Topic Mining-Based Research on Consumer Purchase Behavior of Geographical Indication Agricultural Products: A Case Study of JD.com Online Reviews

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Abstract

The online marketing of geographical indication agricultural products constitutes a vital approach for establishing brand effects in the agricultural sector. To investigate the behavioral path mechanism underlying consumer purchases of geographical indication agricultural products, this study employs Python to collect online reviews from JD.com, and utilizes Snownlp sentiment analysis, TF-IDF algorithm, and LDA topic clustering to identify external cues influencing consumer purchase intention: product quality, logistics and distribution, e-commerce service, product cost-effectiveness, origin image, and brand reputation. Based on consumer perceived value theory, a theoretical model depicting the effect of external cues on consumer purchase intention is constructed, and the mechanism of action among external cues, perceived value, and consumer purchase intention is analyzed through structural equation modeling. The results indicate that external cues of geographical indication agricultural products positively influence consumer purchase intention. External cues of geographical indication agricultural products affect consumer purchase intention by influencing different dimensions of perceived value, with functional perceived value exerting a greater impact on consumer purchase intention than emotional perceived value. This study aims to address the "black box" problem concerning the internal influence mechanism of consumer purchase intention for geographical indication agricultural products, thereby providing decision-making support for the marketing of geographical indication agricultural products.

Full Text

Research on Consumer Purchase Behavior of Geographical Indication Agricultural Products Based on Topic Mining: A Case Study of JD.com Online Reviews

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Abstract

The online promotion of geographical indication (GI) agricultural products represents a crucial pathway for establishing brand effects in agricultural products. To investigate the behavioral mechanism underlying consumer purchases of GI agricultural products, this study employs Python to collect online reviews from JD.com. Through Snownlp sentiment analysis, TF-IDF algorithm, and LDA topic clustering, we identify external cues influencing consumer purchase intention: product quality, logistics and distribution, e-commerce service, product cost-performance ratio, origin image, and brand reputation. Grounded in consumer perceived value theory, we construct a theoretical model examining how external cues affect purchase intention and analyze the mechanism among external cues, perceived value, and purchase intention using structural equation modeling. Results demonstrate that external cues of GI agricultural products positively influence consumer purchase intention. These external cues affect purchase intention through different dimensions of perceived value, with functional perceived value exerting a stronger effect than emotional perceived value. This study aims to unravel the "black box" of the internal influence mechanism of consumer purchase intention for GI agricultural products, providing decision support for marketing strategies.

Keywords: geographical indication agricultural products; external cues; perceived value; online reviews; LDA

As market competition intensifies, establishing, promoting, and maintaining agricultural product brands has become essential for sales. Factors such as product quality, yield, and production technology constitute the basic conditions for competition among agricultural enterprises. However, GI agricultural products face numerous bottlenecks, including market confusion, brand misuse, lack of quality distinction, and free-riding behaviors by producers, all of which erode consumer trust. Despite possessing premium resources, many GI products lack competitive advantages due to weak brand awareness. The information asymmetry inherent in online transactions prevents consumers from verifying authentic product information, making the online shopping environment more complex than traditional offline contexts. Consequently, consumers rely on product brands, origin image, pricing, logistics, and other information as important cues to evaluate perceived value and enhance purchase intention for agricultural products.

Perceived value plays a pivotal role in consumers' online purchasing of GI agricultural products, offering a robust framework for understanding the psychological processes underlying online shopping behavior. Existing research indicates that external cues influence consumer purchase intention by affecting perceived value [11]. While previous studies on GI agricultural products have focused primarily on brand image, they have not adequately contextualized the dimensional breakdown of perceived value within the specific scenario of online GI product purchases. Given the multidimensional attributes of GI agricultural products, this study divides perceived value into functional perceived value and emotional perceived value. Moreover, existing research has only examined whether GI labels affect purchase intention without precisely identifying which external cues influence which dimensions of perceived value. Therefore, investigating external cues and their impact on consumer perceived value represents a necessary research direction.

This study focuses on external cues of GI agricultural products to address several key questions: Do product factors, service factors, and brand factors differ in their effects within the GI purchase context? Do different factors exert varying influences on consumer purchase intention? Do these factors affect consumer perceived value differently? How do different dimensions of perceived value impact purchase intention? Answering these questions holds significant implications for GI agricultural product sales. By mining thematic factors from online reviews and constructing a structural equation model linking external cues, perceived value, and purchase intention, this research explores how external cues affect different dimensions of perceived value and how these dimensions subsequently influence purchase intention. Through this investigation of the influence mechanism, we aim to dissect the "black box" of consumer purchase processes, open new avenues for online promotion of GI agricultural products, meet diverse market demands, advance agricultural transformation, and support rural revitalization strategies.

