Research on Influencing Factors of User Purchase Behavior in Live-Streaming E-Commerce: Post-print

Authors: Huang Wei, Wang Shanshan, Dai Xinyu

Date: 2023-10-08T00:00:00+00:00

Abstract

[Purpose/Significance] Research on user purchasing behavior in live-stream e-commerce is of great significance for the development of live-stream e-commerce, as it facilitates targeted adjustments and improvements to live-streaming strategies. [Method/Process] This study investigates the influencing factors of user purchasing behavior in live-stream e-commerce, constructing an indicator system for these factors from four dimensions: anchor capability, product information, user attributes, and comprehensive capability of the live-streaming team, and draws conclusions combined with practical examples. Data were collected through questionnaire distribution and expert consultation. The fuzzy comprehensive evaluation method was employed for initial assessment of indicators at all levels, followed by the Analytic Hierarchy Process (AHP) for pairwise comparisons, matrix construction, and final weight determination to precisely analyze the influencing factors of user purchasing behavior. [Results/Conclusion] The credibility and comprehensiveness of product information presentation constitute the primary factor influencing user purchasing behavior. When broken down into finer indicators, product quality, level of information detail, and online reputation have the greatest impact. This is followed by the professional selling capability of anchors. Users in different age groups show significant differences in their susceptibility to anchors with varying social identities, and real-time comment interaction more effectively promotes user consumption. The continuous penetration of online shopping among the public has led to a gradual expansion of middle-aged and elderly user groups in live-stream e-commerce, indicating strong development potential.

Full Text

1 Introduction

The rapid development of internet technology, accelerating societal networking processes, and the widespread adoption of smart communication devices have transformed people' s lifestyles, production methods, and thinking patterns. According to the 47th Statistical Report on China' s Internet Development released by the China Internet Network Information Center, as of December 2020, China' s internet user base reached 989 million, with online shopping users totaling 782 million, accounting for 79.1% of all internet users [1]. This indicates that compared to offline shopping, people increasingly prefer convenient and efficient online shopping, and this massive user base has further stimulated the vigorous growth of domestic consumer markets.

With the advent of the Web 4.0 era and the continuous improvement and expansion of e-commerce platforms, the information available in online shopping has become increasingly complex. Consumers who cannot gain comprehensive understanding of products struggle to filter useful information within short timeframes. Moreover, compared to offline shopping experiences, online shopping lacks real-scenario experiences, making it difficult to create direct stimulation for consumers. Consequently, supported by new internet technologies, a novel business format has emerged—live-stream e-commerce [2].

Reports show that in 2020, China' s live-stream e-commerce industry reached a total scale of 961 billion yuan, projected to approach 1,201.2 billion yuan in 2021. The user base for e-commerce live streaming stood at 309 million, representing 32.9% of all internet users [3]. During the 2019 "618" Shopping Festival, Taobao generated 3 billion yuan in sales through live-stream marketing. On "Double 11" 2019, Taobao Live alone achieved 20 billion yuan in transaction volume, with over 10 individual live-stream rooms exceeding 100 million yuan in sales [4]. Live streaming became the largest contributor to brand sales during the "Double 11" event. As a digital economy model of "online traffic attraction + offline consumption," live-stream e-commerce offers high purchase conversion rates and effective marketing, gradually becoming a new growth driver for e-commerce platforms. It also aligns perfectly with the national goal of "bridging the information gap, achieving secure transactions, and forming healthy cycles." Data indicates that users who purchase products through live-stream e-commerce account for 66.2% of all e-commerce live-stream users, with 17.8% of users spending more than 30% of their total online shopping budget on live-stream e-commerce [5].

Compared to traditional marketing models, live-stream e-commerce offers three distinct advantages: low cost, high timeliness, and easier promotion. Traditional marketing relies primarily on television and outdoor billboards, which are not only costly but also yield unsatisfactory results. Live-stream e-commerce uses mobile phones and computers as mediums, fully utilizing consumers' leisure time to subtly promote products [6]. Unlike static images on traditional e-commerce

platforms, live streaming enables consumers to receive product information more directly. The real-time emotional expression of hosts and immediate interactive feedback from viewers create a greater sense of authenticity than pure image or video displays, thereby reducing trust costs.

