

Article

Mukbang Live Streaming Commerce and Green Agri-Food Products Consumption: Exploring the New Dynamics of Consumer Purchasing Decisions

Xinqiang Chen ¹, Jiangjie Chen ^{2,*} and Zhiwen Cai ^{1,3}

¹ School of Economics and Management, Xiamen University of Technology, Xiamen 361024, China; chenxq23@xmut.edu.cn (X.C.)

² College of Fine Arts, Huaqiao University, Quanzhou 362021, China

³ School of Management, Xiamen University, Xiamen 361005, China

* Correspondence: chenjiangjie@hqu.edu.cn

Abstract: China's live streaming boom has led to mukbang live streaming as a unique food marketing tool. Hosts interact with viewers by tasting and showcasing diverse cuisines in real time. This form of mukbang live streaming has recently been utilized to promote and sell green agri-food products. However, in-depth research into how mukbang live streaming affects the purchase intention for green agri-food products and the underlying mechanisms remains scant. We developed a theoretical model based on stimuli–organism–response theory to explore the impact mechanism. Data was collected via a survey of 455 users from agriculture-related live streaming platforms and analyzed using structural equation modeling with partial least squares. The study found that professional recommendation, audiovisual experience, and social interaction enhance consumers' perceived utilitarian value; green advocacy, audiovisual experience, and social interaction positively affect consumers' perceived social value. Both perceived utilitarian value and perceived social value positively affect the intention to purchase green agri-food products. Additionally, we used importance-performance map analysis to compare the model's effects with latent variable averages, revealing each factor's importance and performance. The findings offer new insights and recommendations for agri-food marketing strategies, particularly in enhancing consumer behaviors towards green agri-food products, aiding suppliers and mukbang live streaming platforms in more effectively promoting these products.

Keywords: mukbang; live streaming; green agri-food marketing; green agri-food consumption; perceived value; purchase intention



Citation: Chen, X.; Chen, J.; Cai, Z. Mukbang Live Streaming Commerce and Green Agri-Food Products Consumption: Exploring the New Dynamics of Consumer Purchasing Decisions. *Agriculture* **2024**, *14*, 1862. <https://doi.org/10.3390/agriculture14111862>

Academic Editors: Karel Malec, Stanislav Rojik and Martina Zámková

Received: 19 August 2024

Revised: 11 October 2024

Accepted: 22 October 2024

Published: 23 October 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

With the rapid advancement of Internet technology, mukbang live streaming has emerged as a popular mode of food marketing. Mukbang live streaming commerce refers to the live streaming platform, in which the host shows and tastes various kinds of food in the live streaming, and recommends the purchase link, which prompts viewers to make purchases [1]. This combination of entertainment and shopping is highly sought after, and the mukbang industry has now earned a large user base worldwide. As mukbang content diversifies and consumer demand becomes more segmented, the market is experiencing robust growth, indicative of significant potential [2].

Several undesirable phenomena have emerged in the development of mukbang live streaming commerce. To attract audience attention and increase traffic, some hosts have engaged in extreme and wasteful behaviors. These behaviors include displaying large quantities of food but only consuming a few bites or absurdly wasting food. Research indicates that watching mukbang can induce consumers to overbuy, overeat, and waste food [3]. For instance, Lee and Wan [4] found that viewer interaction with hosts during mukbang significantly enhances the perceived value of the video, stimulating impulse

purchases and potentially leading to overconsumption. Kircaburun et al. [5] demonstrated a positive correlation between exposure to problematic mukbang videos and irregular eating habits in minors. Stein and Yeo [6] further revealed that eating while watching mukbang videos can lead to overeating, potentially increasing obesity rates.

Fortunately, the increasing focus on healthy living and environmental awareness has positively influenced mukbang content. More and more hosts have begun to advocate healthy eating, focusing on ingredients' nutritional value and environmental significance [7]. Through live streaming, these hosts promote healthy foods and guide viewers toward healthier eating and consumption habits. Data indicate that in China, over 30% of mukbang now promote healthy foods, with this percentage increasing annually. Consequently, green agri-food products, symbolizing health and environmental sustainability, are increasingly preferred by both mukbang hosts and viewers [8].

Green agri-food products align with modern dietary health trends, and their environmentally protective production processes resonate with contemporary sustainable development ideals [9]. As green agri-food products gain more exposure on mukbang, they have become significant drivers of the healthy eating trend. Although mukbang has become a novel marketing channel for green agri-food products with considerable market potential, research into how mukbang stimulating factors can more effectively guide consumer purchasing decisions remains sparse. Existing research seldom investigates the specific mukbang factors that resonate with consumers and influence their purchasing behaviors. This gap in understanding not only hampers the marketing effectiveness of mukbang but also constrains the broader market penetration of green agri-food products.