1.1 Geographical Indication Agricultural Products

GI agricultural products differ from ordinary agricultural products by originating from specific regions with unique natural environments and historical-cultural characteristics. Examples include Pinggu peaches, Dalian sea cucumbers, and Pingyao beef. Compared with conventional products, GI agricultural products offer higher quality, stronger brand promotion capabilities, and greater economies of scale. Their unique growing conditions endow them with rich nutritional value. Fresh agricultural products possess abundant sensory attributes that consumers prefer to inspect personally. However, e-commerce's virtual nature limits such direct inspection, compelling consumers to rely on external cues to evaluate product quality online. Enhancing the identifiability of GI agricultural products and traceability of their origins can reduce shopping uncertainty and prevent counterfeit goods from damaging brand reputation.

Research on GI agricultural products concentrates on two aspects: First, factors influencing consumer purchases. Lee [1] examined external cues' impact on GI product purchases, finding that online product reviews significantly boost order volume and sales. Roselli [2] discovered that GI labels and organic production positively affect sales volume. Fatima [3] identified GI, origin, organic certification, and fair trade as primary purchase decision factors. Lu Zhaoyang [4] found that GI certification impacts cross-border e-commerce development through production, supply, and sales channels. Tu Hongbo [5] applied cue utilization theory and cognitive-affective personality system theory, using positive online word-of-mouth, price discounts, and origin image as external cues to test their influence on online purchase intention for GI products. Second, the distinctive attributes of GI products themselves. Zhu Zhanguo [6] confirmed that cultural factors, quality assurance, and economic support of GI products positively affect perceived value. Zhang Gangren [7] constructed a model examining how product origin influences premium payment willingness from psychological ownership and nostalgia perspectives, finding that GI labels and origin significantly impact consumers' willingness to pay premiums. Zhu [8] investigated consumer evaluations of single, dual, and multiple labels, revealing that consumers value dual labels more than single labels and are willing to pay premiums for different label combinations, with notable substitution effects among collective and private brands. Lei Bing [9] studied the mechanism linking local characteristics, online reputation, and agricultural product promotion.

1.2 Online Reviews

Online reviews constitute a critical factor influencing consumer online purchase intention. Research on online reviews focuses on two dimensions: First, review characteristics, including usefulness, involvement, similarity, quality, length, and source credibility. Wei Hua [10] constructed a model of factors influencing consumers' adoption intention of green product online reviews on e-commerce platforms, incorporating social environmental and individual trait factors. Zhu Liye [11] examined how reviewer quality affects purchase intention under high and low product involvement scenarios. Zeng Xiangjun [12] applied fine-grained opinion mining technology to extract features from user reviews. Sun Baosheng [13] built an evaluation index system and model for purchase intention using review data to quantitatively assess tourists' ecotourism purchase intention. Kim [14] proposed a "topic consistency" metric to explore overlap between critic and user review content. Jung [15] investigated how review reminder timing affects review posting likelihood and quality. Wang [16] studied review rating, timing, and length features, finding that review tendencies influence consumer satisfaction.

Second, algorithmic and model-based thematic summarization. Bi Datian [17] used LDA to explore whether merchants' requests for positive reviews affect consumers' negative review behavior. Zhang Wen [18] proposed a new review text analysis method based on the Help-LDA model combined with SVM for review usefulness prediction. Fei Wei [19] mined Pinduoduo agricultural product sales data using LDA. Xie [20] used Pycharm to collect online reviews of fresh agricultural products to identify factors influencing consumer preferences. Cao [21] extracted consumer demand for agricultural product attributes from online reviews, proposing an agricultural evaluation classification algorithm that effectively determines text sentiment. Hussain [22] developed a quantitative model using online reviews and an effect-based Kano model to understand purchase intention. Alantari [23] examined the fundamental relationship between overall ratings and textual reviews. Lee [24] found that differences in quality and taste reviews impact company sales.