This study investigates the most influential factors affecting consumer purchasing behavior in live-stream e-commerce, aiming to provide managerial insights and practical guidance for enterprises seeking to enhance brand influence and sales through live-streaming. It also offers reference value and practical significance for live-stream e-commerce platforms and consumers.

2 Literature Review on Factors Influencing User Behavior on E-Commerce Live-Streaming Platforms

Research on e-commerce live streaming by Chinese scholars began in 2016, with most studies focusing on characteristics, development status, countermeasures, and KOL (Key Opinion Leader) economics. Master' s and doctoral theses constitute a significant proportion of this research. In recent years, with the widespread adoption of live-stream e-commerce, research on consumer purchase intention and behavior has gradually deepened.

Regarding purchase intention studies, the interaction between hosts and fans significantly influences consumers. Tao Bingxin et al. [7] approached from a psychological perspective, utilizing utility-hedonic theory to identify usage needs and hedonic needs as key drivers of user interaction in e-commerce live streaming. Tan Yuli [8] employed case studies and in-depth interviews, concluding that the presentation format of product recommendations by opinion leaders most significantly impacts consumer purchase intention. Wang Xiwei et al. [9] focused on live-streaming apps, combining questionnaire surveys with structural equation modeling to determine that perceived interactivity most strongly influences user intention to use. Tian Xinxin et al. [10] found that cost reduction, opinion leaders, and purchase scenarios all enhance consumer purchase intention. Regarding purchase behavior research, most scholars still analyze from psychological perspectives. Wei Hua et al. [11] and Dong Fang [12] both employed the SOR (Stimulus-Organism-Response) model framework to deeply investigate the mechanisms influencing users' online purchase behavior. They constructed models for the impact of information interaction on user participation in e-commerce live streaming and factors influencing purchase intention in mobile e-commerce live streaming, respectively, concluding that responsiveness, entertainment, and mutual assistance in information interaction significantly affect user participation. Tang Shutian [13] used content analysis to explore specific factors through which Weibo influencers affect fans' consumption behavior, including attracting attention, consumption carnival, and fan aggregation. Due to relatively conservative e-commerce environments abroad and lower penetration of live-stream e-commerce compared to China, current international research remains limited, primarily focusing on factors influencing users' willingness to watch live streams in social e-commerce contexts. Social e-commerce represents a new marketing

approach for e-commerce conducted through social platforms. Regarding factors influencing users' intention to watch e-commerce live streams, perceived value, real-time interaction, and entertainment show substantial impact. For instance, C. C. Chen et al. [14] noted that entertainment and social interaction positively influence users' intention to watch live programs. F. F. Hou et al. [15] found that interactivity, humor, entertainment, and interaction positively affect users' continuous watching intention, while social status promotes consumption willingness. I. Erkan and C. Evans [16] indicated that experiential and scenario-based marketing methods significantly increase consumer engagement, thereby stimulating purchase desire.

In summary, domestic research on user purchase behavior in live-stream e-commerce environments is not scarce, but most studies focus on single-factor influences or analyze from communication or psychological perspectives, rarely providing comprehensive multi-dimensional analysis. Due to underdeveloped live-stream e-commerce environments abroad, international research focuses on attracting viewership rather than purchase conversion. Therefore, this study employs fuzzy comprehensive evaluation and analytic hierarchy process methods to investigate from multiple dimensions—host capabilities, product information, user attributes, and live-stream team competence—to identify the most influential factors affecting consumer purchase behavior in live-stream e-commerce. This research aims to provide insights and reflections for practitioners in the live-stream e-commerce field while offering reference value for studies on consumer purchase behavior under new online shopping models.