To address this gap, we utilize the stimuli–organism–response (S–O–R) theory, a foundational theory in modern psychology introduced by Mehrabian and Russell [10], which posits that external stimuli affect an individual's psycho-cognitive state, ultimately triggering a specific behavioral response [11]. At present, the S–O–R theory has been applied in live streaming e-commerce to explore how shopping-related environmental factors stimulate consumers. Xu et al. [12] analyzed 300 questionnaires, identifying that live streaming factors like host charisma, quasi-social interactions, and information quality positively impact viewers' cognitive and affective states, influencing behaviors such as hedonic consumption, impulsive purchasing, and social sharing. Ye et al. [13] delved into consumer behavior in live streaming shopping for tourism, considering visual effects and interactivity as external stimuli. Tan [14] extended this to agricultural products, analyzing 433 responses and finding that interactive features like personalization, responsiveness, and entertainment positively affected consumers' perceived values, thereby enhancing purchase intention (PI). Although various stimulating factors have been studied in live streaming contexts, many remain unexplored in the specific scenario of mukbang shopping for green agri-food products. Therefore, we gathered data from viewers of mukbang and utilized the S–O–R theory, exploring the effects of various stimulating factors in mukbang live streaming on the purchase intention for green agri-food products and their underlying mechanisms.

2. Literature Review and Research Hypotheses

2.1. Stimulating Factors in Mukbang Live Streaming Shopping

Previous research has extensively explored the stimulating factors in live streaming shopping, identifying the host's expertise as a key influence on consumer purchasing decisions. Chen et al. [15] noted that consumers tend to rely on industry experts' opinions and recommendations in markets with asymmetric information. When hosts introduce and recommend products in detail with their professional knowledge and insights, consumers are likelier to build trust and recognition of the products. Wang et al. [16] further supported this, finding that hosts' professional knowledge effectively stimulates consumer impulse buying in a study on Chinese consumers' live streaming shopping behavior. In live streaming of green products, the hosts' advocacy of a green lifestyle also significantly influences consumer purchasing behavior. As environmental awareness grows, consumers

increasingly focus on the environmental attributes of products and businesses' sustainable development strategies [17]. Zheng et al. [18] found that hosts' explanations of green agri-food products and environmental concepts enhance consumer acceptance of them. In mukbang live streaming, visual and auditory experiences are crucial for attracting and retaining consumers. Live streaming that showcases cooking and tasting allows viewers to visually engage and appreciate the food's flavor and quality through auditory and imaginative cues [19].

Finally, many researchers have recognized social interaction as a critical stimulating factor in live streaming [20–22]. Live streaming allows consumers to interact in real time with hosts via bullet-screen comments and comments, sharing their views and experiences. Interaction enhances viewer participation and enables hosts and merchants to gauge consumer needs promptly, optimizing products and services accordingly [23]. To summarize, we identify professional recommendation (PR), green advocacy (GA), audiovisual experience (AE), and social interaction (SI) as core stimulating factors in live streaming. Specifically, PR involves detailed product explanations by knowledgeable hosts; GA encompasses promoting a green lifestyle and explaining green product characteristics and environmental protection concepts; AE relates to engaging consumers through visual and auditory elements; and social interaction focuses on the degree of real-time consumer-host interaction. Perceived value represents the consumer's assessment of the benefits versus costs of a product or service [24], encompassing utility, quality, experiential aspects, and social identity in live streaming e-commerce [25–27]. Joo and Yang [28] categorized perceived value into utilitarian (functionality) and hedonistic (emotional experiences) dimensions, while Zhang et al. [29] added social value (society and environment impacts, social identity). In this study, focusing on consumers' PI for green agri-food products in mukbang, we prioritize utilitarian (nutrition, quality) and social values (environmental protection, social responsibility).

2.2. Stimulating Factors and Perceived Value of Mukbang Live Streaming Shopping

Perceived value represents the consumer's assessment of the benefits versus costs of a product or service [24], encompassing utility, quality, experiential aspects, and social identity in live streaming e-commerce [25–27]. Joo and Yang [28] categorized perceived value into utilitarian (functionality) and hedonistic (emotional experiences) dimensions, while Zhang et al. [29] added social value (societal and environmental impacts, social identity). In this study, focusing on consumers' PI for green agri-food products in mukbang, we prioritize utilitarian (nutrition, quality) and social values (environmental protection, social responsibility).