1.3 Consumer Perceived Value

Perceived value refers to consumers' utility evaluation of a product or service based on comparing perceived benefits against costs. Research on perceived value concentrates on value trade-off theory and multi-factor theory. This study applies multi-factor theory, recognizing that consumers' varying cognitive systems and experiences lead to different value judgments across purchase contexts. Perceived value represents a subjective process, prompting scholars to develop multidimensional, multi-scenario applications. Sheth [25] constructed a five-dimensional perceived value hierarchy model encompassing emotional, social, functional, epistemic, and conditional value perceptions. Liu Yiwei [26] divided consumer perceived value into five dimensions, finding that both perceived value and purchase intention promote behavioral intention toward specialty agricultural products. Wu Shuilong [27] subdivided perceived value into functional, hedonic, and social values to examine their impact on purchase intention. Zhang Hongli [28] segmented perceived value to study its influence on farmers' resource utilization behavior. This study divides perceived value into functional and emotional dimensions, integrating the economic and cultural values inherent in GI agricultural products with consumer perceived value.

2 Topic Mining of Online Reviews for GI Agricultural Products

This section employs Snownlp sentiment analysis, TF-IDF algorithm, and LDA topic clustering to analyze online review text.

[Figure 1: see original paper] Research framework

2.1 Online Review Collection

JD.com's specialty pavilion plays a significant role in regional brand communication and rural assistance. The platform's product and review authenticity makes it an important data source for analyzing consumer purchase intention. We selected JD.com's specialty pavilion as our data platform, collecting reviews from April 20 to May 10, 2023. GI agricultural products were categorized into planting, aquatic, and livestock types. Using Houyi Collector, we crawled online reviews of products from JD.com's specialty pavilion across 34 Chinese provinces, selecting 1-2 products per province (22 planting, 14 aquatic, and 19 livestock products, totaling 54 products) and obtaining 45,660 reviews. Aquatic products included Panjin river crabs, Dalian sea cucumbers, and Sanmen blue crabs; livestock products included Pingyao beef, Yanbian yellow beef, and Yanchi tan lamb; planting products included Pinggu peaches, Wuchang rice, and West Lake Longjing tea. Sample collected data is shown in [Figure 2: see original paper].

[Figure 2: see original paper] Collected data sample

2.2 Text Segmentation

Online reviews contain numerous interfering comments such as invalid, duplicate, irrelevant, or spam comments that cannot be directly analyzed. Original reviews underwent data cleaning to remove interfering, blank, and irrelevant comments, leaving 43,760 reviews (14,497 aquatic, 13,463 meat, and 15,801 planting). After preprocessing, Python's jieba library performed word segmentation and stop-word removal using the "Harbin Institute of Technology Stopword Lexicon" and "Baidu Stopword List" to eliminate meaningless words like 'le', 'ne', 'de', and 'de'. A custom stopword list was created to improve segmentation effectiveness. Segmentation results are partially illustrated in , with high-frequency words subsequently counted.

Example of word segmentation results

2.3 TF-IDF Feature Weighting

Consumers attach varying degrees of importance to different influencing factors, necessitating weight assignments to distinguish attention differences among factors. Unlike simple word frequency statistics, TF-IDF (Term Frequency-Inverse Document Frequency) assigns weights based on keyword importance within documents, evaluating term significance across the corpus while avoiding distortion from frequently occurring but low-importance words. TF represents term frequency, measuring descriptive capacity, while IDF (inverse document frequency) measures discriminative power. Higher TF-IDF values indicate greater term importance, reflecting consumer attention levels. The TF-IDF calculation formula is:

$$TFIDF = \frac{n}{N} \times \log \frac{D}{d}$$

where n represents term frequency in a document, N is total word count, d is the number of documents containing the term, and D is total documents in the corpus.

This study extracted online review text features using TF-IDF, selecting the top 30 high-frequency terms for analysis as shown in . Terms like 'not bad', 'delicious', 'taste', 'very good', 'packaging', 'texture', 'logistics', 'very fast', 'JD.com', 'fresh', 'price', 'quality', 'speed', and 'express delivery' ranked highly, indicating consumer priorities. A word cloud visualizing the top 100 high-frequency terms is presented in [Figure 3: see original paper].