3 Evaluation Indicators for User Purchase Behavior in Live-Stream E-Commerce

The authors reviewed extensive literature and followed principles of comprehensiveness, representativeness, objectivity, rationality, and measurability to initially establish the indicator system. To obtain more comprehensive indicators and enable more accurate description and evaluation of the research object, the authors subsequently employed questionnaire surveys to further refine the indicator system [17]. The online questionnaire underwent two revisions before finalizing the Survey on Factors Influencing User Purchase Behavior in Live-Stream E-commerce. The target respondents were primarily users of live-stream e-commerce, as this group represents the main subjects of this study and possesses relatively clear understanding of various aspects of live-stream e-commerce (such as hosts, products, and the entire live-stream team), enabling them to provide accurate feedback for this research. Within seven days of distribution, 203 responses were received. All questionnaires were reviewed, organized, and categorized. By integrating multi-perspective viewpoints and incorporating referential opinions with primary indicators, the authors optimized and refined indicators at all levels. The final evaluation indicator system for factors influencing user purchase behavior in live-stream e-commerce consists of 4 first-level indicators, 8 second-level indicators, and 33 third-level indicators,

as shown in Table 1 :

4 Index Weight Calculation

The authors employed three methods to determine indicator weights: the Delphi method, fuzzy comprehensive evaluation, and analytic hierarchy process. The Delphi method and AHP have certain subjective limitations due to individual understanding, but weights obtained by combining expert suggestions from the field with scientific calculation methods are reasonable and valid. Fuzzy comprehensive evaluation processes evaluation objects through numerical means, enabling more scientific, reasonable, and realistic quantitative evaluation of information with fuzzy characteristics, significantly enhancing the scientific validity of this research.

4.1 Methods

4.1.1 Delphi Method The Delphi method (also known as "expert survey method") is the simplest approach for determining weights. It primarily collects experts' opinions, experiences, and perceptions of the importance of each indicator to allocate weights, with more important indicators receiving greater weights. Through continuous feedback and modification, satisfactory results are obtained [18]. The authors employed the Delphi method when initially establishing indicators, integrating opinions from various experts in the live-stream e-commerce field to assign values to each indicator. Since human selection involves subjective consciousness and different scholars hold different viewpoints, to ensure weight rationality and achieve consensus, only a minimal number of inconsistent opinions were ignored. Based on the rationality of each weight, continuous trade-offs and adjustments were made to finalize the preliminary weights.

4.1.2 Fuzzy Comprehensive Evaluation Fuzzy comprehensive evaluation is a comprehensive assessment method based on fuzzy mathematics that effectively addresses fuzzy or difficult-to-quantify problems, making it suitable for various non-deterministic issues [19]. Therefore, this method was employed to evaluate certain qualitative indicators. The specific steps are as follows: (1) Establish the factor set U and evaluation set V for the evaluation object; simultaneously, determine the weight W of each influencing factor. (2) Determine the scoring membership function and comprehensive evaluation matrix R for each factor, calculate membership degrees, and obtain fuzzy comprehensive evaluation. (3) Derive the fuzzy comprehensive evaluation set B from the comprehensive evaluation matrix R, namely:

The final fuzzy value, that is, the comprehensive evaluation score E of the evaluation object is calculated using the fuzzy comprehensive evaluation set B and measurement scale H:

4.1.3 Analytic Hierarchy Process The Analytic Hierarchy Process (AHP) was employed for weight calculation: experts conducted pairwise comparisons of the importance of indicators at the same level, scoring them to construct pairwise comparison judgment matrices. The eigenvector method was ultimately used to determine indicator weights W = (w1, w2, ···wn)T, followed by consistency verification. By analyzing the factors contained in complex systems and studying their relationships, problems are hierarchized to construct a hierarchical analysis structure model. Elements at each level are then compared pairwise according to certain standards to obtain comparative scales of relative importance. Judgment matrices are established to calculate the maximum eigenvalue and eigenvector, yielding the importance order of elements at each level relative to an element in the upper level, thereby establishing weight vectors [20]. The main steps are as follows: (1) Select the SAATY 1-9 scaling method to quantitatively analyze pairwise importance comparisons between indicators and construct judgment matrices. Formula (3) (2) Calculate the maximum eigenvalue and eigenvector.

