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Determinants of Customers' Purchasing Intention of Fresh Agricultural Products: SEM Analysis

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Abstract

With the ongoing advancement and widespread use of internet technologies, e-commerce has become a dominant retail channel, and the emergence of live-streaming platforms now offers companies a dynamic new way to market and sell products. Nevertheless, this business model also heightens the issue of information asymmetry, as consumers often face challenges in accurately assessing product quality and determining the credibility of sellers, making the enhancement of consumer trust a key concern for e-commerce enterprises. This study examines how information acquisition ability and online word of mouth regarding fresh agricultural products on Chinese live-streaming platforms influence consumers' purchase intentions, with a particular focus on the mediating role of perceived value. Analysis of 372 valid survey responses reveals that both information acquisition ability and online word of mouth significantly increase purchase intentions, and that perceived value acts as a critical mechanism linking these factors. The findings also indicate the importance of real-time interaction in boosting sales and fostering deeper consumer engagement. Based on these insights, the study recommends strengthening consumers' ability to access and evaluate product information, cultivating credible and positive online word of mouth, and leveraging interactive live-streaming features to enhance product displays and review systems. These contributions advance theoretical understanding of consumer behavior in digital marketing contexts and provide practical guidance for enterprises seeking to improve their live-streaming e-commerce strategies.

Keywords:

Information Acquisition Ability;
Live-Streaming e-Commerce;
Online Word of Mouth;
Perceived Value;
Purchase Intention.

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1- Introduction

With the rapid advancement of digital technologies and the widespread diffusion of e-commerce, live streaming commerce has emerged as a disruptive retail model that fundamentally reshapes how consumers search for information, evaluate products, and make purchasing decisions. By integrating real-time interaction, visual demonstration, and social engagement, live-streaming platforms significantly reduce spatial and temporal constraints while enhancing the immediacy and richness of information exchange between sellers and consumers [1]. This retail format has proven particularly influential in the marketing of fresh agricultural products, which are characterized by high purchase frequency, strong quality sensitivity, and pronounced information asymmetry [2].

Fresh agricultural products present unique challenges in online consumption contexts due to their perishability, quality uncertainty, and consumers' inability to physically inspect products prior to purchase [3]. In live streaming environments, consumers rely heavily on live demonstrations, interactive communication, and socially generated cues to infer product attributes such as freshness, safety, and value for money. Prior studies indicate that the interactive and

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immersive features of live-streaming commerce can significantly enhance consumers' trust formation and purchase intention by reducing perceived uncertainty and information asymmetry [4].

As a result, consumers' purchase decisions in live-streaming contexts are shaped not only by external information cues—most notably online word of mouth (OWM)—but also by their own ability to acquire, process, and evaluate information effectively. Existing research on live-streaming e-commerce has primarily emphasized streamer characteristics, platform trust, entertainment value, and impulsive purchasing behavior [5, 6]. Although these studies provide important insights, they often conceptualize consumers as passive recipients of information and largely overlook individual differences in information acquisition and processing ability.

Moreover, while online word of mouth has been widely recognized as a critical determinant of consumer behavior in digital environments [7], prior research has predominantly examined its direct effects on purchase intention, paying limited attention to how OWM interacts with consumers' cognitive capabilities in dynamic and information-rich live-streaming settings. In addition, perceived value widely acknowledged as a core mechanism linking information cues to behavioral intention [8]—has rarely been incorporated into an integrated framework that simultaneously accounts for information acquisition ability and OWM, particularly in the context of fresh agricultural products.

To address these gaps, this study draws on perceived value theory and information processing theory to develop an integrated analytical framework for examining consumers' purchase intention in live streaming commerce. Specifically, information acquisition ability is conceptualized as a multidimensional construct encompassing direct information access, indirect information sourcing, and information processing capability. Online word of mouth is examined through content related, product-related, and service-related dimensions, capturing diverse evaluative signals embedded in live streaming interactions. Perceived value is positioned as a mediating mechanism through which information acquisition ability and OWM influence purchase intention, thereby offering a more comprehensive explanation of consumers' cognitive and evaluative processes.

Focusing on live streaming platforms in China and the fresh agricultural product sector, this study empirically tests the proposed framework using survey data from live-streaming consumers and structural equation modeling techniques. By integrating information acquisition ability, online word of mouth, and perceived value into a unified model, this research extends existing literature and provides practical insights for optimizing live-streaming marketing strategies in digital agricultural markets.

2- Literature Review

2-1- Information Acquisition Ability

With the increasing advancement of information and communication technologies (ICTs), information resources have become embedded in all stages of economic activity, from production and distribution to market exchange and final consumption, making the ability to acquire and use information a decisive factor shaping economic decision-making [9]. As digital environments generate vast, rapidly accessible, and often complex information flows, both producers and consumers must rely on their information acquisition ability to interpret market signals, evaluate alternatives, and reduce uncertainty. This recognition has driven a growing body of research examining how information acquisition ability influences behavioral outcomes in digital economies, highlighting its relevance not only for firms' strategic choices but also for consumers' perceptions, value assessments, and purchasing decisions.

In agricultural contexts, information asymmetry remains a persistent challenge. Producers often operate under conditions of incomplete and rapidly changing information, which undermines traditional economic models based on perfect information. Recent studies indicate that access to accurate and timely market data—such as pricing information, input costs, and policy support—significantly shapes farmers' production and land-use decisions [10]. Moreover, the development of information literacy and information-processing capability enables agricultural stakeholders to better interpret digital signals and dynamically adjust strategies in increasingly complex market environments [11]. From a consumer-oriented perspective, these challenges are even more pronounced in fresh agricultural product markets, where product quality is difficult to verify prior to purchase and decision-making relies heavily on mediated information cues [8].

From the consumer perspective, information acquisition ability refers to an individual's capacity to search for, process, and evaluate product-related information in order to make informed purchasing decisions. This ability becomes particularly critical in digital marketplaces characterized by high levels of information asymmetry, such as agricultural e-commerce and live-streaming platforms, where consumers depend extensively on visual cues, credibility signals, and interactive communication to reduce perceived uncertainty [1]. Drawing on information processing theory, consumer

decision-making in such environments can be conceptualized as a multi-stage cognitive process involving information exposure, interpretation, and integration prior to the formation of value judgments [12].

Prior research commonly conceptualizes information acquisition ability as consisting of three interrelated dimensions. The first is information search ability, which refers to the proficiency with which individuals locate and filter relevant information using tools such as search engines, databases, and recommendation systems; in live-streaming contexts, this includes evaluating streamers' expertise, assessing product reviews, and interpreting real-time feedback [13]. The second dimension is information comprehension ability, defined as the capacity to interpret, analyze, and evaluate the quality, authenticity, and relevance of acquired information [14]. The third is information integration ability, which reflects the capability to combine information from multiple sources—such as live chat discussions, external reviews, and product demonstrations—into coherent and well-reasoned judgments that support decision-making [7].

In line with the characteristics of fresh agricultural product consumption, this study operationalizes information acquisition ability into three constructs: direct information acquisition capability, indirect information acquisition capability, and information-processing capability. These dimensions provide a structured basis for understanding how consumers navigate dynamic, information-rich live-streaming environments and how their interactions with such information shape purchase intentions and trust formation in e-commerce settings.

Based on this theoretical foundation, and considering the interactive and information-intensive characteristics of live-streaming e-commerce, this study further reorganizes prior dimensions into three analytically distinct but sequential capabilities. Direct information acquisition capability captures consumers' ability to obtain information directly from live-streaming content and real-time interactions; indirect information acquisition capability reflects the ability to seek and evaluate supplementary information from external sources such as historical reviews and social media; and information-processing capability represents the cognitive capacity to synthesize diverse information inputs into coherent value assessments. This reclassification aligns closely with the stages proposed by information processing theory and allows for clearer differentiation of consumers' active roles in live-streaming purchase decision-making.

2-2- Online Word of Mouth

Online word of mouth (OWM) refers to consumer-generated opinions and evaluations about products or services shared through digital platforms such as e-commerce sites, social media, and online forums. On e-commerce platforms, OWM typically appears in the form of post-purchase reviews that merchants actively encourage consumers to submit. These reviews, whether favorable or critical, play a significant role in shaping product reputation, influencing brand perceptions, and guiding the purchasing decisions of potential buyers [15, 16].