Word frequency statistics and TF-IDF weighted feature words

[Figure 3: see original paper] TF-IDF feature words word cloud

2.4 Snownlp Sentiment Analysis

Current sentiment analysis methods include machine learning, deep learning, and sentiment lexicon approaches, primarily applied to online review analysis to explore consumer sentiment tendencies. This study employs machine learning, training a sentiment classifier on labeled data to analyze review sentiment and improve accuracy for domain-specific analysis. Python's SnowNLP library specializes in e-commerce review sentiment analysis, though its default model suits hotels and restaurants. Different domains require customized sentiment lexicons for accurate analysis of GI agricultural products. SnowNLP's sentiment scoring ranges from [0-1]. We randomly selected 4,000 reviews for manual annotation (satisfied=1, unsatisfied=0), divided into positive and negative TXT files for training, tested accuracy on a subset, then applied SnowNLP to score all 43,760 GI product reviews. By default, scores >0.5 indicate positive sentiment and <0.5 negative. However, research shows 0.5 is often suboptimal as a threshold. This study adjusted the criteria: >0.7 as positive, 0.4-0.7 as neutral, and <0.4 as negative reviews.

Post-analysis results show: 34,382 positive reviews (78.57%), 4,717 negative reviews (10.78%), and 4,660 neutral reviews (10.65%). The top 50 feature words for sentiment analysis are exemplified in .

Examples of top 50 sentiment analysis feature words

2.5 LDA Topic Clustering

The LDA (Latent Dirichlet Allocation) model effectively mines latent semantics in text data, using probability distributions to summarize thematic processes into concise expressions. By converting review data into vectors, LDA obtains topic probabilities and is widely applied to analyze consumer product and service experience evaluations. This study used Python's gensim package for LDA topic clustering to extract key topic numbers. Scholars have proposed minimum perplexity algorithms and Bayesian methods to determine optimal topic numbers. This study employed both data visualization and minimum perplexity approaches, confirming six optimal topics. Visualization results showed good clustering effects at six topics ([Figure 4: see original paper]), with the elbow method also identifying K=6 as optimal. The top 10 keywords and weights for each topic are presented in .

[Figure 4: see original paper] Minimum perplexity elbow plot
[Figure 5: see original paper] pyLDA visualization results

Based on LDA results and existing literature, multiple researchers iteratively summarized the topic names: Topic 1—Product Quality; Topic 2—E-commerce Service; Topic 3—Origin Image; Topic 4—Brand Reputation; Topic 5—Logistics and Distribution; Topic 6—Product Cost-Performance Ratio. Terms like "brand," "trademark," and "authentic" reflect attention to brand reputation; "authentic," "hometown," "memory," "childhood," "family," "children," and "elderly" indicate origin image importance; "good value," "affordable," and "cheap" show cost-performance concerns; "quality," "meat quality," "size," "aroma," "taste," "texture," "freshness," and "cleanliness" reflect product quality priorities; "logistics," "JD Logistics," "speed," "delivery," and "arrival" demonstrate high logistics expectations; and "service attitude," "seller," and "merchant" reveal e-commerce service importance. Product quality emerges as the most critical factor with high emotional consistency and greatest consumer impact, followed by logistics, e-commerce service, cost-performance ratio, origin image, and brand reputation.

LDA topics and top 10 characteristic words

3 Empirical Study on Consumer Purchase Intention for GI Agricultural Products

Based on perceived value theory, this section analyzes the path mechanism between the identified themes and consumer purchase intention. Current research on GI product consumption has focused on perceived value as a holistic concept without clarifying which dimensions are affected, failing to explain which external cues influence which aspects of perceived value. This study addresses this gap by dividing perceived value into functional and emotional dimensions to examine how external cues affect each dimension. A structural equation model linking perceived value and purchase intention is constructed to analyze the influence mechanism, broadening research perspectives and providing insights for online GI product sales.

3.1 Conceptual Model Construction

[Figure 6: see original paper] Conceptual model of GI agricultural product purchase intention

Variable measurements were adapted from established scales and refined for the GI product context, using five-point Likert scales. Product quality drew from Zhao Lei [31]; brand reputation and origin image from Zhao Lei [31]; cost-performance ratio from Yin Tong [33]; e-commerce service from Hussain [27];

logistics from Yin Tong [33]; and functional perceived value, emotional perceived value, and purchase intention from Tu Hongbo [5] and Zhu Zhanguo [6].

