3.1 | Measures

To test the hypotheses, a total of nine scales were used to measure the latent variables in this study, and the items of all the scales were measured on a 5-point Likert scale ranging from (1) '*strongly disagree*' to (5) '*strongly agree*'. In the value innovation scale (see Supporting Information S1: Appendix Scale S1–S4 for details), the interesting innovation subscale was adapted from Xu (2024), and the interactivity innovation subscale from Leiner and Quiring (2008). The integration innovation subscale was adapted from Oh et al. (2012). individualization innovation subscale was adapted from Xu et al. (2011). In the perceived value scale (see Appendix Scale S5–S7 for details), the perceived benefits subscale is from Davis (1989), the perceived costs subscale is from Li et al. (2019), and the perceived risks subscale is from Cui et al. (2023). Purchase intention scale (see Supporting Information S1: Appendix Scale S8 for details) is from Esfahani and Reynolds (2021). Consumer innovativeness scale (see Supporting Information S1: Appendix Scale S9 for details) is from Seyed Esfahani and Reynolds (2021).

In translating and revising the scales for this study, bilingual experts employed a systematic "forward translation–back

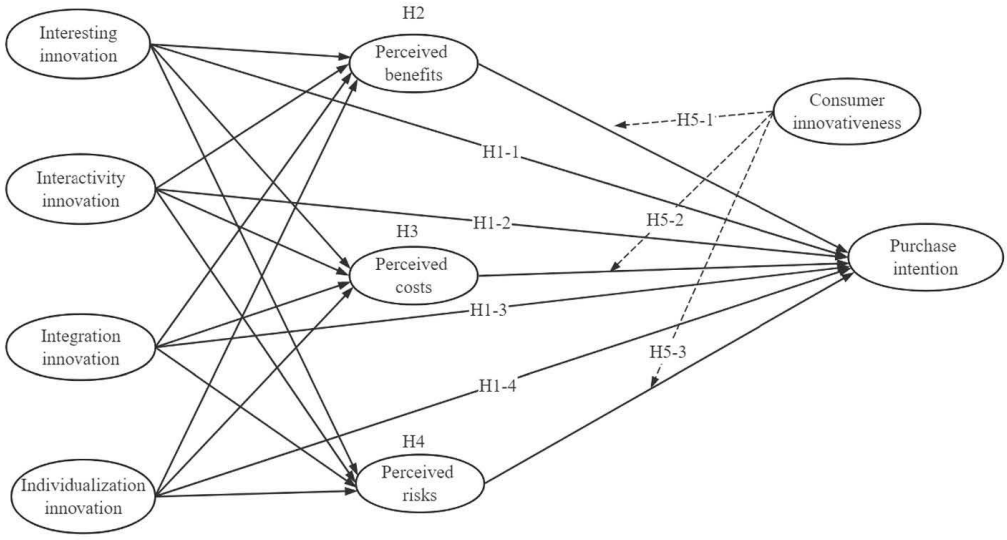


FIGURE 1 | Research model of fresh food e-commerce's value innovation on consumer purchase intention. *Note:* Solid lines indicate direct pathways and mediating pathways; dashed lines indicate moderating pathways.

translation–centralized proofreading" procedure to ensure linguistic accuracy and cultural appropriateness within the Chinese context. During the forward translation stage, two bilingual experts with expertise in academic research and the e-commerce sector translated the original English scales into Chinese, paying close attention to semantic nuances in academic terminology and consumer experience-related expressions. In the back translation stage, another bilingual expert translated the Chinese version back into English, conducting a line-by-line comparison with the original text to detect any potential discrepancies in meaning. Finally, in the centralized proofreading stage, three bilingual experts collaboratively refined the content to enhance sentence fluency and ensure consistency with expressions commonly used by Chinese respondents.

3.2 | Sampling Design and Data Collection

3.2.1 | Research Subject Selection and Rationale

This study selects fresh food consumers in Shanghai as the research subjects, primarily based on their typicality at the theoretical level and demonstrative, forward-looking significance at the practical level.

In terms of theoretical rationale, firstly, as one of China's most digitally advanced cities, Shanghai has a consumer base with high receptivity to innovative models in fresh produce e-commerce. This aligns with the characteristics of "early adopters" in the Innovation Diffusion Theory, making it a representative theoretical sample for investigating the impact mechanism of value innovation on purchase intention. Secondly, the core objective of this study is to systematically uncover the operational pathways of the internal psychological mechanisms connecting value innovation, perceived value, and purchase intention, rather than conducting broad regional comparisons. Therefore, in selecting the sample, the primary consideration was to establish internal validity. Thus, choosing Shanghai as a theoretically ideal context provides robust empirical support for testing the hypotheses among the core variables.

In terms of practical rationale, Shanghai, Beijing, and Guangdong collectively host 71% of China's fresh produce e-commerce enterprises, with Shanghai leading with 37 leading enterprises. Shanghai not only boasts the largest market size for fresh produce e-commerce in China and a digital payment penetration rate exceeding 75%, but its well-established cold chain logistics system and highly competitive platform ecosystem also provide a typical setting for observing value innovation practices within the industry. Furthermore, the sensitivity of Shanghai consumers to service quality and experiential innovation makes their consumption behavior significantly indicative of other domestic first-tier cities like Beijing and Guangzhou, as well as developed markets overseas such as Singapore and South Korea. Following the development pattern of the fresh produce e-commerce industry, which diffuses from higher-tier cities to lower-tier ones, Shanghai's development model often serves as a blueprint for subsequent regional development. Therefore, research conclusions based on this context also possess strong potential for external inference.