Let the indicator vector be W = (w1, w2, ···wn)T. The result of right-multiplying the judgment matrix is: Formula (4) It can be seen that λmax is the unique non-zero maximum eigenvalue of the judgment matrix R, and W is its corresponding eigenvector. The elements in this vector can serve as the indicator weight values for the matrix. (3) Consistency verification of the judgment matrix. Calculate consistency; Identify the corresponding random consistency indicator RI; Calculate consistency ratio = . When CR $<$ 0.1, the consistency test is passed; otherwise, matrix A must be modified.

Integrating expert opinions and employing AHP to calculate indicators at all levels, examples of second-level indicator calculations and AHP hierarchical analysis results for second-level indicators are shown in Table 2 and Table 3 :

Table 2 Example of Second-Level Indicator Calculations Table 3 AHP Hierarchical Analysis Results for Second-Level Indicators Eigenvector Weight Value/% Host Attractiveness Host Professionalism Product Comprehensiveness Product Credibility Team Business Capability 0.554 User Dynamic Attributes 0.447

(4) Calculate the indicator system with weight values. As shown in Table 3, a 7th-order judgment matrix was constructed for seven items: host attractiveness, host professionalism, product comprehensiveness, product credibility, team business capability, live-stream environment, and user dynamic attributes. AHP hierarchical analysis yielded the eigenvector W = (0.210, 0.738, 3.324, 1.384, 0.554, 0.343, 0.447), with corresponding weight values of 3.005%, 10.538%, 47.418%, 19.777%, 7.912%, 4.902%, and 6.386%, respectively. Additionally, the maximum eigenvalue was calculated as 7.212 from the eigenvector, yielding a CI value of 0.035. The RI value was found to be 1.360 from the table, resulting in a CR value of 0.026 $<$ 0.1. This indicates that the judgment matrix in this study satisfies the consistency test, and the calculated weights are consistent.

4.2 Indicator Weights

The authors comprehensively employed three indicator calculation methods to obtain the final weight table for indicators at all levels, as shown in Table 4 . The relatively significant weight gaps among third-level indicators under the same second-level indicator suggest low correlation and high discrimination among indicators, thereby further verifying their relevance, rationality, and validity.

First-Level Indicator Weight Second-Level Indicator Weight Third-Level Indicator Weight Table 4 Weight Table for Indicators at All Levels Product Image Fit Degree User Interaction Degree Information Detail Level Display Comprehensiveness Brand Awareness

5 Experimental Design and Results

5.1 Experimental Design

To conduct a more comprehensive and effective evaluation of factors influencing user purchase behavior in live-stream e-commerce, the authors selected three live-stream rooms with high, relatively high, and average sales volumes based on current popularity: "Li Jiaqi" and "Zhao Daxi daxi" from the Taobao platform, and "Zhang Ting" from the Douyin platform. Each live-stream room was observed online, and three best-selling products from each broadcast were selected for detailed recording of the live-stream process. Quantifiable indicators were documented, scores were averaged, and comprehensive evaluations were conducted.

5.2 Experimental Results

The results obtained using the Delphi method are shown in Table 5 . Fifteen experts in the live-stream e-commerce field provided reasonable and effective scores for the lowest-level indicators of the three selected live-stream e-commerce cases based on the aforementioned evaluation indicator system. According to the weight table for indicators at all levels in Table 4, new weight proportions were obtained after removing non-quantifiable indicators. The data in the table reveals significant differences in scores for aspects such as quality, information detail level, and user interaction degree. The evaluation indicator system constructed by the authors does not include negative indicators, meaning each indicator exerts some influence on user purchase behavior in live-stream e-commerce.