3.2.1 GI Agricultural Product External Cues and Functional Perceived Value

GI agricultural products possess uniqueness derived from rich natural resources, historical culture, and quality support. As a quality signal, GI certification provides consumers with product quality assurance information. Boncinelli [29] validated that origin labeling is a primary factor influencing purchase intention for Italian pasta, with consumers perceiving origin-labeled products as tastier, healthier, and more environmentally friendly, commanding price premiums. GI labels, as origin indicators, have been confirmed to positively affect perceived value. GI products' regional specificity, uniqueness, and scarcity generate widespread praise, with long production histories, good taste, and rich nutritional value representing functional value manifestations. Zhao Lei [30] analyzed factors influencing fresh agricultural product purchase intention from product environment, consumer cognition, and e-commerce platform perspectives based on social cognition and perceived value theories. In virtual online environments, consumers compare multiple brands and choose relatively trusted ones, with external cues enhancing functional perceived value. Therefore, we propose:

H1a: Product cost-performance ratio positively affects functional perceived value.
H1b: Product quality positively affects functional perceived value.
H1c: Origin image positively affects functional perceived value.
H1d: Brand reputation positively affects functional perceived value.
H1e: Logistics and distribution positively affect functional perceived value.
H1f: E-commerce service positively affects functional perceived value.

3.2.2 GI Agricultural Product External Cues and Emotional Perceived Value

Consumer emotional perceived value results from multiple factors. Considering GI products' unique economic-cultural support, quality assurance, and multi-dimensional sensory attributes, consumers generate different perceived value dimensions during shopping. He Biao [31] subdivided perceived value into economic, learning, relational, and hedonic values. Existing research has largely examined external cues and purchase intention from a cognitive perspective while neglecting emotional impacts. GI labels can trigger additional associations, offering high cultural-historical experiences and emotional value. Our online review analysis reveals that many GI product consumers are expatriates from the production regions, with emotional perceived value stemming from origin attachment and brand memory—core components of GI product emotional value. GI products represent regional history and culture, accompanying local consumers' growth and holding irreplaceable significance. Their historical and cultural experiences can evoke positive humanistic associations. Therefore, we propose:

H2a: Product cost-performance ratio positively affects emotional perceived value.
H2b: Product quality positively affects emotional perceived value.
H2c: Origin image positively affects emotional perceived value.
H2d: Brand reputation positively affects emotional perceived value.
H2e: Logistics and distribution positively affect emotional perceived value.
H2f: E-commerce service positively affects emotional perceived value.

3.2.3 Perceived Value and Consumer Purchase Intention

Under combined external influences, consumers' perceived value for GI agricultural products varies. Unlike offline shopping where consumers can directly assess product color, aroma, size, and shape, online GI product purchases lack direct quality perception. Thus, enhancing perceived value and shopping experience becomes critical. Consumers evaluate product quality through external cues, with product elements, brand factors, and platform services reducing uncertainty and increasing perceived value to boost purchase intention. Zhu Zhanguo [6] examined relationships among multidimensional GI image, multidimensional perceived value, and purchase intention, dividing perceived value into social, emotional, and functional dimensions—all significantly and positively affected by GI image dimensions with varying effect sizes. Yin Tong [32] found that logistics service, product quality, merchant service, and sales platform differently affect purchase intention for poverty alleviation e-commerce products. Consumers make decisions after comparing products based on cognitive level, shopping experience, product category, quality, origin, cost-performance ratio, and brand. This study divides perceived value into functional and emotional dimensions, both of which enhance purchase intention. Therefore, we propose:

H3a: Functional perceived value positively affects consumer purchase intention.
H3b: Emotional perceived value positively affects consumer purchase intention.

3.3.1 Research Method

The questionnaire comprises three sections: (1) Whether consumers have purchased GI agricultural products online and what products; non-purchasers skip directly to the end. (2) Demographics: gender, occupation, age, monthly income, education level, 2023 online shopping expenditure, time spent per GI product purchase, and monthly GI product expenditure. (3) Main questionnaire section measuring nine variables (independent, mediating, and dependent) using five-point Likert scales.

3.3.2 Data Source

The questionnaire was administered from May 25 to June 25, 2023, for 30 days, collecting 643 responses, with 602 valid questionnaires (93.6% validity). Sample characteristics are shown in . Males accounted for 49% and females 51%, with most respondents aged 18-40, aligning with China's younger online shopping demographic. Students and enterprise employees comprised high proportions, with 35.5% earning ¥5,000-8,000 monthly. Regarding GI product purchase experience, 49.3% spent ¥300-500 monthly; 48.5% spent 10-30 minutes per purchase; and most reported ¥5,001-10,000 in annual online shopping expenditure, indicating that online agricultural product shopping is becoming a modern trend.