Empirical research consistently shows that both the volume and emotional tone of online reviews exert a significant influence on consumer behavior. For example, review valence (positive versus negative sentiment) and emotional intensity can directly shape purchase intentions and even macro-level outcomes such as product sales performance [17]. Positive reviews enhance perceived quality and trust, whereas negative and emotionally charged reviews often exert a disproportionately strong deterrent effect [18]. These findings are consistent with earlier studies emphasizing the joint importance of review quantity and sentiment in influencing consumer choice [19].

Online word of mouth functions as a powerful mechanism of social influence, transmitting not only factual information about product attributes but also emotional and experiential cues among consumers. In markets characterized by high levels of information asymmetry—such as live-streaming e-commerce—OWM plays a critical role in reducing uncertainty and facilitating trust-based decision-making [7, 20].

Building on prior research and considering the characteristics of fresh agricultural product consumption, this study conceptualizes OWM as a multidimensional construct encompassing content-related, product-related, and service-related dimensions. Content-related OWM captures consumers' evaluations of the clarity, usefulness, and informativeness of live-streaming content, including demonstrations and explanations provided during broadcasts. Product-related OWM reflects assessments of intrinsic product attributes such as freshness, quality, safety, and price–value consistency. Service-related OWM refers to evaluations of logistics efficiency, after-sales service, and overall transaction experience. This classification enables a focused examination of evaluative information directly related to the consumption and transaction processes of fresh agricultural products.

Although platform-related and streamer-related word-of-mouth have been emphasized in existing live-streaming studies, these dimensions are not explicitly included in the present framework for theoretical reasons. Platform-related WOM is conceptually closer to institutional trust and system reliability, while streamer-related WOM primarily reflects source credibility and personal influence. Both constructs have been extensively examined as independent antecedents

of consumer behavior in live-streaming commerce. Incorporating them as OWM dimensions may therefore lead to conceptual overlap and reduce analytical clarity. To maintain theoretical parsimony and focus on evaluative information most directly associated with perceived value formation, this study deliberately excludes platform- and streamer-related WOM from the OWM construct.

2-3- Perceived Value

Perceived value has been widely recognized as a central concept in consumer behavior research, referring to consumers' overall evaluation of a product or service based on a trade-off between perceived benefits and perceived costs [21]. Prior studies commonly conceptualize perceived value as a multidimensional construct, incorporating functional, emotional, social, and economic dimensions, which together capture consumers' cognitive and affective evaluations during the decision-making process [8, 22].

In the context of fresh agricultural products, perceived value plays a particularly important role due to product perishability, quality uncertainty, and consumers' limited ability to physically inspect products prior to purchase [23]. Functional value reflects consumers' perceptions of product performance, quality, and usefulness; emotional value captures affective responses such as enjoyment, satisfaction, or pleasure derived from the purchasing experience; social value refers to the extent to which consumption enhances social approval or self-image; and economic value represents consumers' evaluation of price fairness and value for money [8, 22]. These dimensions collectively provide a comprehensive framework for understanding how consumers assess the overall attractiveness of fresh agricultural products in live-streaming environments.

Existing literature has also highlighted the relevance of perceived risk and trust-related perceptions in online consumption contexts, particularly for fresh agricultural products characterized by high uncertainty and information asymmetry [24, 25]. However, prior research generally treats perceived risk and trust as antecedent constructs that shape consumers' evaluations of functional and emotional value, rather than as core components of perceived value itself [26].

Drawing on perceived value theory, this study conceptualizes perceived value as an outcome of consumers' information evaluation processes, while perceived risk and trust are viewed as influencing conditions that affect how value is formed [21, 26]. Including risk- or trust-related dimensions as value components may therefore lead to conceptual overlap and blur the theoretical distinction between value perceptions and their antecedents. To maintain conceptual clarity and theoretical parsimony, this study adopts a four-dimensional perceived value framework consisting of functional, emotional, social, and economic value [8, 22].

This conceptualization is particularly appropriate in live-streaming e-commerce settings, where consumers' risk and trust perceptions are largely shaped by information acquisition ability and online word of mouth [7, 20]. These factors influence perceived value indirectly by reducing uncertainty and enhancing confidence, rather than functioning as independent value dimensions [24, 25]. Accordingly, the four-dimensional framework allows for a clearer examination of the mediating role of perceived value between information cues and purchase intention [21, 22].

2-4- Purchase Intention

Purchase intention, a central construct in marketing and consumer behavior research, refers to a consumer's conscious plan or willingness to purchase a specific product or service in the future [27]. It is widely regarded as a reliable predictor of actual purchasing behavior and is therefore frequently used as an important proxy for understanding consumer decision-making processes [28, 29]. In the digital economy, particularly within e-commerce and live-streaming environments, purchase intention has become a key behavioral indicator reflecting consumers' readiness to engage in online transactions and their confidence in digital purchasing channels [30].

According to the Theory of Planned Behavior (TPB), behavioral intention is determined by three core antecedents: attitude toward the behavior, subjective norms, and perceived behavioral control [31]. Extensive empirical evidence demonstrates that stronger purchase intentions are associated with more favorable attitudes, greater perceived social approval, and higher confidence in one's ability to perform the behavior [32, 33]. Studies applying TPB in live-streaming and social commerce contexts further indicate that perceived trust and platform interactivity significantly enhance consumers' behavioral intentions [34, 35].

In the context of agricultural and live-streaming e-commerce, perceived usefulness of live-streaming content and streamer credibility have been shown to directly strengthen purchase intention, with trust functioning as a key mediating mechanism [34]. Similarly, research demonstrates that live-streaming features such as interactivity, immediacy, and entertainment value enhance consumer engagement and subsequently increase purchase intention [32]. These findings

suggest that behavioral intentions in digital commerce are shaped not only by cognitive evaluations but also by emotional responses driven by social presence and interactive experiences.

A variety of measurement scales have been developed to operationalize purchase intention. Foundational studies introduced multi-item scales assessing consumers' willingness to buy under varying price and quality conditions [21, 26]. Subsequent research expanded this construct to incorporate perceived value and preference-based choice, recognizing the broader set of evaluative judgments underlying purchasing decisions [36]. More recent scales extend the concept beyond purchase likelihood to include recommendation intention and advocacy behavior, making them particularly suitable for social commerce and live-streaming environments where peer influence and interaction are salient [37].

In line with this stream of research, the present study adopts the purchase intention scale developed by Moon et al. [37], which integrates both willingness to buy and perceived value considerations. This operationalization provides a comprehensive measure of consumer behavioral intention in the context of fresh agricultural products marketed through live-streaming e-commerce, capturing both rational assessments of product utility and pricing as well as emotional engagement generated through interactive shopping experiences.

2-5- Conceptual Framework

Creating a positive customer experience is widely regarded as a fundamental driver of customer loyalty and purchase intention. In the context of e-commerce and live-streaming shopping, customer experience encompasses consumers' cognitive, emotional, and sensory interactions with platforms and sellers, which collectively shape their overall perception of value [38, 39]. A rich and engaging experience not only enhances satisfaction but also fosters long-term behavioral loyalty, thereby strengthening consumers' intentions to repurchase or recommend products [40].

The argument advanced by Balakrishnan and Griffiths—that converting first-time buyers into repeat customers represents the cornerstone of sustainable online business models—has been consistently supported by subsequent empirical research [41]. Recent studies further demonstrate that customer loyalty functions as a critical mediating mechanism linking customer experience and purchase intention in live-streaming commerce [42, 43]. Specifically, immersive and interactive live-streaming environments enhance emotional attachment, perceived trust, and brand identification, all of which contribute to stronger purchase intentions [44].

In addition, research in digital marketplace contexts confirms that customer loyalty significantly influences purchase intention, serving as a behavioral manifestation of long-term satisfaction and perceived value [45]. Chain mediation models proposed in recent studies indicate that customer experience indirectly affects purchase intention through perceived value and trust, highlighting the interconnected roles of experience, value evaluation, and relational perceptions in shaping consumer behavior in live-streaming e-commerce [46, 47].