3.2.2 | Sampling Methods

This study targets fresh food consumers in the Shanghai region. To determine sample size, this study follows two key criteria. First, a minimum sample size of 200 is required for SEM analysis to avoid unstable or inaccurate results (Wolf et al. 2013). Second, it is generally recommended that the sample size-to-parameter ratio in SEM parameter estimation be at least 5:1, with a higher ratio of 10:1 being more favorable (Christopher Westland 2010). With 58 questionnaire items in the formal questionnaire, and following the ideal 10:1 ratio, the final sample size was set to exceed 580. This ensures reliable parameter estimation and valid significance testing.

The sampling method combines stratified and proportional sampling, based on the following considerations. First, different ring road areas in Shanghai (inner, outer, and suburban) may vary in economic development, population density, and consumption habits. Therefore, stratified sampling is used to divide administrative districts based on their ring road locations. Second, to ensure sample representativeness, the sample size within each district was determined using the latest population statistics from the Shanghai Bureau of Statistics, according to each district's actual population proportion. This sampling design has two main advantages. Stratified sampling ensures adequate representation of areas with different characteristics. Proportional sampling avoids bias by aligning sample contributions with each district's population size. This scientific sampling approach effectively enhances the diversity and representativeness of the sample, thereby strengthening the external validity of the research findings.

3.2.3 | Data Collection Process

Data collection was conducted in two phases: a pre-survey and a formal survey.

(1) *Pre-survey phase*: A total of 130 questionnaires were distributed, both on site in residential and commercial areas and online via QuestionStar. Of these, 108 were returned, giving a response rate of 83.1%. Based on the results of the reliability analysis, five items with a Corrected Item–Total Correlation (CITC) value lower than 0.5 were removed. For example, item PR7 in the "Perceived Risk Scale" (original statement: "The overall risk of online fresh grocery shopping is high") had a CITC value of 0.147, which is below the 0.5 threshold. Its removal increased the overall reliability of the scale (Cronbach's α) from 0.75 to 0.81, indicating that this item was poorly consistent with the other items; therefore, it was excluded from the analysis. Based on the results of the validity analysis, the KMO value for each scale was between 0.66 and 0.93, which is greater than 0.6, and the p-value was less than 0.05. This indicates that the pre-study scale questionnaire had good structural validity. Afterward, three ambiguous items were revised. First, semantic clarity and contextual relevance were enhanced by changing the subject from "company" or "customer" to "I," thus focusing on the consumer's own behavior. Second, ambiguous terms were replaced with expressions more consistent with Chinese language conventions. For example, "take a long time" was changed to "the delivery time of the fresh food e-commerce platform is too long, affecting product freshness." These optimizations significantly improved the content and face validity of the scale. As a result, respondents could accurately

understand the questions and answer them based on their actual experiences with fresh food e-commerce, thus enhancing the reliability and validity of the formal survey data.

(2) *Formal survey phase*: A mixed-mode survey was conducted in March 2025. This design aimed to achieve the most comprehensive coverage possible of fresh produce consumer groups with varying digital usage habits. The online component utilized geofencing technology through a professional survey platform to target users in Shanghai. For the offline component, survey stations were established in large supermarkets and community centers within the sampled administrative districts. A specific purpose of this offline approach was to reach and include potential consumers with relatively lower levels of digital engagement (such as middle-aged and elderly groups who prefer offline shopping), thereby mitigating potential biases inherent in purely online sampling. In total, 1000 questionnaires were distributed (650 online and 350 offline), and 905 complete questionnaires were collected. After data cleaning, 45 questionnaires with more than 5% missing values were excluded. Additionally, 22 questionnaires with response times below the theoretical minimum (120 s) were removed. This resulted in 838 valid questionnaires, with a validity rate of 83.8%. The sample size distribution is shown in Table 1.

3.3 | Code of Research Ethics

This study strictly followed the "Ethical Guidelines for Social Science Research". First, all participants signed an electronic informed consent form that explained the study's purpose, data use, and their right to withdraw. Second, data were collected anonymously, with personal information and questionnaire responses stored separately. Third, a risk warning was presented on the first page of the questionnaire, and an "opt-out" option was offered for sensitive items. Fourth, the research findings will be used solely for academic purposes, and the original data will be destroyed 3 years after publication. This research protocol was approved by the Ethics Review Committee of XXX University (Approval No. XXX).

4 | Results

4.1 | Descriptive Statistics

This study used SPSS 26.0 to perform descriptive statistical analyzes on the sample data (see Table 2 for details). Regarding gender composition, females comprised 55.01% of the sample, slightly higher than males at 44.99%. This finding is consistent with previous research, which indicates that women play a dominant role in household consumption decisions (iResearch 2023).

In terms of marital status, married individuals represent the largest group (54.89%), followed by unmarried individuals (31.03%). Divorced (6.80%) and widowed (7.28%) individuals make up smaller proportions. The age distribution is typical of a middle-aged and young population. The 31–40 age group is the largest (25.42%), followed by the 25–30 (19.93%) and 18–24 (14.92%) age groups. This closely matches the age structure of the primary online consumer demographic (iResearch 2023). For income levels, individuals earning 3001–5000 yuan per month accounted for the largest proportion (32.10%), followed by those earning 5001–10,000 yuan (26.25%). Regarding educational attainment, individuals with a bachelor's degree made up the largest group (34.96%), followed by those with an associate degree (29.95%). This reflects the generally high educational level of online consumers. With respect to consumption behavior, those who purchase 2–3 times per month constitute the largest group (29.95%), followed by those who purchase once per month (19.93%) and 4–5 times per month (17.90%). For occupational composition, company employees comprise the largest group (31.98%), followed by government and public institution employees (27.92%) and self-employed individuals (19.93%).