Sample descriptive statistics

3.4.1 Reliability and Validity Analysis

SPSS 24.0 analyzed reliability and validity. The overall Cronbach's α coefficient was 0.965, indicating excellent reliability and internal consistency. KMO sampling adequacy (0.960) and Bartlett's sphericity test (^{2} significant at p<0.001) confirmed suitability for confirmatory factor analysis. Amos convergent validity tests showed all standardized factor loadings >0.8, with all AVE values >0.5 and CR values >0.7, demonstrating good convergent validity.

3.4.2 Model Path Testing

AMOS 25.0 assessed structural equation model fit: ^{2}/df = 4.513 (<5, acceptable), RMSEA = 0.076 (<0.08, acceptable), and NFI, IFI, CFI all >0.9 (acceptable), indicating good model-data fit overall given model complexity and sample size.

Results of structural equation model path relationship test

Standardized path coefficients are shown in [Figure 7: see original paper]. Product quality features positively affect purchase intention as the primary factor influencing perceived value. Product quality encompasses freshness, taste, nutritional value, packaging integrity, quality certification, damage condition, and consistency with web descriptions. Cost-performance ratio reflects GI products' premium pricing due to brand and quality advantages; when premiums align with consumer price expectations, purchases feel worthwhile.

Brand image factors include origin image and brand reputation. Many GI product purchasers are region natives. While emotional perception types are dispersed, "hometown," "memory," "childhood," "family," "children," and "elderly" are universally salient factors. Consumers perceive GI origins as having unique geographical conditions and mature production technologies, yielding superior appearance, taste, and nutrition that signify high quality. Brand reputation reflects consumer preference for certified products, representing not only product value but also safety certification. Developing GI brands helps build regional public brands, create brand effects, provide premium advantages, and increase farmer income.

Service features positively affect purchase intention. Logistics speed, delivery timeliness, packaging integrity, and aesthetics all influence decisions. As food products, quality and safety are paramount concerns. Freshness preservation measures affect loss, freshness, and perceived value. Additionally, due to network virtuality and information asymmetry, customer service attitude, response timeliness, return policies, and merchant credibility constitute significant e-commerce service factors. Quality services add value, resolve trust issues, and match consumers with suitable products.

3.5 Results Analysis

Findings reveal that product quality, brand reputation, origin image, logistics, and e-commerce service significantly affect both functional and emotional perceived value, though importance varies. Functional value influences purchase intention more than emotional value. Different feature factors exert varying impacts, ranked by importance as: product quality, logistics, e-commerce service, cost-performance ratio, origin image, and brand reputation. GI product external cues affect purchase intention through different perceived value dimensions. Improvements in these elements can open new sales channels, increase seller volume, and build positive GI product images while providing quality products and services. Notably, most consumers remain in the functional value stage, paying less attention to emotional value, which refers to purchasing based on emotional attachment. Consumers currently pay primarily for functional value rather than the status associations, cultural heritage, or mature craftsmanship embodied in GI products.

4.1 Research Conclusions

Based on perceived value theory, this study identifies factors influencing GI agricultural product purchases. First, external cues rank in importance as: product quality, logistics, e-commerce service, cost-performance ratio, origin image, and brand reputation, categorized into product, service, and brand image factors. Second, external cues, perceived value, and purchase intention exhibit utility transmission, with external cues affecting purchase intention through different perceived value dimensions. Third, all external cues positively affect perceived value, but dimensional impacts differ, with functional value exerting stronger effects than emotional value. Greater perceived value leads to higher purchase intention. This comprehensive perspective broadens research on external cues' influence on purchase intention.

4.2 Theoretical Significance

This study provides new perspectives on GI product purchase behavior through perceived value theory: (1) By extracting purchase factors from online reviews, it explores path mechanisms between features and purchase intention, enriching GI product consumption behavior theory and examining external cues' joint impact on brand cognition from a consumer perspective. (2) Subdividing perceived value into functional and emotional dimensions integrates GI products' economic-cultural values with consumer perceived value, offering theoretical support for agricultural enterprises using product and service information while broadening brand cognition research. (3) Combining qualitative and quantitative methods (online reviews and structural equation modeling) overcomes single-method limitations, providing recommendations for building regional public brands and aiding traditional agricultural transformation and high-quality rural development.

4.3 Practical Implications

External cues are critical factors in GI product promotion that significantly enhance purchase intention. As product diversification and purchase channels multiply, leveraging external cues' role in decision-making becomes essential for competitive advantage. Based on findings, we propose:

(1) **Build GI product brand image**. Increase brand reputation and origin image promotion to create premium advantages and brand effects. Highlight traditional craftsmanship and historical-cultural features to enhance perceived value, emphasizing experiential value and status associations to facilitate brand establishment. Improve origin information disclosure to boost consumer cognition.