Based on the above theoretical foundations and empirical evidence, this study proposes a conceptual framework in which information acquisition ability and online word of mouth influence perceived value, which in turn shapes purchase intention, with customer experience and loyalty playing critical mediating roles. Hence, we hypothesize that (See Figure 1):

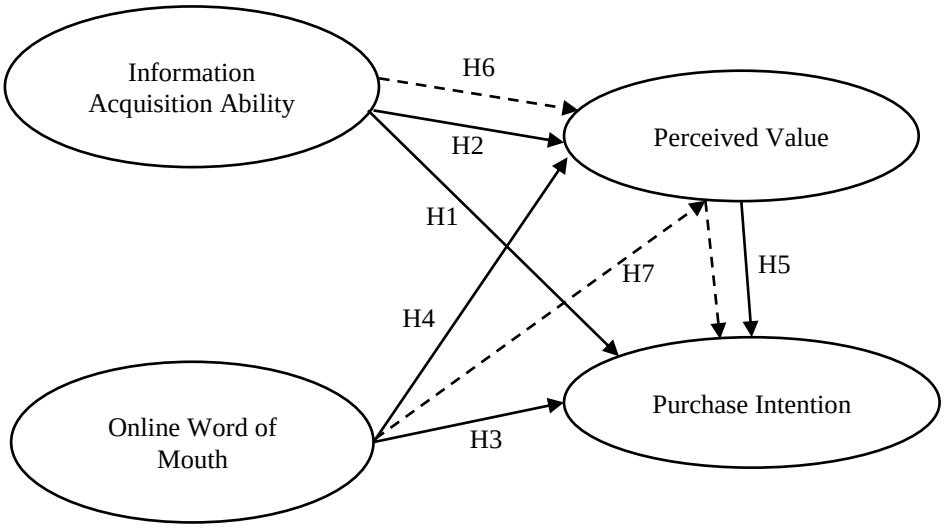

Figure 1. Conceptual Framework of the study

The credibility of information sources remains a crucial determinant of consumer purchase intentions. Prior research has demonstrated that source credibility significantly enhances persuasion effectiveness and strengthens consumers' purchase intentions, consistent with the classic findings in communication and persuasion theory [48, 49]. Subsequent empirical studies further confirm that credible experts exert stronger influence on consumers than anonymous or unverified sources [50].

Although access to information is generally beneficial, excessive exposure may lead to information overload, thereby reducing consumers' decision quality. Empirical evidence shows that information overload induces decision fatigue and cognitive confusion, ultimately diminishing purchase intentions [50, 51]. This phenomenon has been further supported in live-streaming e-commerce contexts, where information saturation may overwhelm consumers and weaken the persuasive impact of content [52].

H1: Information acquisition ability has a significant impact on the purchase intention of fresh agricultural products.

Cross-cultural research indicates that the effect of information acquisition ability on perceived value varies across cultural contexts. In collectivist cultures, stronger information acquisition ability enables consumers to align their choices with socially endorsed norms, thereby enhancing perceived value [53]. In contrast, consumers in more individualistic markets tend to emphasize personalized and self-relevant information, resulting in different value formation patterns. Evidence from developing economies further suggests that consumers with stronger information acquisition ability are better equipped to navigate environments characterized by limited or inconsistent product information, leading to more confident evaluations and higher perceived value [54].

H2: Information acquisition ability has a significant impact on consumers' perceived value.

Prior studies also suggest that firms' response strategies, such as apology and compensation, can mitigate the negative impact of unfavorable electronic word of mouth (eWOM), highlighting the complex interplay between emotional responses and information credibility [55]. Online word of mouth (OWM) has thus emerged as a dominant influence shaping consumer decision-making in digital environments, with its effectiveness determined jointly by trustworthiness, sentiment valence, and source expertise [56].

H3: Online word of mouth has a significant impact on the purchase intention of fresh agricultural products.

Empirical evidence shows that OWM originating from recognized experts or influencers significantly enhances perceived value and purchase intention due to higher credibility [57]. In addition, a greater volume of positive OWM has been found to correlate strongly with increased product interest and purchasing rates, an effect often explained by the bandwagon phenomenon [58].

H4: Online word of mouth has a significant impact on consumers' perceived value.

Perceived value theory has long served as a foundational framework for understanding consumer purchase motivation. Empirical studies in agricultural and live-streaming contexts demonstrate that consumers' evaluations of functional, social, and emotional benefits strongly predict purchase intention [59]. Research in agricultural marketing further confirms that perceived value influences purchase willingness both directly and indirectly through trust and brand cognition [60, 43].

H5: Consumers' perceived value has a significant impact on the purchase intention of fresh agricultural products.

Individual differences and platform characteristics further shape the mediating role of perceived value. Younger and digitally literate consumers tend to exhibit stronger information acquisition ability, which enhances perceived value and purchase intention, whereas older or less technologically proficient consumers show weaker mediation effects [61]. Platform design also moderates this relationship, as user-friendly interfaces and advanced filtering tools significantly enhance perceived value by reducing cognitive effort during decision-making [62].

H6: Consumers' perceived value plays a mediating role between information acquisition ability and purchase intention of fresh agricultural products.

Similarly, consumers rely heavily on detailed user-generated reviews when assessing product value, particularly for high-involvement products [63]. Generational differences in OWM utilization have also been identified, with younger consumers exhibiting stronger responsiveness to social media recommendations [64]. Moreover, advanced and personalized recommendation systems amplify the influence of OWM on perceived value and subsequent purchase intentions [62].

H7: Consumers' perceived value plays a mediating role between online word of mouth and purchase intention of fresh agricultural products.

3- Methodology

As shown in Figure 2, the research methodology consists of questionnaire design, data collection, data screening, reliability and validity testing, common method variance assessment, and structural equation modeling for hypothesis testing.

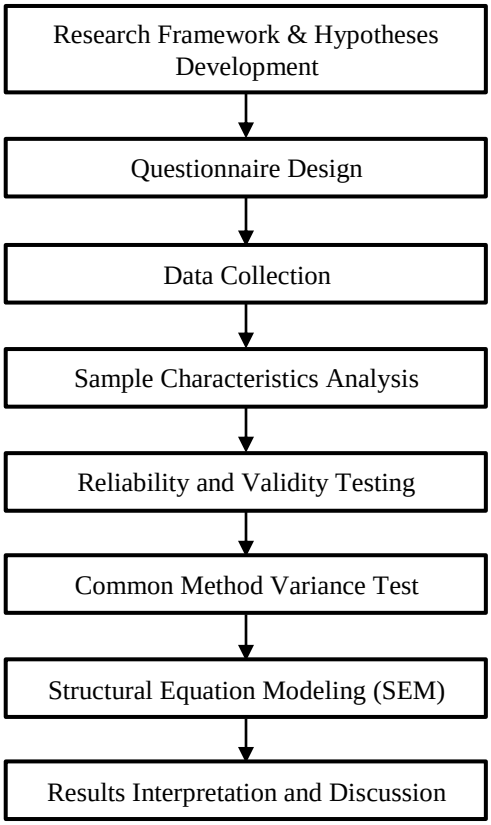

Figure 2. Research methodology workflow

3-1- Data Sources

3-1-1- Data Collection and Sample Characteristics

A structured questionnaire survey was conducted to collect data from consumers who had prior experience purchasing fresh agricultural products through live-streaming e-commerce platforms. Data were collected through online survey platforms over a four-week period. After removing incomplete or invalid responses, a total of 372 valid questionnaires were retained for subsequent analysis.

The demographic characteristics of the respondents indicate that male participants accounted for 72.85% of the sample, while female participants represented 27.15%. This gender distribution reflects a notable imbalance in the sample composition. However, this pattern may partly mirror the demographic characteristics of users actively engaged in fresh agricultural product purchases on live-streaming platforms, where male consumers are often more involved in price comparison, bulk purchasing, and household provisioning decisions.

Nevertheless, gender differences in value perception and purchasing behavior may still introduce potential bias into the estimation of purchase intention. Therefore, the findings of this study should be interpreted with caution when generalizing to more gender-balanced consumer populations. Future research is encouraged to adopt more balanced sampling strategies or conduct gender-based comparative analyses to further validate the robustness of the results.