To further evaluate the representativeness of the sample, a Chi-square goodness-of-fit test was conducted, comparing the demographic data of the sample with the demographic profile of fresh produce consumers from the China Fresh e-commerce industry research report (iResearch 2023). The results indicated no significant differences between the two in terms of gender ($p = 0.356$), age structure ($p = 0.104$), education level ($p = 0.312$). The analysis of these indicators supports the representativeness of the study's sample.

4.2 | Reliability and Validity Analysis

This study used the PLS-SEM method to assess the reliability and validity of the scale. The results (Table 3) show that all variables had Cronbach's α coefficients ranging from 0.758 to 0.911 and composite reliability (CR) values from 0.81 to 0.93. Both exceeded the recommended threshold of 0.7 (Ahmad et al. 2024; Raykov 1998). The average variance extracted (AVE) values ranged from 0.5 to 0.72, all surpassing the standard requirement of 0.5 (García-García et al. 2024). For discriminant validity (Table 4), the square root of each variable's AVE was greater than the absolute value of its correlations with other

TABLE 1 | Sample sampling table.

District	Resident population (10,000)	Sample size (number)
Xuhui district, central Shanghai	109.85	97
Jing'an district, central Shanghai	94.05	83
Putuo district, central Shanghai	124.29	110
Minhang district of Shanghai	268.88	238
Songjiang suburban district of Shanghai	195.45	172
Fengxian suburban district of Shanghai	112.63	100

Note: Resident population data is from the Seventh National Population Census Bulletin of Shanghai.

TABLE 2 | Descriptive statistics ($N = 838$).

Statistical variable	Typology	Frequency	Percentage (%)
Gender	Man	377	44.99
	Woman	461	55.01
Marital status	Unmarried	260	31.03
	Married	460	54.89
	Divorced	57	6.80
	Widowed	61	7.28
Age	< 18	41	4.89
	18–24	125	14.92
	25–30	167	19.93
	31–40	213	25.42
	41–50	167	19.93
	> 51	125	14.92
Monthly income	< 3000 RMB	95	11.34
	3001–5000 RMB	269	32.10
	5001–10,000 RMB	220	26.25
	10,001–20,000 RMB	157	18.74
	> 20,001 RMB	97	11.58
Education background	High school and below	150	17.90
	College	251	29.95
	Undergraduate	293	34.96
	Master or above	144	17.18
Number of monthly uses	Almost never	25	2.98
	1	167	19.93
	2–3	251	29.95
	4–5	150	17.90
	6–8	100	11.93
	> 8	145	17.30
Occupation	Student	92	10.98
	Government or public institution employee	234	27.92
	Corporate staff	268	31.98
	Self-employed	167	19.93
	Other	77	9.19

variables. In summary, all the scales in this study showed a high level of reliability, convergent validity and discriminant validity.

4.3 | Common Method Bias and Multicollinearity Tests

To address potential common method bias resulting from the use of self-report measures, this study applied Harman's single-factor test by conducting an unrotated exploratory factor analysis on all items. The results indicated that the first factor accounted for 38.7% of the variance, which is below the critical threshold of 40%, suggesting that common method bias is not a serious concern.

To assess multicollinearity among the predictor variables, this study examined the variance inflation factor (VIF) and tolerance index of the internal model matrix (see Table 5). The results showed that all VIF values ranged from 2.911 to 6.081, all below the recommended threshold of 10, while the tolerance indices ranged from 0.164 to 0.343, all exceeding the minimum requirement of 0.1 (Salmerón-Gómez et al. 2024). These findings indicate the absence of significant multicollinearity in the model. Therefore, when determining the path coefficients of the structural model, errors do not exert a substantial impact, and the analysis can proceed smoothly.

4.4 | Hypothesis Validation

4.4.1 | *Direct Path Test*

This study empirically analyzed the impact of value innovation in fresh food e-commerce on consumer purchase intentions

using a structural equation model (PLS-SEM). The model structure is illustrated in Figure 2. Model parameters were estimated using maximum likelihood estimation. The results indicate a good model fit: chi-square/degrees of freedom (χ^2/df) = 2.315, Normed Fit Index (NFI) = 0.925, Comparative Fit Index (CFI) = 0.934, Goodness-of-Fit Index (GFI) = 0.925, and Root Mean Square Error of Approximation (RMSEA) = 0.045. The internal consistency coefficient α was 0.88, suggesting good reliability and validity of the scale.

Further analysis (see Table 6) showed that all path *p*-values were statistically significant ($p < 0.05$). Interesting innovation (IIA), interactivity innovation (IIB), integration innovation (IIC), and individualization innovation (IID) each had a significant positive effect on purchase intention (PI) ($\beta = 0.164$, $p < 0.001$; $\beta = 0.080$, $p = 0.004$; $\beta = 0.058$, $p = 0.020$; $\beta = 0.052$, $p = 0.048$). These results support the validity of hypotheses H1-1 to H1-4.

4.4.2 | *Mediating Path Test*

This study used Model 6 of the PROCESS plugin in SPSS 26. A bias-corrected bootstrap method with 5000 resamples was applied to calculate the 95% confidence intervals (CIs) for the mediating. Based on survey data from 838 fresh food customers in Shanghai, effects. The results showed that all mediating effects were significant ($p < 0.001$), and none of the confidence intervals included zero. This suggests that perceived benefits, perceived risks, and perceived costs play important mediating roles between value innovation dimensions and purchase intention. Detailed results of the mediation tests are shown in Table 7.