Regarding platform selection, since specific backend data cannot be obtained and both platforms exhibit both high and low sales volumes, the specific influencing factors on user purchase behavior cannot be confirmed. Therefore, platform selection is not addressed here.

5.3 Analysis

5.3.1 Product Information This study finds that product information is the primary factor influencing user purchase behavior in live-stream e-commerce, with product quality, information detail level, and online reputation being the most impactful. Li Jiaqi' s live-stream room achieved the highest final score of 92.80 among the three selected cases. Through online observation and time recording of his live-stream room, it was found that product introduction and display time accounted for approximately 60% of the total duration, followed by atmosphere creation, which also reflects the substantial impact of product information delivery on user purchase behavior. However, scores for product display comprehensiveness, brand awareness, and media recommendations were relatively low. As live-stream e-commerce scales continue expanding, minimal differences exist across live-stream rooms in product display and brand promotion, resulting in relatively low impact on users.

5.3.2 Host Capability

(1) Host Identity. Regarding host attractiveness, audiences for hosts with different social identities show significant differences. Overall, users trust professional hosts more. According to data analysis, when segmented by age groups, young adults aged 18-39 are most influenced by professional hosts in their purchase behavior. For middle-aged and elderly users over 40, ordinary individuals exert greater influence (see Figure 1 [Figure 1: see original paper]).

(2) Host Professionalism. Regarding host professional capability, the ability to guide users toward real-time comments and interaction to promote consumption serves as an important evaluation criterion. Observation records of Li Jiaqi's and Zhang Ting's live-stream rooms revealed that while meeting basic product information introduction requirements, they maximized fan interaction and addressed questions from comments, whereas "Zhao Daxi daxi' s" live-stream room was somewhat deficient in this aspect. In traditional marketing, interaction between consumers and marketers is limited, often leading to inadequate understanding of marketing needs, communication delays, and information asymmetry. However, professional hosts can continuously guide users during live streaming, allowing them to experience pleasure while participating, thereby satisfying users' perceived needs for service quality and product value and positively influencing their purchase behavior [21]. Therefore, for live-stream e-commerce, more sufficient interpersonal interaction strengthens users' sense of closeness and satisfaction with products, which is more beneficial in clearing obstacles for users with purchase concerns [22].

5.3.3 User Attributes

(1) The Middle-Aged and Elderly User Group Is Gradually Expanding with

Strong Development Potential. As internet penetration increases among middle-aged and elderly populations and their consumption concepts continue evolving, today's middle-aged and elderly increasingly pursue free, independent, and diversified lifestyles. Their mindsets are becoming younger and more fashionable, with noticeable growth in online consumption. For middle-aged and elderly users, having more time to watch live streams and facing fewer price barriers in live-stream e-commerce enables greater purchasing power.

According to questionnaire survey results, among frequent live-stream e-commerce viewers, the 40-49 age group accounts for 31.11%, exceeding the 18-29 age group by 6.67% (see Figure 2 [Figure 2: see original paper]). While many perceive live-stream e-commerce as popular among younger generations, China' s population aged 60+ has reached 249 million, with those aged 50+ totaling 400 million, among whom internet users have increased to 90 million. Moreover, middle-aged and elderly internet users continue to grow at a rate of 8-10 million annually, demonstrating strong future development potential.

(2) Different Occupations Show Significant Differences in Live-Stream E-Commerce User Purchase Behavior. Questionnaire results reveal that among the 200+ respondents, 35% of full-time students and 33% of sales personnel shop online 1-2 times per week, representing relatively high frequency. This is followed by 25% of managers, 25% of marketing/public relations personnel, and 22% of human resources practitioners. Among frequent live-stream viewers, 77.78% are teachers, 67% are human resources practitioners, 66.67% are customer service personnel, and 66.67% are professionals (accountants, lawyers, etc.) (see Figure 3 [Figure 3: see original paper]). This indicates that live-stream e-commerce penetration varies across occupational groups. Although full-time students shop online frequently, their attention to live-stream e-commerce remains low. Sales personnel, despite frequent online shopping, rarely watch live-stream e-commerce due to their work nature. While teachers show high attention to e-commerce live streaming, their online shopping frequency is not high, suggesting relatively low conversion rates in the teaching profession. Conversely, human resources practitioners and managers demonstrate prominent frequencies in both online shopping and live-stream viewing. Different occupations exhibit significant differences in professional attributes, work schedules, and consumption needs, leading to varying demands for live-stream e-commerce.