3-1-2- Sampling Design

This study employed a stratified sampling approach to enhance the representativeness of the collected data. The strata were defined based on key demographic and usage-related characteristics, including gender, age group, and frequency of live-streaming e-commerce usage. These criteria were selected because prior research suggests that demographic factors and usage intensity significantly influence consumers' information processing behavior and purchase intention in digital commerce environments.

Within each stratum, respondents were recruited to ensure coverage of major consumer segments actively participating in live-streaming commerce. Although strict proportional control across all strata was constrained by

practical limitations in online data collection, efforts were made to avoid overrepresentation of any single group. As a result, the final sample includes respondents from diverse demographic backgrounds and usage patterns, providing a reasonable (though not perfectly proportional) representation of live-streaming e-commerce consumers.

3-1-3- Measurement and Common Method Variance

All constructs in this study were measured using self-reported questionnaire items adapted from validated scales in prior research. Given that data for all variables were collected from the same respondents using a single survey instrument, potential common method variance (CMV) was considered. To assess the extent of CMV, Harman's single-factor test was conducted using exploratory factor analysis. The results indicate that the first unrotated factor accounts for less than 50% of the total variance, suggesting that common method variance is unlikely to pose a serious threat to the validity of the empirical findings. In addition, several procedural remedies were implemented during questionnaire design and data collection to mitigate potential CMV, including ensuring respondent anonymity and emphasizing that there were no right or wrong answers.

3-1-4- Methodological Limitations

Despite these efforts, this study relies on cross-sectional, self-reported data, which may still be subject to response bias. Future research may apply longitudinal designs or incorporate objective behavioral data and advanced statistical techniques, such as marker variables or latent method factor approaches, to further address common method bias concerns.

3-2- Descriptive Analysis

The analysis encompasses a total valid sample of 372 respondents (see Table 1). In terms of demographic profile, the sample is predominantly male (72.85%). Regarding age distribution, the largest segment of respondents falls within the 26-35 years old category (55.38%), indicating a relatively young sample. Educational attainment is notably high, with the vast majority of respondents holding a bachelor's degree (35.48%) or a postgraduate degree (35.76%). Income levels are distributed across four brackets: less than ¥3,000 (18.56%), ¥3,000-5,000 (33.33%), ¥5,000-8,000 (28.49%), and more than ¥8,000 (19.62%).

Concerning shopping experience, the data reveals that a significant proportion of respondents are experienced online shoppers. Only a small minority reported having no online shopping experience (3.23%). The largest group has 1-3 years of experience (47.85%), followed closely by those with over three years of experience (34.41%). Combined, these two categories indicate that over 80% of the sample has substantial familiarity with online shopping.

Table 1. Demographic information

	Items	Frequency	Percent
Gender	Male	271	72.85
	Female	101	27.15
Age	Less than 25 years old	42	11.29
	26-35 years old	206	55.38
	36-45 years old	82	22.04
	More than 46 years old	42	11.29
Education level	Junior High School or Below	31	8.33
	High School	76	20.43
	Bachelor's Degree	132	35.48
	Postgraduate	133	35.76
Income	Less than 3000	69	18.56
	3000-5000	124	33.33
	5000-8000	106	28.49
	More than 8000	73	19.62
Shopping experience	No experience	12	3.23
	Less than 1 year	54	14.51
	1-3 years of experience	178	47.85
	Over 3 years of experience	128	34.41

Descriptive statistics for the key variables, including information acquisition ability, online word of mouth, perceived value, trust, and purchase intention, are presented in Table 2. Prior studies [11-13, 37] have emphasized the importance of these variables in explaining consumers' purchasing behavior regarding fresh agricultural products.

Table 2. Variables in the research

Observed Variables	Items	Development of Research Variables
Information acquisition ability		
Direct acquisition capability Indirect acquisition capability Information processing capability	9	[11, 12, 13]
Online word of mouth		
Content word of mouth Product word of mouth Service word of mouth	9	[15, 16, 19]
Perceived value		
Economic value Social value Emotional value Functional value	12	[8,21, 22]
Purchase intention		
Personal purchase Recommended purchase	6	[27, 37]

Descriptive statistics in Table 3 show consistently positive consumer perceptions across all constructs. Information acquisition ability (M = 3.61) is moderately high, suggesting consumers can effectively access product-related information. Online word of mouth (M = 4.11) and perceived value (M = 3.95) are both rated favorably, indicating recognition of shared experiences and product benefits. Trust records a higher mean (M = 4.15) but with greater variability, reflecting differences in confidence toward sellers and platforms. Purchase intention reports the highest mean (M = 4.39), accentuating strong willingness to buy fresh agricultural products via live streaming. Collectively, the results highlight that consumers hold positive attitudes overall, with purchase intention emerging as the most prominent outcome.

Table 3. Mean and standard deviation for each variable

Variable	Min	Max	Mean	S.D.
Information acquisition ability (IAA)	1	5	3.60941	0.412563
Online word of mouth (OWM)	1	5	4.11333	0.45010
Perceived value (PV)	1	5	3.94967	0.40373
Purchase intention (PI)	1	5	4.39071	0.39577

After conducting, analyzing and studying relevant theories, literature reviews and concepts, this study created potential and observable variables. A structured questionnaire survey was used to obtain the main data of this study. Some analyses, including correlation and descriptive statistics, were conducted to examine the relationship between the variables.

4- Empirical Results

4-1- Reliability and Validity Analysis

Table 4 presents Cronbach's Alpha values and the items for each variable measured in the study. All variables demonstrate Cronbach's Alpha values exceeding 0.7, indicating excellent questionnaire reliability. Cronbach's alpha value for purchase intention was 0.764, which represents the lowest among all the variables. This indicates a relatively high level of reliability, thereby supporting the appropriateness of proceeding with subsequent analyses in this study.

Table 4. The reliability analysis for each variable

Variable	Cronbach's Alpha	N of Items
Information acquisition ability	0.876	9
Online word of mouth	0.886	9
Perceived value	0.782	12
Purchase intention	0.764	6

Table 5 reports the Kaiser–Meyer–Olkin (KMO) values, F statistics, and significance levels (Sig.) for all observational variables included in the study. Each variable demonstrates a KMO value above the recommended threshold of 0.5, indicating satisfactory sampling adequacy and strong construct validity of the questionnaire. Given these results, the data meet the necessary conditions for factor analysis, allowing the study to proceed to subsequent analytical stages.

Table 5. The validity analysis for each variable

Variable	KMO value	F value	Sig.
Information acquisition ability (IAA)	0.890	2335.795	0.000
Online word of mouth (OWM)	0.793	1779.263	0.000
Perceived value (PV)	0.772	860.190	0.000
Purchase intention (PI)	0.832	971.479	0.000

Following an extensive review of relevant literature and theoretical frameworks, a confirmatory factor analysis (CFA) was performed to evaluate the measurement model [65]. The analysis, conducted using AMOS 28.0, demonstrated an adequate model fit. The model was statistically non-significant ($p > 0.05$), with a χ^2/df ratio ≤ 2.00 and an RMSEA value ≤ 0.05, both within recommended thresholds. The comparative fit index (CFI) was 0.986, further confirming the model's robustness, as values above 0.90 are considered acceptable and those exceeding 0.95 reflect excellent fit [66].

Figure 3 presents the results of the confirmatory factor analysis (CFA) conducted on the external latent variables information acquisition ability and online word of mouth using a sample of 372 respondents. The model fit indices were as follows: $\chi^2 = 8.913$ with 8 degrees of freedom (df), Comparative Fit Index (CFI) = 0.964, Tucker–Lewis Index (TLI) = 0.933, and Root Mean Square Error of Approximation (RMSEA) = 0.046. Collectively, these indices indicate an acceptable model fit, with CFI and TLI values exceeding the recommended threshold of 0.90 and RMSEA falling below the 0.05 benchmark.