According to the S–O–R theory, stimulating factors initially affect consumers' psychological motivations rather than directly inducing a willingness to shop [30]. Perceived value, a crucial cognitive and affective state in this psychological process, reflects the consumer's subjective evaluation of a product's benefits and overall value [31]. Existing research indicates that in mukbang live streaming scenarios, stimulating factors primarily affect perceived value, which subsequently influences shopping intentions and behaviors [4,32].

Stimulating factors in live streaming shopping significantly affect consumers' perceived utilitarian value (PUV). As a key stimulating factor in live streaming, PR involves hosts using their extensive product knowledge to provide detailed information and demonstrate usage, effectively enhancing consumers' PUV. Gaberamos and Pasaribu [33] confirmed that high-quality information significantly enhances customers' perceived value in their study of 100 young GoFood app users. Similarly, emphasizing the natural, non-polluting, and healthy properties of green products increases consumer trust and enhances the PUV [34–36]. A high-quality AE significantly affects consumers' PUV [37]. High-definition images and vivid sound effects provide multifaceted sensory stimulation that enhances consumers' recognition of the product and positively affects their perceived value [38].

Additionally, SI, a pivotal feature of live streaming e-commerce, facilitates real-time communication between consumers and hosts, enhancing engagement. Zhang and Liu [39]

noted that online comments, a primary method for interaction in live streaming, not only enhance consumer engagement but also positively influence PUV. Furthermore, Chang and Yu [40] showed that during live streaming, hosts could guide consumers to participate more actively by adopting gamification methods, such as setting up rewards and competition mechanisms, which can also positively affect consumers' PUV. Therefore, we propose the following hypotheses:

Hypothesis 1 (H1): *PR positively affects PUV.*

Hypothesis 2 (H2): *GA positively affects PUV.*

Hypothesis 3 (H3): *AE positively affects PUV.*

Hypothesis 4 (H4): *SI positively affects PUV.*

In examining how the stimulating factors of live streaming shopping affect consumers' perceived social value (PSV), Meng and Wei [41] discovered that PR from opinion leaders in live streaming provides practical product information and enhances the PSV associated with the products. GA is more directly related to environmental protection and social responsibility. Liao et al. [42] found that marketers' promotion of green lifestyles and advocacy of environmental protection concepts can significantly enhance consumers' PSV of green agri-food products. In addition, during the live streaming process, by intuitively displaying the growing environment of green agri-food products, the production process, and their positive impact on the environment and society, it can also indirectly enhance consumers' recognition of the social value of the product [43]. Lastly, SI, as an important channel for consumers to participate and express their opinions, can further enhance the social value and sense of belonging brought by purchasing green agri-food products through various forms such as Q&A between the hosts and the viewers, real-time text communication between the audience, and interactive games [27,44,45]. Therefore, we propose the following hypotheses:

Hypothesis 5 (H5): *PR positively affects PSV.*

Hypothesis 6 (H6): *GA positively affects PSV.*

Hypothesis 7 (H7): *AE positively affects PSV.*

Hypothesis 8 (H8): *SI positively affects PSV.*

2.3. PUV and PSV

Modern consumers focus not only on the actual efficacy of products but also on the social values these products represent. PUV primarily assesses whether a product meets consumers' needs in terms of quality, performance, and effectiveness [46]. In contrast, PSV is more concerned with the product's social significance, such as its alignment with environmental protection and social responsibility [47]. Existing research indicates a correlation between consumers' perceptions of utilitarian value and their acceptance of a product's social value [48,49]. This is because utilitarian values emphasize attributes like quality and efficacy—foundational aspects for consumer purchasing—while social values represent additional, higher-order attributes [50,51]. When consumers perceive that green agri-food products perform well, their trust in and feelings about these products improve, enhancing their acceptance of the associated social values. Therefore, we propose the following hypotheses:

Hypothesis 9 (H9): *PUV positively affects PSV.*

2.4. Perceived Value and Purchase Intention of Green Agri-Food Products

The role of PUV is critical in exploring factors that affect consumer PI. Gan and Wang [52] found in a survey of Chinese social commerce users that utilitarian value significantly affects PI, highlighting consumers' focus on the actual utility and performance of products. Escobar-Rodríguez and Bonsón-Fernández [53] also noted that utilitarian consumer characteristics significantly predict purchase behaviors. In a survey of Brazilian organic food consumers, Watanabe et al. [54] found that PUV positively affects consumer trust; consumers are likelier to trust products they perceive as beneficial. Lavuri et al. [55] observed that in Indian online shoppers, PUV significantly affects attitudes toward online shopping, underscoring PUV's importance in consumer decision-making. In mukbang live streaming shopping, hosts can boost PUV perception by showcasing and explaining green agri-food products in real time, allowing consumers to assess the quality and practicality intuitively. This enhanced perception increases trust in the product, stimulating PI. Therefore, we propose the following hypothesis:

Hypothesis 10 (H10): PUV positively affects the purchase intention of green agri-food products.