(3) Users with Different Live-Stream Viewing Frequencies Show Significant Differences in Influencing Factors and Degrees. A scale of 1 to 5 represents "no influence," "slight influence," "moderate influence," "considerable influence," and "very strong influence," respectively. Data analysis reveals that occasional live-stream e-commerce viewers are more influenced by product information and host professionalism than frequent or non-viewers. For users who rarely watch live-stream e-commerce, the span of influence

across different factors is largest, with product information having the highest impact at 3.34, followed by host professional capability at 3.04 and live-stream environment at 2.8 (see Figure 4 [Figure 4: see original paper]). For frequent viewers, based on their comprehensive understanding of various aspects of live-stream e-commerce, the influence span across different factors is smaller, though product information remains the most significant factor. This further substantiates the earlier conclusion that product information output is the primary factor influencing user purchase behavior.

5.3.4 Live-Stream Team Comprehensive Capability According to the final indicator weights, users are overall more influenced by team business capability than by the live-stream environment. Among the lowest-level indicators, users value merchant recruitment capability most, which refers to discounts and promotions during live streaming, followed by others' purchase behavior and customer service capability. Most live-stream e-commerce users watch live streams because they offer greater discounts, more gifts, and limited-time/limited-quantity deals than direct online purchases, satisfying users' competitive psychology regarding price and scarce product availability. Most users watching live streams have purchase potential, and under such circumstances, broadcasting others' purchase behavior fully satisfies users' conformity consumption psychology, thereby promoting purchase conversion.

6 Recommendations

As an emerging phenomenon, live-stream e-commerce has attracted substantial attention from consumers, enterprises, and media within a short period, with many speculating it may become the next internet economy 风口 [23]. Major news reports have showcased numerous live-stream sales myths, sparking a live-stream marketing boom. However, from an industry development perspective, when an industry enters a state of frenzy, it faces the danger of collapse at any time—a concerning signal that requires sufficient corporate vigilance.

The authors have constructed an indicator system for factors influencing user purchase behavior in live-stream e-commerce and validated it through specific cases. In determining indicator weights, the comprehensive use of the Delphi method, analytic hierarchy process, and fuzzy comprehensive evaluation enhances indicator credibility. This further validates the rationality of the constructed evaluation indicator system. Based on the research findings, the following recommendations are proposed for e-commerce enterprises:

(1) Regarding Product Information: Control product quality and display comprehensive product information during live streams. Live-stream e-commerce represents a trinity model based on trust in individuals, with sales as its essence and live streaming as its form. Although live-stream e-commerce has maximized the presentation of real products to users compared to traditional online shopping, for live-stream e-commerce users, the

comprehensiveness of product information display and product quality remain the sources of their trust in products and decisive factors in facilitating purchases. Among all influencing factors, enterprises should first ensure product quality, continuously improve online reputation, display products as comprehensively as possible during live streams to gain user trust, and then optimize hosts and teams.