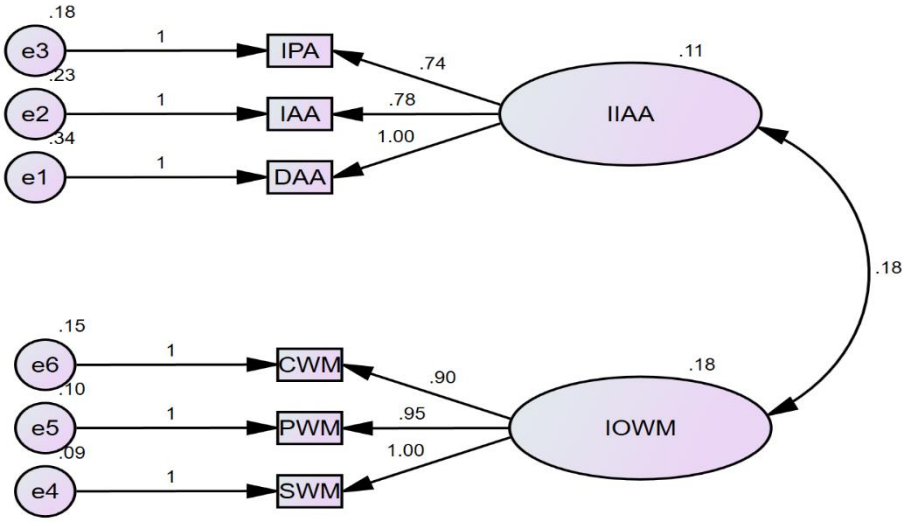

Figure 3. CFA of external latent variables IIAA & IOWM (Note: Chi-Square (χ^2) = 8.913, df = 8, CFI = 0.964, TLI = 0.933, RMSEA = 0.046)

Figure 4 shows the results of the confirmatory factor analysis (CFA) on the external latent variables PV (Mediating variable Perceived Value) and PI (Dependent variable purchase intention) with a sample size of 372. Model fit indices are as follows: Chi-Square (χ^2) = 18.582 with 18 degrees of freedom (df), Comparative Fit Index (CFI) = 0.944, Tucker-Lewis Index (TLI) = 0.953, and Root Mean Square Error of Approximation (RMSEA) = 0.038. These indices indicate an acceptable fit of the model to the data.

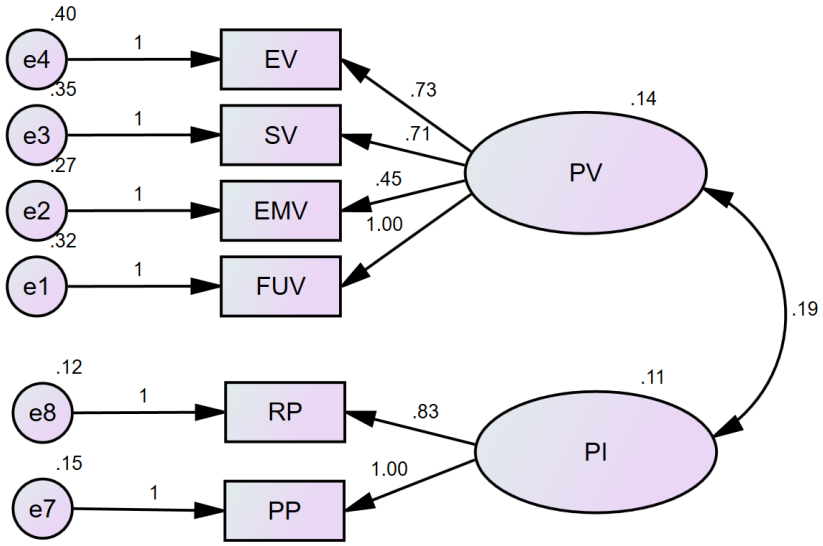

Figure 4. CFA of external latent variables PV & PI (Note: Chi-Square (χ^2) = 18.582, df = 18, CFI=0.944, TLI=0.953, RMSEA = 0.038)

4-2-Correlation Analysis

Correlation analysis is a fundamental statistical technique used to assess the strength and direction of relationships between variables. The most common measure, the Pearson correlation coefficient, quantifies linear associations between continuous variables on a scale from −1 to +1, where values close to ±1 indicate strong correlations and 0 reflects no linear relationship. Alternative measures, such as Spearman's rank correlation and Kendall's tau, are applied when data are ordinal or non-linear. Even though widely used across disciplines, correlation analysis does not establish causality and may be affected by outliers or confounding factors; thus, results should be interpreted with caution and supported by visualization tools.

In this study, correlation analysis is applied as a preliminary step to examine associations among key variables, providing insights into their interrelationships and guiding subsequent modeling, including regression and structural equation analysis. This ensures that only theoretically and empirically relevant variables advance to more complex testing.

Average Variance Extracted (AVE) is commonly used to evaluate the convergent validity of latent variables in a measurement model. It reflects the extent to which a latent construct explains the variance of its observed indicators. An AVE value above 0.50 is generally considered acceptable, indicating adequate convergence (see Table 6).

Table 6. The correlation coefficient, reliability, and AVE of the latent variables

Latent variables	IAA	OWM	PV	PI
IAA	1.00			
OWM	0.592**	1.00		
PV	0.392**	0.504**	1.00	
PI	0.429**	0.562**	0.464**	1.00
Construct Reliability	0.875	0.902	0.872	0.910
AVE	0.701	0.844	0.723	0.616
$\sqrt{AVE}$	0.837	0.919	0.850	0.785

Note: **. At 0.01 level (two-tailed), the correlation was significant.

The correlation analysis revealed highly significant positive relationships among all latent variables ($p < 0.01$, two-tailed), with coefficients ranging from 0.392 to 0.592. The strongest association was observed between IAA and OWM ($r = 0.592$), suggesting potential overlap or shared variance between these constructs. Construct reliability was consistently strong (0.872-0.910), surpassing the recommended 0.70 threshold [67]. Convergent validity, as measured by average variance extracted (AVE), ranged from 0.616 to 0.844, with purchase intention (PI) exhibiting the lowest AVE (0.616), which approaches the lower acceptable boundary and suggests relatively weaker convergence.

To further assess construct validity, both convergent and discriminant validity were examined using confirmatory factor analysis (CFA) within a structural equation modeling (SEM) framework. Prior methodological guidelines recommend standardized factor loadings above 0.50 to establish convergent validity [68], a criterion satisfied by all

constructs in this study (see Table 7). The CFA results indicated a good overall model fit (χ^2 = 128.364, df = 98, p > 0.05), supported by additional fit indices, including GFI = 0.953 and AGFI = 0.978 [69], as well as RMSEA = 0.012, which is well below the recommended 0.05 threshold for excellent model fit [70].

All these findings confirm that the measurement model demonstrates strong reliability, satisfactory convergent validity, and an overall robust fit with the empirical data.

Table 7. Criteria and theory of goodness-of-fit values

Criteria Index	Criteria	Values	Results
Chi-square: χ^2	$p \geq 0.05$	128.364	passed
χ^2/df	≤ 2.00	1.310	passed
GFI	≥ 0.90	0.953	passed
AGFI	≥ 0.90	0.978	passed
RMSEA	≤ 0.05	0.012	passed
Cronbach's Alpha	≥ 0.70	0.856	passed

The hypotheses testing results are presented in Table 8. All five hypotheses were supported at the 0.001 significance level (see Table 8). H1 confirmed that information acquisition ability (IAA) has a significant positive impact on purchase intention (PI) of fresh agricultural products (β = 0.160, CR = 11.827). H2 demonstrated that IAA significantly influences consumers' perceived value (PV) (β = 0.343, CR = 8.322). H3 showed that online word of mouth (OWM) positively affects purchase intention of fresh agricultural products (β = 0.757, CR = 12.033). H4 indicated that OWM significantly impacts consumers' perceived value (β = 0.158, CR = 4.116). Finally, H5 confirmed that consumers' perceived value (PV) has a significant positive effect on purchase intention of fresh agricultural products (β = 0.195, CR = 5.840). These findings collectively support all proposed hypotheses in the conceptual framework.