Specifically, the mediating effect of perceived benefits on the path from interesting innovation (IIA) to purchase intention (PI) is 0.282, accounting for 47.24% of the total effect. This result indicates that perceived benefits play an important mediating role in the impact of value innovation on consumers' purchase intentions. Similarly, the mediating effects of interactivity innovation (IIB), integration innovation (IIC), and individualization innovation (IID) on purchase intention were also mediated by perceived benefits. The effect values were 0.494, 0.447, and 0.414, accounting for 58.81%, 60.08%, and 66.56% of the total effect, respectively. These findings indicate that perceived benefits have significant mediating effects across different dimensions of value innovation.

TABLE 3 | Reliability and validity analysis.

Variable	Cronbach's alpha (α)	AVE	CR
Interesting innovation	0.826	0.68	0.87
Interactivity innovation	0.865	0.61	0.93
Integration innovation	0.833	0.58	0.91
Individualization innovation	0.758	0.6	0.81
Perceived benefits	0.87	0.52	0.91
Perceived risks	0.787	0.5	0.85
Perceived costs	0.762	0.72	0.89
Purchase intention	0.911	0.61	0.83
Consumer innovativeness	0.826	0.68	0.87

TABLE 5 | VIF value of the inner model matrix.

Variable	VIF value	Tolerance
Interesting innovation	5.518	0.181
Interactivity innovation	4.486	0.223
Integration innovation	4.249	0.235
Individualization innovation	3.045	0.328
Perceived benefits	5.603	0.178
Perceived risks	3.328	0.300
Perceived costs	3.441	0.291
Purchase intention	2.911	0.343
Consumer innovativeness	3.147	0.275

Abbreviations: IIA, interesting innovation; IIB, interactivity innovation; IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PI, purchase intention; PR, perceived risks.

TABLE 4 | Discriminant validity (Pearson correlation and AVE square root value).

Variable	IID	IIC	IIB	IIA	PC	PR	PB	PI	CI
IID	0.774								
IIC	0.206	0.761							
IIB	0.259	0.191	0.781						
IIA	0.22	0.247	0.181	0.824					
PC	0.138	0.217	0.197	0.256	0.848				
PR	0.15	0.195	0.175	0.377	0.191	0.707			
PB	0.247	0.147	0.187	0.169	0.112	0.124	0.848		
PI	0.171	0.47	0.157	0.271	0.201	0.196	0.129	0.781	
CI	0.015	−0.024	−0.011	0.016	−0.02	0.008	0.037	−0.102	0.824

Abbreviations: IIA, interesting innovation; IIB, interactivity innovation; IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PI, purchase intention; PR, perceived risks.

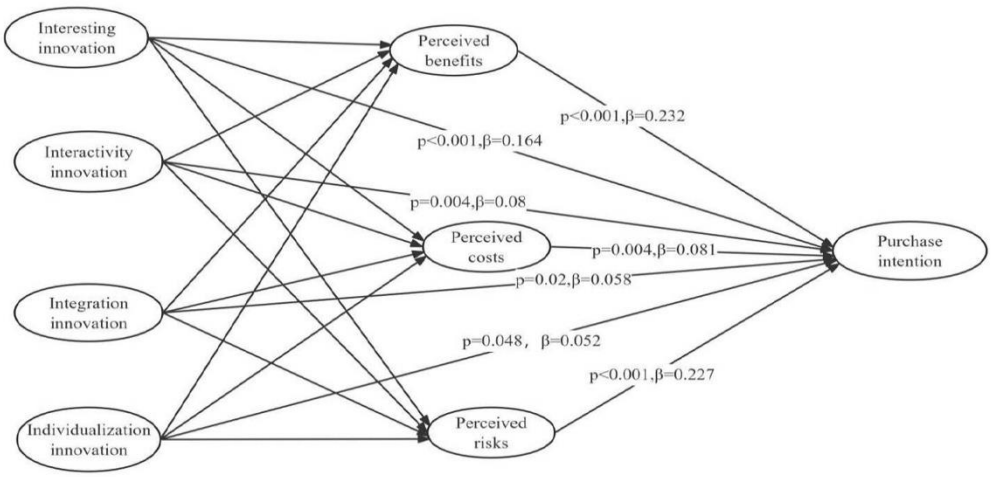


FIGURE 2 | Structural equation modeling.

TABLE 6 | Path coefficient.

Route	Estimate	Standard error (SE)	Critical ratio (CR)	*p*-value	Hypothesis
IIA → PI	0.164	0.025	6.639	< 0.001***	H1-1 Support
IIB → PI	0.080	0.028	2.846	0.004**	H1-2 Support
IIC → PI	0.058	0.025	2.332	0.020*	H1-3 Support
IID → PI	0.052	0.028	1.894	0.048*	H1-4 Support

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Abbreviations: IIA, interesting innovation; IIB, interactivity innovation; IIC, integration innovation; IID, individualization innovation.

TABLE 7 | Mediating effect test results.