(2) Regarding Host Capability: User and fan preferences differ, leading to targeted host selection. Host professionalism impacts user purchases more than celebrity effects. Unlike the early days of live-stream e-commerce, after nearly half a year of ups and downs, celebrity-driven sales as a novel "traffic attraction method" for the live-stream e-commerce model has become much less effective. Today, live-stream marketing has shifted from incremental competition to fighting for existing users. In live-stream e-commerce sales, host performance ability, oral presentation skills, and problem-solving capabilities become crucial components. Hosts need to interact frequently with users to compensate for the lack of face-to-face interaction. Appropriate frequency and degree of interaction help increase fan stickiness and maintain long-term live-stream room benefits for enterprises [24]. Moreover, with live-stream technology development, hosts can fully achieve high-intensity one-to-many interaction. Fans can consult hosts about popular products through comments and connections, and communicate with other platform participants to deeply understand purchase and usage experiences, thereby perceiving product credibility and usefulness in advance and helping enterprises gain benefits.

(3) Regarding User Attributes: How to increase traffic users' loyalty to live-stream rooms and brands is an area requiring corporate innovation. Influenced by many influencer live streams, some small and medium-sized hosts have begun imitating top hosts' approaches. The "anyone can be a host"phenomenon has caused host numbers across platforms to surge, with Taobao Live' s host count exceeding 20,000 in 2019 [25]. However, after audience aesthetic fatigue, hosts without distinctive features quickly disappear from public view. Therefore, enterprises need to create distinctive brand live-stream rooms based on their product characteristics to satisfy users' need for novelty and increase user attention. Fan behavior records in live-stream rooms can be more detailed, considering viewing frequency, order frequency, order amount, and other aspects to distinguish fans with different loyalty levels and provide varying discounts, thereby positively promoting user stickiness and loyalty to live-stream rooms.

(4) Regarding Live-Stream Team Comprehensive Capability: Enterprises still need to continuously innovate content and format. First is business model innovation. Based on new industry chains, fully utilize 5G, cloud computing, blockchain, and other resources to enable more holographic product displays; improve procurement, service, delivery, and other processes to provide users with higher-quality and more considerate services [26]. Sec-

ond is emphasizing personalization and differentiation. Modern commercial sales models and online communication in live-stream e-commerce increasingly show segmented and differentiated trends. To address this development, corresponding strategies need strengthening. Segment products and audiences, implement precise policies and timely push notifications, increase community interaction functions, and simultaneously fulfill information transmission, brand input, and mass entertainment functions to increase user stickiness to platforms and merchant hosts, enhance live-stream marketing benefits, and promote sustainable development of enterprise live-stream marketing.

References

[1] China Internet Network Information Center (CNNIC). The 47th Statistical Report on China' s Internet Development [R/OL]. [2021-02-03]. http://www.cnnic.cn/hlwfzyj/hlwxzbg/hlwtjbg/202102/t20210203_{71361}.htm.

[2] Zhou Yongsheng, Tang Shihua, Xiao Jing. Research on Consumers' Purchase Intention in E-commerce Live Streaming Platforms–Based on the Perspective of Social Presence [J/OL]. Contemporary Economic Management, 2021, 43(1): 40-47. [2021-02-03]. http://202.114.181.48:80/rwt/CNKI/http/NNYHGLUDN3WXTLUPMW4A/kcms/detail/13

[3] Yu Fahe. Problems and Regulations in Live-Stream E-commerce [J]. China Business Review, 2021(14): 9-11.

[4] Chen Jie. Top 10 Trends in China' s FMCG in 2020 [J]. Shanghai Business, 2020(S1): 97-101.

[5] Huan Jing. Agriculture is "Changing Dramatically" [J]. 风流一代, 2021(9): 32-33.

[6] Shen Baogang. Analysis and Standardized Development of the Live-Stream Marketing Business Model [J]. Theory Monthly, 2020(10): 59-66.

[7] Tao Bingxin, Tao Bingqian. An Empirical Study on the Driving Factors of User Interaction in Mobile E-commerce Live Streaming and Its Impact on User Purchase Behavior [J]. Modern Business, 2020(10):

[8] Tan Yuli. Research on the Influence of Opinion Leaders on Consumers' Purchase Intention in E-commerce Live Streaming [D]. Beijing: Beijing Institute of Graphic Communication, 2017.