Table 8. Hypotheses testing results

Hypotheses	Estimate	S.E.	C.R.	P-Label	Results
H1: The information acquisition ability has a significant impact on the purchase intention of fresh agricultural products. (PI← IAA)	0.160	0.029	11.827	***	Accepted
H2: The information acquisition ability has a significant impact on the perceived value of consumers. (PV← IAA)	0.343	0.161	8.322	***	Accepted
H3: Online word of mouth has a significant impact on the purchase intention of fresh agricultural products. (PI← OWM)	0.757	0.063	12.033	***	Accepted
H4: Online word of mouth has a significant impact on consumers' perceived value. (PV← OWM)	0.158	0.038	4.116	***	Accepted
H5: Consumers' perceived value has a significant impact on the purchase intention of fresh agricultural products. (PI← PV)	0.195	0.033	5.840	***	Accepted

Note: *Sig.<0.05, **Sig.<0.01, ***Sig.<0.001, Critical ratios (t-values) more than 1.96 are significant at the 0.05 level. S.E. = standard error, CR = critical ratio(t-value).

4-3- Mediator Effect Analysis

To further verify the mediating roles of perceived value, the bootstrapping method with 5,000 resamples was applied. This analysis tested both the parallel mediation (IAA/OWM → PV → PI), including direct and indirect effects and the 95% bias-corrected confidence intervals (see Table 9).

Table 9. Results of the mediation effect test

Mediation Path	Direct Effect	Indirect Effect	95% CI (Boot)	Mediation Type
IAA → PV → PI	0.093***	0.067*	[0.001, 0.133]	Partial
OWM → PV → PI	0.726***	0.031*	[0.013, 0.049]	Partial

The bootstrapping results confirmed that perceived value plays a significant mediating role. Perceived value acts as a partial mediator in the relationships between IAA/OWM and PI. This mediation effect demonstrates that cognitive and relational factors jointly explain consumers' purchase intentions.

So, the following assumptions hold.

H6: Perceived value mediates the relationship between the information acquisition ability and fresh agriculture product purchasing intention. Information acquisition ability has enhanced customers' trust and recognition of fresh

agriculture product, improve customer perceived value making them more aware of its practical benefits and encouraging them to purchase fresh agriculture product more actively. Customers who perceive higher value from products believe that the impact of Information acquisition ability is more significant.

H7: Perceived value plays an intermediary role between the online word of mouth and the purchase intention of fresh agricultural products, especially in the process of choosing products through video live streaming. Consumers attach great importance to the online reputation of the products. When the perceived value is high and the online reputation is good, they are more willing to purchase the products. If the online reputation is poor, even if the perceived value is high, it will still affect consumers' purchasing intention.

4-4- Structural Equation Modeling (SEM) Results

Hooper [71] recommended excluding items with low R^2 values (≤ 0.20), as such values indicate substantial error. The results of the structural equation modeling (SEM), presented in Figure 4, confirm that the proposed model satisfies the required fit criteria, with the Test of Close Fit (p-close) found to be non-significant, indicating adequate model fit. Moreover, all latent constructs demonstrated positive effects on purchase intention (PI). Among these, online word of mouth exerted the strongest influence ($\beta = 0.76$), and information acquisition ability ($\beta = 0.34$).

Figure 5 presents the final structural equation model (SEM) with estimated values based on a sample size of 372. Model fit statistics are as follows: Chi-Square (χ^2) = 128.364 with 98 degrees of freedom (df), p-value = 0.62502, and Root Mean Square Error of Approximation (RMSEA) = 0.012. These values indicate a strong fit of the model to the observed data, suggesting that the final SEM adequately represents the relationships among the variables.

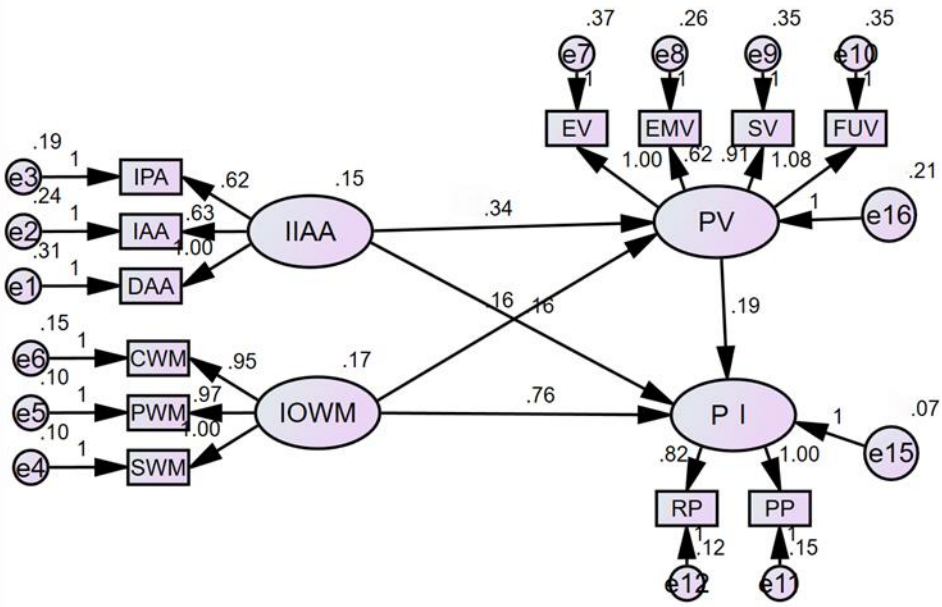

Figure 5. SEM final model with values from estimates (n = 372): (Note: Chi-Square (χ^2) = 128.364, df = 98, p-value = 0.62502, RMSEA = 0.012)

4-5- Discussion

This study investigates consumers' purchase intention toward fresh agricultural products in live-streaming e-commerce environments by integrating information acquisition ability, online word of mouth, and perceived value into a unified analytical framework. The empirical results confirm that information acquisition ability and online word of mouth both exert significant positive effects on purchase intention, and that perceived value plays a critical mediating role in this process. These findings extend existing research on live-streaming commerce by highlighting the active cognitive role of consumers in information-rich digital environments.

First, the results demonstrate that information acquisition ability significantly enhances consumers' purchase intention. This finding supports information processing theory, which posits that consumers with stronger capabilities to search for, interpret, and integrate information are better equipped to reduce uncertainty and make confident purchase decisions. Unlike prior studies that primarily emphasize streamer characteristics or entertainment features, the present study reveals that consumers' own cognitive competence constitutes a fundamental driver of purchase intention in live-streaming contexts. This insight is particularly relevant for fresh agricultural products, where quality uncertainty and information asymmetry are pronounced, and where consumers' ability to evaluate freshness, safety, and value-for-money becomes crucial.

Second, online word of mouth is found to exert a significant positive influence on purchase intention, consistent with previous studies highlighting the persuasive power of peer-generated evaluations in online marketplaces. However, this study advances the literature by demonstrating that different dimensions of OWM (namely content-related, product-related, and service-related evaluations) jointly shape consumers' value perceptions in live-streaming settings. Compared with traditional e-commerce environments, live-streaming commerce amplifies the immediacy and vividness of OWM through real-time comments and interactive feedback, thereby strengthening its impact on consumers' evaluative judgments.

Third, perceived value is confirmed as a key mediating mechanism linking both information acquisition ability and online word of mouth to purchase intention. This finding aligns with perceived value theory, which conceptualizes purchase intention as the outcome of consumers' evaluations of functional, emotional, social, and economic benefits. The mediating role of perceived value suggests that information cues alone do not directly translate into purchasing decisions; rather, consumers interpret and internalize these cues through value assessments before forming behavioral intentions. This result also helps explain why risk- and trust-related perceptions, although important, operate indirectly by shaping value formation rather than functioning as independent value dimensions.

When compared with existing research, the findings of this study complement and extend prior work in several ways. While previous studies have emphasized streamer credibility, platform trust, or impulsive buying behavior, the present study foregrounds consumers' information acquisition ability as an endogenous cognitive factor. Moreover, by integrating information acquisition ability and online word of mouth within a perceived value framework, this study provides a more comprehensive explanation of purchase intention formation in live-streaming commerce.

These results are broadly consistent with earlier findings on the importance of information quality and social influence, yet they also reveal that consumer heterogeneity in information-processing capability plays a decisive role in determining how such information is interpreted and acted upon.