Mediating route	Total effect	Boot SE	*p*-value	95% Boot CI	Mediating effect value	Mediating effect ratio
IIA → PB → PI	0.597	0.032	< 0.001***	0.280–0.403	0.282	47.24%
IIB → PB → PI	0.84	0.027	< 0.001***	0.342–0.451	0.494	58.81%
IIC → PB → PI	0.744	0.026	< 0.001***	0.351–0.450	0.447	60.08%
IID → PB → PI	0.622	0.03	< 0.001***	0.379–0.499	0.414	66.56%
IIA → PC → PI	0.597	0.022	< 0.001***	0.140–0.229	0.151	25.29%
IIB → PC → PI	0.84	0.022	< 0.001***	0.189–0.277	0.287	34.17%
IIC → PC → PI	0.744	0.021	< 0.001***	0.192–0.278	0.26	34.95%
IID → PC → PI	0.622	0.023	< 0.001***	0.203–0.295	0.235	37.78%
IIA → PR → PI	0.597	0.026	< 0.001***	0.228–0.329	0.228	38.19%
IIB → PR → PI	0.84	0.023	< 0.001***	0.276–0.367	0.399	47.5%
IIC → PR → PI	0.744	0.023	< 0.001***	0.284–0.374	0.363	48.79%
IID → PR → PI	0.622	0.027	< 0.001***	0.301–0.406	0.334	53.7%

Note: ***$p < 0.001$; bootstrap type = bias-corrected bootstrap method.
Abbreviations: IIA, interesting innovation; IIB, interactivity innovation; IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PI, purchase intention; PR, perceived risks.

For perceived risks, interesting innovation, interactivity innovation, integration innovation, and individualization innovation have indirect effects on purchase intention, with effect values of 0.228, 0.399, 0.363, and 0.334. These indirect effects account for 38.19%, 47.5%, 48.79%, and 53.7% of the total effect, respectively. This suggests that perceived risks play an important mediating role in the relationship between value innovation and purchase intention, especially within the interactivity and individualization dimensions.

Additionally, the mediating effect of perceived costs was also significant. The effect values were 0.151, 0.287, 0.26, and 0.235, representing 25.29%, 34.17%, 34.95%, and 37.78% of the total effect, respectively. These results indicate that perceived costs have a notable mediating function in the process of value innovation influencing purchase intention, particularly in the interactivity and integration innovation dimensions.

In summary, perceived benefits exhibit the most prominent mediating effect in the process by which value innovation influences purchase intention. Meanwhile, individualization innovation demonstrates the strongest effect in value transmission.

4.4.3 | *Moderating Effects Test*

This study used a hierarchical regression model to investigate the moderating role of consumer innovativeness (CI) in the relationship between perceived variables and purchase intention (PI). Overall, the three regression models showed strong explanatory power, with adjusted R^2 values of 0.592, 0.578, and 0.599, respectively. This indicates that the models fit the data well. All *F*-tests were significant ($p < 0.01$), supporting the overall validity of the models (see Table 8 for details).

After introducing the interaction term, the interaction effect between perceived risks (PR) and CI (PR × CI) on PI was statistically significant ($\beta = 0.032$, $t = 2.081$, $p = 0.042$). The explanatory power of the model increased slightly ($\Delta R^2 = 0.001$, $\Delta F = 2.081$, $p = 0.042$). These results indicate that consumer innovativeness significantly moderates the effect of perceived risks on purchase intention. Simple slope analysis (see Table 9 and Figure 3) further confirmed this relationship. At high levels (+1SD) of consumer innovativeness, the influence of perceived risks on PI was more pronounced ($\beta = -0.354$, $p < 0.01$). This finding suggests that as consumer innovativeness increases, sensitivity to perceived risks decreases, thereby weakening the negative impact of perceived risks on purchase intention.

In contrast, the interaction between PC and CI (PC × CI, $\beta = 0.020$, $t = 0.863$, $p = 0.388$), as well as the interaction between PB and CI (PB × CI, $\beta = 0.012$, $t = 0.511$, $p = 0.610$), were not statistically significant. This suggests that, in this sample, the moderating effect of consumer innovativeness on the impact of perceived costs and perceived benefits on purchase intention is weak or absent.

TABLE 8 | Moderating effects analysis of consumer innovativeness ($n = 838$).

	PB-PI			PC-PI			PR-PI		
Moderating effect	**t**	**p**	**β**	**t**	**p**	**β**	**t**	**p**	**β**
Constant	44.227	< 0.001***		43.43	< 0.001***		44.452	< 0.001***	
Gender	−0.264	0.792	−0.006	−0.258	0.796	−0.006	−0.547	0.584	−0.012
Marital status	1.128	0.26	0.025	0.919	0.358	0.021	0.812	0.417	0.018
Age	−0.546	0.585	−0.012	−0.612	0.541	−0.014	−0.736	0.462	−0.016
Monthly income	1.652	0.099	0.043	1.946	0.052	0.051	2.08	0.038*	0.054
Education background	−0.463	0.644	−0.011	−0.487	0.626	−0.011	−0.829	0.408	−0.019
Online shopping frequency	0.889	0.374	0.023	1.076	0.282	0.028	0.93	0.353	0.024
Occupation	−0.566	0.572	−0.016	−0.694	0.488	−0.02	−0.231	0.818	−0.006
Purchased Type	−0.94	0.348	−0.021	−1.267	0.206	−0.029	−0.917	0.36	−0.02
Location	1.193	0.233	0.033	1.553	0.121	0.044	2.023	0.043*	0.056
PC				5.06	< 0.001***	0.174			
PB	7.241	< 0.001***	0.324						
PR							8.187	< 0.001***	0.299
CI	10.642	< 0.001***	0.473	18.093	< 0.001***	0.623	14.148	< 0.001***	0.516
PC × CI				0.863	0.388	0.02			
PB × CI	0.511	0.61	0.012						
PR × CI							1.442	0.042	0.032
R^2		0.598			0.585			0.605	
F	$F_{(13,824)} = 94.371$, p = 0.000			$F_{(13,824)} = 89.312$, p = 0.000			$F_{(13,824)} = 97.025$, p = 0.000		
△R^2		0.000			0			0.001	
△F	$F_{(1,824)} = 0.261$, p = 0.610			$F_{(1,824)} = 0.745$, p = 0.388			$F_{(1,824)} = 2.081$, p = 0.042		

Note: ***$p < 0.001$.
Abbreviations: CI, consumer innovativeness; IIA, interesting innovation; IIB, interactivity innovation; IIC, integration innovation; IID, individualization innovation; PB, perceived benefits; PC, perceived costs; PI, purchase intention; PR, perceived risks.