[9] Wang Xiwei, Liu Weili, Jia Fengqi, et al. Research on the Influencing Factor Model and Empirical Study of Live Streaming APP Usage Behavior [J]. Library and Information Service, 2020, 64(5): 22-31.

[10] Tian Xinxin, Tian Jingjing. Research on Influencing Factors of Consumers' Purchase Intention in E-commerce Live Streaming–Taking Taobao Live as an Example [J]. Science Technology and Innovation, 2020(20):

[11] Wei Hua, Gao Jinsong, Duan Feifei. The Influence of Information Interaction on User Participation Behavior in E-commerce Live Streaming Mode [J]. Information Science, 2021, 39(4): 148-156.

[12] Dong Fang. Research on Consumers' Purchase Intention Based on Mobile E-commerce Live Streaming Context [J]. Marketing World, 2019(25): 137, 162.

[13] Tang Shutian. Research on the Advertising Effect of Influencer Live-Stream Marketing—The Mediating Role of Emotional Consumption [J]. Communication Power Research, 2020, 4(12): 100-101.

[14] CHEN C C, LIN Y C. What drives live-stream usage intention? the perspectives of flow, entertainment, social interaction, and endorsement [J]. Telematics & Informatics, 2018, 35(1): 293-303.

[15] HOU F F, GUAN Z, LI B, et al. Factors influencing people' s continuous watching intention and consumption intention in live streaming: evidence from China [J]. Internet Research, 2019, 30(1): 141-163.

[16] ERKAN I, EVANS C. The influence of eWOM in social media on consumers' purchase intentions: an extended approach to information adoption [J]. Computers in Human Behavior, 2016, 61(AUG): 47-55.

[17] Huang Jianqiao, Huang Wei, Cheng Yu, et al. Evaluation Research on "Internet +" College Student Entrepreneurship Models [J]. Hubei Agricultural Sciences, 2017, 56(1): 181-186.

[18] Huo Jianmei, Li Shuning. Research on Introducing Crowdsourcing Mode into Digital Reference Services in University Libraries—Survey Analysis Based on Delphi Method [J]. Library and Information Service, 2013, 57(6): 73-78.

[19] Yang Ruixian, Liang Yanping. Comparative Study on Domestic and Foreign University Research Evaluation Methods [J]. Journal of Intelligence, 2015, 34(9): 107-110.

[20] Deng Xue, Li Jiaming, Zeng Haojian, et al. Analysis and Application Research on AHP Weight Calculation Methods [J]. Mathematics in Practice and Theory, 2012, 42(7):

[21] Liu Jia, Zou Yunjie, Liu Zexi. Analysis of Influencing Factors of Consumers' Purchase Intention in E-commerce Live Streaming Based on SEM Model [J]. Statistics and Decision, 2021, 37(7): 94-97.

[22] Liu Pingsheng, Shi Yongdong. The Influence Mechanism of Live-Stream Marketing Models on Consumers' Purchase Decision [J]. China Circulation Economy, 2020(10): 38-47.

[23] Yao Linqing, Yu Haixia. The Prosperity and Chaos of Live-Stream Marketing [J]. People' s Tribune, 2020(25): 85-87.

[24] Pei Xueliang, Deng Huimei. Research on the Value Co-creation Behavior Process of E-commerce Platform Live-Stream Marketing Based on Taobao Live

[J]. Chinese Journal of Management, 2020, 17(11): 1632-1641, 1696.

[25] Song Linlin, Huang Yazhuo. "Change" and "Constant": Problem Examination and Countermeasure Exploration of E-commerce Live-Stream Supervision [J]. Henan Social Sciences, 2020, 28(12):

[26] Li Qiuhong. Live-Stream Marketing Boom Still Requires Cool Thinking [J]. Media, 2020(17): 1.

Author Contribution Statement:

Huang Wei: Provided topic guidance and proposed research ideas; Wang Shanshan: Collected literature, wrote and revised the paper, and checked article content; Dai Xinyu: Conducted live-stream e-commerce data collection and analysis.

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