(2) **Enhance service awareness to create competitive advantages**. E-commerce platforms should clearly display product information without false advertising, ensure food quality and safety, and design promotional strategies. Actively encourage online reviews and sharing of shopping experiences, particularly positive comments on taste and freshness to improve user experience. Develop integrated, unbroken cold chain logistics systems to provide quality GI products at competitive prices, implementing precision pricing based on consumer segments, needs, and product types.

(3) **Strengthen supervision and regulate production environments**. Regulators should formulate policies standardizing GI product production and processing, strictly combat counterfeits, clearly define property rights, construct legal protection systems, promote standardized large-scale production, intensify promotion efforts, and protect origin image. Enhance government-enterprise cooperation, implement support policies, and reward honest producers and operators.

4.4 Research Limitations and Future Directions

This study has limitations. Consumer decision-making patterns may differ across platforms (e-commerce vs. social media), warranting future investigation. Additionally, questionnaire data relies on recent consumer experiences, which may suffer from timeliness and memory biases. Future research could employ experimental methods to explore interaction effects and more directly measure purchase decisions.

References

[1] Lee D, Moon J, Ryu M H. The effects of extrinsic cues on online sales of fresh produce: a focus on geographical indications[J]. Cahiers Agricultures, 2019, 28: 13.
[2] Roselli, L, Giannoccaro, G, Carlucci, D, & De Gennaro, B. EU quality labels in the Italian olive oil market: How much overlap is there between geographical indication and organic production? Journal of Food Products Marketing, 2017,24(6), 784–801.
[3] El Hadad-Gauthier F, Monhoussou B B, Hammoudi A, et al. European consumers attitudes toward ethnic foods: Case of date fruits[J]. Foods, 2022, 11(15): 2192.
[4] Lu Zhaoyang. Empirical Study on the Impact of Geographical Indication of Agricultural Products on Cross-border E-commerce Development of Agricultural Products[J]. China Soft Science, 2019, (06): 67-84.
[5] Tu Hongbo, Zhu Qingjian. The Influence and Mechanism of External Cues on Online Purchase Intention for Geographical Indication Agricultural Products[J]. China Circulation Economy, 2020, 34(08): 37-47.
[6] Zhu Zhanguo, Wang Yue. Impact of Multi-dimensional Geographical Indication Image on Consumers' Online Purchase Intention for Geographical Indication Agricultural Products: Based on Perceived Value Perspective[J]. Journal of Jiangsu University (Social Science Edition), 2022, 24(02): 57-69.
[7] Zhang Gangren, Li Linzhu, Bao Yuze. Research on the Influence Path of Origin on Premium Payment Willingness for Geographical Indication Products from the Perspective of Psychological Ownership and Nostalgia[J]. Journal of Huazhong Agricultural University (Social Science Edition), 2022, No.158(02): 57-66.
[8] Zhu Z, Shen Q, Gao Z. Consumer choices in agricultural markets with multitier collective labels and private brands[J]. Agribusiness, 2022, 38(4): 905-922.
[9] Lei Bing, Wang Qiaoxia, Liu Xiao. Local Characteristics, Online Reputation and Agricultural Products Upward Movement[J]. China Soft Science, 2021, No.362(02): 34-45.
[10] Sheth JN, Newman Bl, Gross B L.Why we buy what we buy: A theory of consumption values [J].Journal of Business Research,1991,22 (2) : 160-162.
[11] Liu Yiwei, Wang Yubin. Consumer Perceived Value, Purchase Intention and Behavioral Intention for Specialty Agricultural Products: Based on a Survey of Donkey Meat Consumption by Urban Residents in Shandong and Hebei[J]. Journal of China Agricultural University, 2021, 26(05): 232-244.
[12] Wu Shuilong, Song Shuqi, Yuan Yongna et al. Impact of Customer Perceived Value on Purchase Intention: The Mediating Role of Self-AI Connection[J]. Journal of Beijing Institute of Technology (Social Science Edition), 2023, 25(03): 117-128.
[13] Zhang Hongli, Zhu Zhenhua, Li Jieyan. Differential Mode of Association, Perceived Value and Resource Utilization Behavior of Livestock and Poultry Waste: Based on Survey Data from Xinjiang Farmers[J]. Journal of Agro-