TABLE 9 | Simple slope analysis plot.

Variables level	β	SE	t	p	95% CI	
Average value	−0.323	0.039	8.187	0.000	0.246	0.400
Low level (−1SD)	−0.292	0.045	6.469	0.000	0.203	0.380
High level (+1SD)	−0.354	0.045	7.879	0.000	0.266	0.442

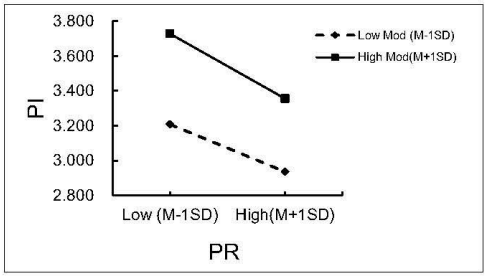


FIGURE 3 | Moderating effect of consumer innovativeness between perceived risks and purchase intention. Abbreviations: PI, purchase intention; PR, perceived risks.

5 | Discussion

5.1 | Impact of Value Innovation on Purchase Intention

5.1.1 | *Differentiated Impact of Value Innovation Dimensions*

Empirical findings indicate that within the fresh food e-commerce sector, the path coefficient linking interesting innovation (IIA) to purchase intention (PI) exhibits statistical significance ($\beta = 0.164$, $p < 0.001$), with the effect size classified as moderately weak. Fresh food e-commerce may mitigate consumer decision fatigue by employing engaging, contextualized content to heighten curiosity and purchase intent. For instance, fresh food e-commerce platforms can transform mere product browsing into an enjoyable content consumption experience by producing creative short videos showcasing the origins of ingredients, cooking tutorials, or seasonal food pairings. This approach effectively sparks consumers' interesting and purchasing desire (Wang et al. 2025), and this study further validates their applicability within the fresh produce context.

The path coefficient of interactivity innovation (IIB) on purchase intention (PI) exhibits statistical significance ($\beta = 0.008$, $p < 0.004$), with an effect size classified as moderately weak. This aligns with findings on the value of two-way interaction in social commerce (Zhao et al. 2023). Real-time customer service and community group buying features in fresh food e-commerce may compensate for the emotional deficit of traditional e-commerce by fostering trust relationships (Qing 2025). Particularly in food safety domains, consumers' access to product traceability information through interactive functions can moderately alleviate perceived risks (Hellali and Korai 2023).

The path coefficient of integration innovation (IIC) on purchase intention (PI) exhibits statistical significance ($\beta = 0.058$, $p < 0.02$), with an effect size classified as relatively weak. This partially reflects the value of cross-channel synergy, aligning with the omnichannel innovation matrix theory (Manouchehri and Bohl 2023). Fresh food e-commerce optimizes the "last mile" experience by integrating offline cold chain delivery with online order management.

The path coefficient of individualization innovation (IID) on purchase intention (PI) is statistically significant ($\beta = 0.052$, $p < 0.048$), with an effect size classified as relatively weak. This partially reveals the value of precision marketing, providing cross-category validation for conclusions regarding personalized recommendations in smart toy research (Zhang et al. 2020). Recommendation algorithms based on consumption history can evoke users' sense of self-identity, with particularly pronounced effects among Generation Z (Qiu et al. 2024).

5.1.2 | *Theoretical Implications and Practical Implications*

The findings from the restructuring of the value innovation hierarchy in this study differ from conventional understanding. In fresh food e-commerce, the influence of emotional value (such as interestingness and interactivity) is slightly stronger than that of functional value (such as integration and personalization). This may be attributed to the high-frequency, low-involvement nature of fresh food categories, where consumers are more inclined to alleviate the pressure of repetitive decision-making through interesting and contextualized content. However, this finding contradicts the results of Basarir-Ozel et al. (2023), who reported that individualization innovation did not have the anticipated effect. One possible explanation is that fresh food consumption is highly planned. Consumers prioritize core attributes, such as product freshness, and are less sensitive to recommendation algorithms than in categories like fashion (Wu and Ho 2014).

From a practical perspective, companies should prioritize interesting innovation, such as creative short videos, narrative-driven marketing, seasonal ingredient-themed events, and visually striking displays of freshness. At the same time, they should enhance the quality of the interaction experience. Combined implementation of these strategies can yield a synergistic effect. For integration innovation, companies should connect data chains across farmers, warehouses, and distribution channels, for example, by adopting blockchain-based traceability systems. This approach not only enhances trust, but also improves consumers' perception of product freshness. For individualization innovation, companies should avoid excessive reliance on algorithmic recommendations. Instead, they should focus on personalizing consumption scenarios, such as offering recipe pairing suggestions.