From a contextual perspective, although this study focuses on Chinese live-streaming platforms, the underlying theoretical mechanisms—information processing, value evaluation, and behavioral intention—are not context-bound. Therefore, the proposed framework may be applicable to other emerging or developed markets where live-streaming commerce is characterized by high information intensity and interactive engagement, albeit with potential variations in magnitude due to cultural or institutional differences.

5- Conclusion

This study investigates consumers' purchase intention toward fresh agricultural products in live-streaming e-commerce by integrating information acquisition ability, online word of mouth, and perceived value into a unified analytical framework. Using survey data from consumers with live-streaming shopping experiences and applying structural equation modeling, the study empirically examines the relationships among these key constructs. The results demonstrate that both information acquisition ability and online word of mouth exert significant positive effects on purchase intention, while perceived value plays a crucial mediating role in this process.

From a theoretical perspective, this study makes several important contributions. First, it extends the live-streaming e-commerce literature by shifting the analytical focus from streamer- or platform-centered explanations to consumers' active cognitive capabilities. By conceptualizing information acquisition ability as a multidimensional construct, the study highlights the role of consumers as information processors rather than passive recipients. Second, this research enriches online word-of-mouth studies by differentiating content-related, product-related, and service-related evaluations, thereby clarifying how diverse informational cues shape value perception. Third, by positioning perceived value as a mediating mechanism, the study advances perceived value theory in live-streaming contexts and explains how information cues are transformed into purchase intention through consumers' evaluative processes.

The findings also offer practical implications for platform operators, streamers, and agricultural sellers. Enhancing the clarity, accuracy, and diagnosticity of information presented during live streams can improve consumers' value perceptions and purchasing confidence. Platforms and sellers should also facilitate consumers' access to supplementary information and encourage high-quality word-of-mouth interactions to reduce uncertainty associated with fresh agricultural products.

Despite its contributions, this study has several limitations. The data were collected from Chinese live-streaming platforms, which may limit the generalizability of the findings to other cultural or institutional contexts. In addition, the use of self-reported, cross-sectional data may introduce response bias. Future research could employ longitudinal designs, incorporate objective behavioral data, or examine cross-country samples to further validate and extend the proposed framework.

6- Declarations

6-1- Author Contributions

Conceptualization, D.M. and S.N.; methodology, D.M.; software, Z.X.; validation, S.N., D.M., and Z.X.; formal analysis, D.M.; investigation, D.M.; resources, S.N.; data curation, Y.C.; writing—original draft preparation, D.M.; writing—review and editing, S.N.; visualization, D.M.; supervision, S.N.; project administration, Y.C. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Sun, Y., Shao, X., Li, X., Guo, Y., & Nie, K. (2019). How live streaming influences purchase intentions in social commerce: An IT affordance perspective. Electronic Commerce Research and Applications, 37. doi:10.1016/j.elerap.2019.100886.

[2] Zhang, M., Qin, F., Wang, G. A., & Luo, C. (2019). The impact of live video streaming on online purchase intention. The Service Industries Journal, 40(9-10), 656–681. doi:10.1080/02642069.2019.1576642.

[3] Liu, C., Li, J., Steele, W., & Fang, X. (2018). A study on Chinese consumer preferences for food traceability information using best-worst scaling. PLoS ONE, 13(11), 206793. doi:10.1371/journal.pone.0206793.

[4] Lim, X. J., Cheah, J. H., Waller, D. S., Ting, H., & Ng, S. I. (2020). What s-commerce implies? Repurchase intention and its antecedents. Marketing Intelligence and Planning, 38(6), 760–776. doi:10.1108/MIP-03-2019-0145.

[5] Hu, M., & Chaudhry, S. S. (2020). Enhancing consumer engagement in e-commerce live streaming via relational bonds. Internet Research, 30(3), 1019–1041. doi:10.1108/INTR-03-2019-0082.

[6] Wongkitrungrueng, A., & Assarut, N. (2020). The role of live streaming in building consumer trust and engagement with social commerce sellers. Journal of Business Research, 117, 543–556. doi:10.1016/j.jbusres.2018.08.032.

[7] Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decision Support Systems, 54(1), 461–470. doi:10.1016/j.dss.2012.06.008.

[8] Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. Journal of Retailing, 77(2), 203–220. doi:10.1016/S0022-4359(01)00041-0.

[9] Acemoglu, D., & Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. Handbook of Labor Economics, Elsevier, Amsterdam, Netherlands. doi:10.1016/S0169-7218(11)02410-5.

[10] Deichmann, U., Goyal, A., & Mishra, D. (2016). Will digital technologies transform agriculture in developing countries? Agricultural Economics (United Kingdom), 47(S1), 21–33. doi:10.1111/agec.12300.

[11] Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS - Wageningen Journal of Life Sciences, 90–91, 100315. doi:10.1016/j.njas.2019.100315.

[12] Simon, H. A. (1979). Information Processing Models of Cognition. Annual Review of Psychology, 30(1), 363–396. doi:10.1146/annurev.ps.30.020179.002051.

[13] Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. Journal of Consumer Research, 25(3), 187–217. doi:10.1086/209535.

[14] Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. Journal of Consumer Research, 13(4), 411. doi:10.1086/209080.

[15] Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? Journal of Interactive Marketing, 18(1), 38–52. doi:10.1002/dir.10073.

[16] Mudambi, S. M., & Schuff, D. (2010). What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.Com1. MIS Quarterly, 34(1), 185–200. doi:10.2307/20721420.

[17] Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. Journal of Marketing, 70(3), 74–89. doi:10.1509/jmkg.70.3.074.

[18] Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive effects of negative publicity: When negative reviews increase sales. Marketing Science, 29(5), 815–827. doi:10.1287/mksc.1090.0557.

[19] Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. Journal of Interactive Marketing, 21(4), 23–45. doi:10.1002/dir.20087.

[20] Filieri, R., Alguezaui, S., & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. Tourism Management, 51, 174–185. doi:10.1016/j.tourman.2015.05.007.

[21] Zeithaml, V. A. (1988). Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. Journal of Marketing, 52(3), 2–22. doi:10.1177/002224298805200302.

[22] Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. Journal of Business Research, 22(2), 159–170. doi:10.1016/0148-2963(91)90050-8.

[23] Fernqvist, F., & Ekelund, L. (2014). Credence and the effect on consumer liking of food - A review. Food Quality and Preference, 32, 340–353. doi:10.1016/j.foodqual.2013.10.005.

[24] Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101–134. doi:10.1080/10864415.2003.11044275.

[25] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in Online Shopping: An Integrated Model1. MIS Quarterly, 27(1), 51–90. doi:10.2307/30036519.

[26] Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. Journal of Marketing Research, 28(3), 307–319. doi:10.1177/002224379102800305.

[27] Hill, R. J., Fishbein, M., & Ajzen, I. (1977). Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. Contemporary Sociology, 6(2), 244. doi:10.2307/2065853.

[28] Morwitz, V. G., Steckel, J. H., & Gupta, A. (2007). When do purchase intentions predict sales? International Journal of Forecasting, 23(3), 347–364. doi:10.1016/j.ijforecast.2007.05.015.

[29] Sheeran, P. (2002). Intention—Behavior Relations: A Conceptual and Empirical Review. European Review of Social Psychology, 12(1), 1–36. doi:10.1080/14792772143000003.

[30] Pavlou, P. A., & Fygenson, M. (2006). Understanding and Predicting Electronic Commerce Adoption: An Extension of the Theory of Planned Behavior1. MIS Quarterly, 30(1), 115–143. doi:10.2307/25148720.

[31] Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. doi:10.1016/0749-5978(91)90020-T.

[32] Guo, J., Li, Y., Xu, Y., & Zeng, K. (2021). How Live Streaming Features Impact Consumers' Purchase Intention in the Context of Cross-Border E-Commerce? A Research Based on SOR Theory. Frontiers in Psychology, 12, 767876. doi:10.3389/fpsyg.2021.767876.

[33] Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144–176. doi:10.1287/isre.6.2.144.