Forestry Economics and Management, 2023, 22(01): 103-112.
[14] Wei Hua, Gao Jinsong, Wan Hui. Research on Consumers' Adoption Intention of Green Product Review Information on E-commerce Platforms[J]. Information Science, 2020, 38(05): 161-168.
[15] Zhu Liye, Yuan Denghua, Zhang Jingyi. Impact of Online User Review Quality and Reviewer Level on Consumer Purchase Intention: The Moderating Role of Product Involvement[J]. Management Review, 2017, 29(02): 87-96.
[16] Zeng Xiangjun, Ye Xiaoqing, Liu Dun. Research on User Purchase Intention Analysis Based on Fine-grained Opinion Mining and Kano Model[J]. Computer Engineering and Science, 2023, 45(04): 701-710.
[17] Sun Baosheng, Ao Changlin, Wang Jingxia et al. Research on Evaluation of Ecotourism Purchase Intention Based on Network Text Mining[J]. Operations Research and Management Science, 2022, 31(12): 165-172.
[18] Kim E, Ding M Q, Wang X, et al. Does Topic Consistency Matter? A Study of Critic and User Reviews in the Movie Industry[J]. Journal of Marketing, 2023, 87(3): 428-450.
[19] Jung M, Ryu S, Han S P, et al. Ask for Reviews at the Right Time: Evidence from Two Field Experiments[J]. Journal of Marketing, 2023: 00222429221143329.
[20] Wang Y, Choudhary V, Yin S. Product design enhancement for fashion retailing[J]. Service Science, 2023.
[21] Bi Datian, Chu Qihuan, Cao Ran. Research on Influencing Factors of Consumers' Negative Review Willingness Based on Text Mining[J]. Information Theory and Practice, 2020, 43(10): 137-143.
[22] Zhang Wen, Wang Qiang, Du Yuhang et al. Research on Topic Analysis and Prediction of Online Product Review Usefulness[J]. System Engineering Theory and Practice, 2022, 42(10): 2757-2768.
[23] Fei Wei, Li Shiyun, Lyu Xinyang. Empirical Analysis of Social E-commerce Helping Agricultural Products Upward Movement Based on Data Mining[J]. Journal of Hunan Agricultural University (Social Science Edition), 2022, 23(04): 104-114.
[24] Xie C, Tian X, Feng X, et al. Preference Characteristics on Consumers' Online Consumption of Fresh Agricultural Products under the Outbreak of COVID-19: An Analysis of Online Review Data Based on LDA Model[J]. Procedia Computer Science, 2022, 207: 4486-4495.
[25] Cao Y, Sun Z, Li L, et al. A Study of Sentiment Analysis Algorithms for Agricultural Product Reviews Based on Improved BERT Model[J]. Symmetry, 2022, 14(8): 1604.
[26] Hussain J, Azhar Z, Ahmad H F, et al. User Experience Quantification Model from Online User Reviews[J]. Applied Sciences, 2022, 12(13): 6700.
[27] Alantari H J, Currim I S, Deng Y, et al. An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews[J]. International Journal of Research in Marketing, 2022, 39(1): 1-19.
[28] Lee N, Bollinger B, Staelin R. Vertical versus horizontal variance in online reviews and their impact on demand[J]. Journal of Marketing Research, 2023, 60(1): 130-154.

[29] Boncinelli F, Dominici A, Bondioni F, et al. Consumers behavior towards the country of origin labeling policy: The case of the pasta market in Italy[J]. Agribusiness, 2023.
[30] Zhao Lei. Research on Influencing Factors of Online Purchase Intention for Fresh Agricultural Products Based on Social Cognition and Perceived Value Theory[J]. Journal of Sichuan Agricultural University, 2022, 40(01): 137-144.
[31] He Biao, Xie Dengming, Wu Chaonan et al. Impact of Exhibitors' Value Co-creation Behavior on Perceived Value, Purchase Intention and Future Behavioral Intention[J]. Tourism Tribune, 2022, 37(05): 137-152.
[32] Yin Tong, Yu Lichao, Bao Wei. Research on Consumer Purchase Intention and Its Influencing Factors for E-commerce Poverty Alleviation Products Under the Background of Targeted Poverty Alleviation[J]. Journal of Mathematical Statistics and Management, 2022, 41(04): 599-609.

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Note: Figure translations are in progress. See original paper for figures.