5.2 | Mediating Role of Perceived Value Between Value Innovation and Purchase Intention

5.2.1 | *Asymmetric Mediating Effects of Perceived Value*

This study confirmed the mediating roles of perceived benefits, perceived risks, and perceived costs in the relationship between value innovation and purchase intention using the PROCESS model. Specifically, the mediating effect of perceived benefits in the individualization innovation (IID) pathway accounted for 66.56%, the highest among all pathways. This finding is consistent with Chandra Pant et al. (2024), who found that in the organic food sector, product innovation targeting personalized needs significantly enhances consumers' perception of core benefits, such as health and convenience, thereby increasing their purchase intention. Seong et al. (2024) similarly demonstrate that consumers' willingness to pay for technology-driven agricultural products is primarily driven by perceived benefits (such as freshness and safety) rather than cost considerations. This further supports the core mediating role of perceived benefits in personalized innovation within this study. Similarly, within the US fresh food e-commerce context, Kang and Namkung (2024) found that hedonic value exerted a dominant influence on impulse purchase intentions, whereas utilitarian value showed no significant effect. This further underscores the primacy of perceived emotional benefits in personalized innovation.

Additionally, perceived benefits represent 60.08% of the mediating effect in the integration innovation (IIC) pathway. This indicates that systemic solutions, such as optimized cold chain delivery, enhance perceived benefits like time savings and quality assurance. As a result, integration innovation serves as a more effective value transmission pathway than interesting innovation. This phenomenon is in line with Zafar et al.'s (2024) "practical value-driven" theory, which suggests that, in fresh food consumption, functional benefits have a greater impact on decision-making than emotional benefits. A Korean study provides corroborating evidence: in the private-label fresh food (PLFF) market, perceived value plays a partial mediating role between perceived quality, perceived price, brand trust and purchase intention, with functional benefits (such as quality assurance and delivery efficiency) being the key driver of purchase intention (Yang and Kang 2022).

The mediating effect of perceived risks in the interactivity innovation (IIB) pathway reached 47.5%, highlighting its double-edged role in technology-driven services. On one hand, innovations such as live streaming and VR experiences can enhance trust (Feng and Wei 2023). On the other hand, increased operational complexity may intensify consumers' concerns about information asymmetry and delivery uncertainty (Pandey et al. 2024). This finding is consistent with Luo et al. (2024), who showed that in luxury e-commerce, the inhibitory effect of perceived risk is significantly strengthened when innovation involves high-tech interaction. Similarly, a European organic food study highlights the significance of risk-related variables. It demonstrates that within an extended TPB model, trust formed through interactions and moral attitude (PoMA) significantly affect purchase intention by acting through reduced perceived risk (Loera et al. 2022), which echoes the mediating role of risk perception observed in our research.

Although perceived costs were significant in all four pathways ($p < 0.001$), their effect sizes (25.29%–37.78%) were much lower than those of perceived benefits. This difference is closely related to the characteristics of fresh food consumption. When the benefits provided by value innovation are substantial (e.g., nutritional customization, freshness guarantees), consumers become less price-sensitive (Lu and Liu 2024; Chandra Pant et al. 2024). This phenomenon was further supported by Lu et al. (2024), who found that in the context of forest-certified products, 68% of green consumers were willing to pay a premium for certification. This result indicates that core value alignment can partially offset cost barriers. Corroborating this finding, a Portuguese study on online fresh food indicates that perceived freshness (as a core benefit) significantly drives repurchase intention, while financial risk exerts a negative impact only when the perception of benefits is inadequate (Ferreira et al. 2025).

The stronger mediating effect of perceived benefits, compared to perceived costs or risks, can be understood through key consumer psychology principles. First, Prospect Theory describes an asymmetry in decision-making: individuals prioritize perceptible gains over potential losses, particularly in low-involvement purchases like fresh food. This primacy of positive attributes (freshness, convenience, trust) over risks such as financial loss or complexity explains the dominant role of benefit perception (Abd-ul-wahid et al. 2024). Second, the Theory of Planned Behavior states that purchase intention is mainly determined by attitude toward the behavior, which for low-involvement products is shaped predominantly by positive expected outcomes (Gu and Wu 2019). Consequently, when innovations strongly elevate core benefit perceptions, consumers are likely to form purchase intentions directly, underweighting associated costs or risks. In summary, both theories confirm that in low-involvement decisions, such as the purchase of fresh food, perceived benefits are prioritized over potential losses.

5.2.2 | *Theoretical Implications and Practical Implications*

The core contribution of this study is in revealing the heterogeneous transmission mechanisms of value innovation. This provides both theoretical support and practical guidance for innovation strategies in fresh food e-commerce enterprises. Interactivity innovation (IIB) requires balancing risks and benefits. Enterprises can mitigate risk suppression effects by increasing supply chain transparency, such as through blockchain-based traceability. This approach strengthens consumer trust in innovation.

Integration innovation (IIC) should focus on saving time and costs by leveraging one-stop solutions. Such strategies reduce perceived costs and improve the overall consumer experience. Individualization innovation (IID) is driven by high perceived benefits. Companies should strengthen the link between precise demand matching and benefit visualization to increase consumer acceptance of individualization innovation.

These findings not only enrich the theoretical framework of fresh food e-commerce but also offer specific practical recommendations for strategic decisions along different innovation pathways. This enables companies to better meet consumer

needs in a highly competitive market and to increase purchase intention.

5.3 | Moderating Role of Consumer Innovativeness in Perceived Risks and Purchase Intention

5.3.1 | Conditional Moderating Effects of Consumer Innovativeness

Regarding the moderating effect of consumer innovativeness, this study partially supports theoretical expectations. Specifically, consumer innovativeness demonstrates a moderating effect only in the relationship between perceived risks and purchase intention ($\beta = 0.032$, $p = 0.042$), whereas its moderating effects concerning perceived benefits and perceived costs are not statistically significant. Given the small ΔR^2, this moderation should be interpreted as limited in magnitude and mainly indicative of a boundary condition rather than a strong behavioral shift.