[34] Quynh, P. N. H., Thu, C. L., Pandey, K. K., & Phuong, N. V. (2025). Impact of Green Marketing Elements on Consumers: A Behavioral Approach. Emerging Science Journal, 9(4), 2244–2260. doi:10.28991/ESJ-2025-09-04-028.

[35] Wen, J., Li, X., & Han, H. (2025). Emotional Resonance and Buying Behavior in Live Streaming: A Study on KOL Influence and the Mediation of Purchase Intentions. Journal of Theoretical and Applied Electronic Commerce Research, 20(2). doi:10.3390/jtaer20020108.

[36] Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The Effects of Price-Comparison Advertising on Buyers' Perceptions of Acquisition Value, Transaction Value, and Behavioral Intentions. Journal of Marketing, 62(2), 46–59. doi:10.1177/002224299806200204.

[37] Moon, J., Chadee, D., & Tikoo, S. (2008). Culture, product type, and price influences on consumer purchase intention to buy personalized products online. Journal of Business Research, 61(1), 31–39. doi:10.1016/j.jbusres.2006.05.012.

[38] Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96. doi:10.1509/jm.15.0420.

[39] Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. Journal of Retailing, 85(1), 31-41. doi:10.1016/j.jretai.2008.11.001.

[40] Oliver, R. L. (1999). Whence Consumer Loyalty? Journal of Marketing, 63(4), 33–44. doi:10.1177/00222429990634s105.

[41] Balakrishnan, J., & Griffiths, M. D. (2018). Loyalty towards online games, gaming addiction, and purchase intention towards online mobile in-game features. Computers in Human Behavior, 87, 238-246. doi:10.1016/j.chb.2018.06.002.

[42] Zhang, Y., Albattat, A., Rehman, A. U., & Azam, S. M. F. (2025). Investigating the trust entities that influence consumers' purchase intention in livestream e-commerce from trust transfer perspective: using analysis of SEM and fsQCA. Cogent Business & Management, 12(1), 2582220. doi:10.1080/23311975.2025.2582220.

[43] Sun, X., Pelet, J. É., Dai, S., & Ma, Y. (2023). The Effects of Trust, Perceived Risk, Innovativeness, and Deal Proneness on Consumers' Purchasing Behavior in the Livestreaming Social Commerce Context. Sustainability (Switzerland), 15(23), 16320. doi:10.3390/su152316320.

[44] Hilvert-Bruce, Z., Neill, J. T., Sjöblom, M., & Hamari, J. (2018). Social motivations of live-streaming viewer engagement on Twitch. Computers in Human Behavior, 84, 58–67. doi:10.1016/j.chb.2018.02.013.

[45] Gu, M., & Zhao, T. (2025). Research on the purchase intention of museum digital cultural and creative products based on value adoption model. Scientific Reports, 15(1), 2140. doi:10.1038/s41598-025-02140-6.

[46] Tao, M., Alam, F., Lahuerta-Otero, E., & Mengyuan, C. (2024). Get Ready to Buy With Me: The Effect of Social Presence Interaction and Social Commerce Intention on S-commerce Live Streaming. SAGE Open, 14(1), 21582440241232750. doi:10.1177/21582440241232751.

[47] Wu, Y., & Huang, S. (2021). How customer experience affects purchase intention in live-streaming commerce: The mediating roles of trust and perceived value. Information & Management, 58(5), 103486. doi:10.1016/j.im.2021.103486.

[48] Hovland, C. I., & Weiss, W. (1951). The influence of source credibility on communication effectiveness. Public Opinion Quarterly, 15(4), 635–650. doi:10.1086/266350.

[49] Zhang, K. Z. K., Benyoucef, M., & Zhao, S. J. (2015). Consumer participation and gender differences on companies' microblogs: A brand attachment process perspective. Computers in Human Behavior, 44, 357–368. doi:10.1016/j.chb.2014.11.068.

[50] Chen, Y. C., Shang, R. A., & Kao, C. Y. (2009). The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment. Electronic Commerce Research and Applications, 8(1), 48–58. doi:10.1016/j.elerap.2008.09.001.

[51] Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. Information Society, 20(5), 325–344. doi:10.1080/01972240490507974.

[52] Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. Computers in Human Behavior, 85, 163–174. doi:10.1016/j.chb.2018.03.023.

[53] Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544–564. doi:10.1016/j.dss.2007.07.001.

[54] Ali, F., Amin, M., & Cobanoglu, C. (2016). An Integrated Model of Service Experience, Emotions, Satisfaction, and Price Acceptance: An Empirical Analysis in the Chinese Hospitality Industry. Journal of Hospitality Marketing & Management, 25(4), 449–475. doi:10.1080/19368623.2015.1019172.

[55] Ranjith, P., Nisansala, S., Jayasingha, N., Weerasekara, K., Wisenthige, K., & Dayapathirana, N. (2025). Does social media information credibility influence social commerce purchase intention of skincare products? Evidence from Facebook. Plos One, 20(10 October), 334126. doi:10.1371/journal.pone.0334126.

[56] Yan, D., Marzuk, A. Bin, Yang, J., Zhou, J., & Tao, S. (2025). Bibliometric Analysis of Smart Tourism Destination: Knowledge Structure and Research Evolution (2013–2025). Tourism and Hospitality, 6(4), 194. doi:10.3390/tourhosp6040194.

[57] Shui, X., Bian, S., & Zhang, P. (2025). How Can AI Virtual Streamers Gain Consumer Trust to Influence Purchase Intention in Live-Streaming E-Commerce? Journal of Theoretical and Applied Electronic Commerce Research, 20(4), 325. doi:10.3390/jtaer20040325.

[58] Wang, X., Yu, C., & Wei, Y. (2012). Social Media Peer Communication and Impacts on Purchase Intentions: A Consumer Socialization Framework. Journal of Interactive Marketing, 26(4), 198–208. doi:10.1016/j.intmar.2011.11.004.

[59] Hu, C., Niu, P., Chen, X., Cheng, P., Jiang, X., Li, R., & Kuang, R. (2026). Does cultural identity catalyze behavior? A TAM-based study on museum cultural creative products consumption in China. PloS One, 21(2), e0341346. doi:10.1371/journal.pone.0341346.

[60] Wu, Z., Zhang, H., & Wang, X. (2025). Correlation between Agricultural Product Purchases and Live-Streaming Economy in the Digital Economy. HighTech and Innovation Journal, 6(4), 1350–1360. doi:10.28991/HIJ-2025-06-04-013.

[61] Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price fairness perceptions. Journal of Marketing, 68(4), 1–15. doi:10.1509/jmkg.68.4.1.42733.

[62] Zheng, X., Zhu, S., & Lin, Z. (2013). Capturing the essence of word-of-mouth for social commerce: Assessing the quality of online e-commerce reviews by a semi-supervised approach. Decision Support Systems, 56, 211–222. doi:10.1016/j.dss.2013.06.002.

[63] Huang, Z., Zhu, Y., Hao, A., & Deng, J. (2023). How social presence influences consumer purchase intention in live video commerce: the mediating role of immersive experience and the moderating role of positive emotions. Journal of Research in Interactive Marketing, 17(4), 493–509. doi:10.1108/JRIM-01-2022-0009.

[64] Chen, Y. H., Lin, I. K., Huang, C. I., & Chen, H. S. (2024). How Key Opinion Leaders' Expertise and Renown Shape Consumer Behavior in Social Commerce: An Analysis Using a Comprehensive Model. Journal of Theoretical and Applied Electronic Commerce Research , 19(4), 3370–3385. doi:10.3390/jtaer19040163.

[65] Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. Psychological Bulletin, 103(3), 411–423. doi:10.1037/0033-2909.103.3.411.

[66] Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55. doi:10.1080/10705519909540118.

[67] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39–50. doi:10.1177/002224378101800104.

[68] Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–152. doi:10.2753/MTP1069-6679190202.

[69] Kline, R.B. (2011) Principles and Practice of Structural Equation Modeling. The Guilford Press, New York, United States.

[70] MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. Psychological Methods, 1(2), 130–149. doi:10.1037/1082-989X.1.2.130.

[71] Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. Electronic Journal of Business Research Methods, 6(1), 53–60. doi:10.21427/D7CF7R.