First, a key reason why consumer innovativeness may moderate the effect of perceived risk lies in risk tolerance and exploratory motivation. Highly innovative consumers tend to have stronger novelty-seeking tendencies and greater tolerance for uncertainty (Midgley and Dowling 1978), which can reduce the inhibiting role of risk on purchase intention. This is broadly consistent with Şahin and Gelmez (2020), who suggest that more innovative consumers are generally more open to new offerings. The results of the simple slope analysis indicate that highly innovative consumers exhibit stronger purchase intention in risk situations, which aligns with their higher level of risk acceptance toward fresh produce. Moreover, although the negative correlation between perceived risk and purchase intention is slightly weaker for highly innovative consumers compared to their less innovative counterparts, the difference is statistically modest, reflecting only a certain degree of buffering effect rather than a fundamental shift in decision-making logic.

Second, the non-significant moderating effect of consumer innovativeness on the paths of perceived benefits and perceived costs also holds profound theoretical rationality. For frequently purchased products tied to health and daily routines, purchase decisions are driven primarily by core value evaluations, such as price and quality/freshness, which function as baseline criteria across consumer segments. Therefore, even highly innovative consumers still evaluate perceived benefits and perceived costs in relatively similar ways. This may differ from contexts involving non-fresh or more hedonic/digital products, where innovativeness can shape how consumers weigh instrumental or experiential value (Khazaei and Tareq 2021).

In summary, consumer innovativeness in fresh e-commerce appears to relate mainly to consumers' responses to uncertainty (risk), while it does not meaningfully alter evaluations of deterministic value (benefits and costs).

5.3.2 | Theoretical Implications and Practical Implications

At a theoretical level, the findings clarify the boundary condition of consumer innovativeness in fresh e-commerce: consumer innovativeness plays at most a small buffering role between perceived risks and purchase intention, rather than reshaping consumers' core value judgments. This suggests that future research should examine moderation by innovativeness more contextually, considering product attributes and decision settings.

From a practical perspective, the findings imply that segmentation by innovativeness is useful for risk-related communication. For highly innovative consumers, platforms can position them as early adopters for new service features (e.g., scheduled delivery, traceability systems, technology-enabled product selection) and leverage their openness to experimentation for seeding and word-of-mouth diffusion. For less innovative consumers, platforms should reduce uncertainty by strengthening information transparency (e.g., richer product descriptions, origin live streams), traceability credibility, and service guarantees (e.g., hassle-free returns, damage compensation).

Overall, platforms should balance innovation with risk control: continue service/technology innovation to activate innovative segments, while maintaining robust supply-chain quality management and after-sales support to meet the baseline value expectations of the broader market.

5.4 | Limitations and Future Research Directions

Notwithstanding the merits of this work, certain limitations must be acknowledged. First, this study predominantly utilizes self-reported questionnaire data. Although this method effectively azsxdc12 captures consumers' subjective perceptions and intentions, it is potentially subject to social desirability bias and common method variance. Future research could incorporate objective behavioral data, such as platform transaction records or user browsing logs, or employ experimental approaches to triangulate self-reported findings, thereby strengthening the robustness and persuasiveness of the conclusions. Second, the sample is confined exclusively to Shanghai. While this design strengthens internal validity, it may constrain the generalizability of the results. Specifically, although the psychological pathways through which value innovation exerts influence are theoretically generalizable, the magnitude of these relationships may be moderated by regional cultural and socioeconomic factors. Future studies should examine the model's robustness across more diverse populations to better delineate its boundary conditions. Third, although the study concentrated on the mediating function of perceived value and the moderating influence of consumer innovativeness, other potential mediators and moderators, such as trust or social influence, may significantly impact purchase intentions and warrant further investigation in future research.

6 | Conclusion

This study uses survey data from 838 fresh food consumers in Shanghai to explore how value innovation in fresh food e-commerce affects consumer purchase intention. The results reveal the mediating effect of perceived value and the moderating effect of consumer innovativeness. These findings offer new insights and guidance for both theoretical research and practical applications in fresh food e-commerce.

Empirical results indicate that value innovation, as an external stimulus, significantly and positively influences purchase intention. This effect mainly operates through the internal psychological mechanism of consumer perceived value. Perceived value plays a significant mediating role between value innovation and purchase intention. Consumer innovativeness significantly moderates the relationship between perceived risks and purchase intention. However, its moderating effect on the relationships between perceived benefits, perceived costs, and purchase intention is not significant.

Author Contributions

Conceptualization: Bing Wu and Hongxia Li. Methodology: Bing Wu and Hongxia Li. Investigation: Bing Wu. Validation: Bing Wu and Hongxia Li. Writing – original draft Preparation: Bing Wu. Writing – review and editing: Bing Wu and Hongxia Li.

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Ethics Statement

The questionnaire and methodology for this study were approved by the Ethical Committee of Mahachulalongkornrajavidyalaya University (Approval No. R.35/2025).

Consent

Informed consent was obtained from all subjects involved in the study, and a written consent form was signed.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Scale 1: Interesting Scale. **Scale 2**: Interactivity Scale. **Scale 3**: Integration Scale. **Scale 4**: Individualization Scale. **Scale 5**: Consumer Perceived Benefits Scale. **Scale 6**: Consumer Perceived Cost Scale. **Scale 7**: Consumer Perceived Risk Scale. **Scale 8**: Consumer Purchase Intention Scale. **Scale 9**: Consumer innovativeness Scale.

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