PSV is a significant factor in consumer purchase decisions, particularly within green consumption research. Khan and Mohsin [56] applied consumption value theory to analyze Pakistani consumers' choice behavior for green products, finding social value to be a crucial antecedent for green consumption. Cheung and To [57] found that consumers' environmental awareness significantly shapes their attitudes toward ecological and social benefits in China, positively influencing green purchasing behaviors. Cao et al. [58] explored the relationship between different consumer values and organic food purchasing behavior in another study on Chinese consumers. They found that social values and attitudes toward sustainable consumption significantly enhance these behaviors. Similarly, in mukbang live streaming, if hosts effectively communicate the social values of green agri-food products, including environmental protection and positive social impacts, this enhances consumers' PSV and stimulates PI.

Hypothesis 11 (H11): PSV positively affects the purchase intention of green agri-food products.

Based on the theoretical analysis and hypothesis derivation outlined above, a model has been constructed to explore the PI of green agri-food products within the context of mukbang live streaming shopping. This model is depicted in Figure 1.

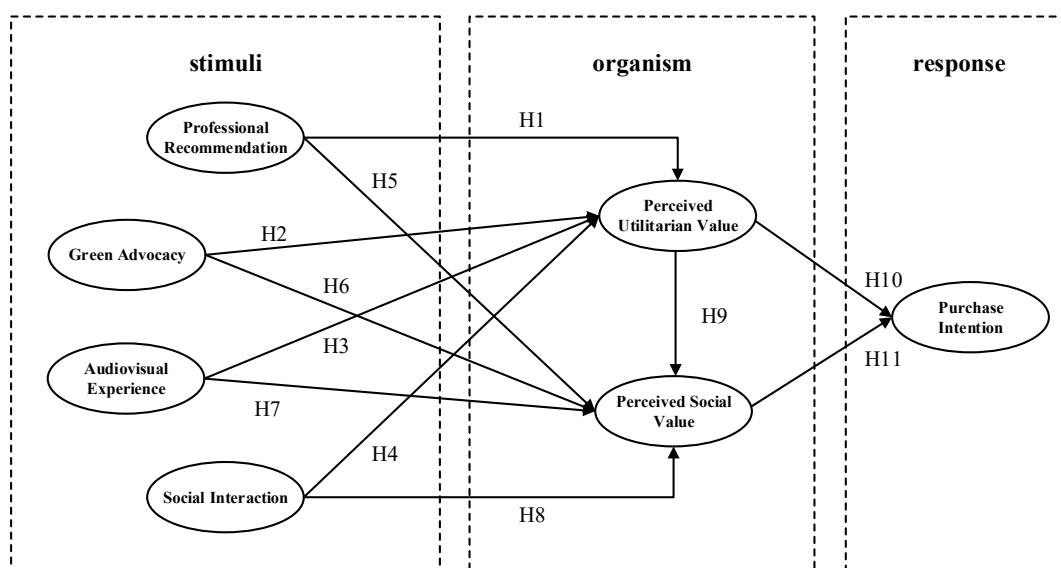


Figure 1. Research model.

3. Materials and Methods

3.1. Variable Measurement

This study involves seven variables: PR, GA, AE, SI, PUV, PSV, and PI. A scale that has undergone multiple tests was employed to ensure measurement accuracy, demonstrating high reliability and validity. It has been suitably adapted to fit the specific characteristics of live streaming shopping. All variables are measured using a 7-point Likert scale, ranging from 1 (“strongly disagree”) to 7 (“strongly agree”), with higher scores indicating greater agreement. The scale’s content and corresponding references are detailed in Table 1.

Table 1. Questionnaire items.

Constructs	Items	Source
Professional Recommendation (PR)	PR1: The mukbang host was very professional about green agri-food products. PR2: The mukbang host provided a detailed nutritional analysis of green agri-food products. PR3: The mukbang host provided detailed information on the growing process and the quality characteristics of green agri-food products.	[59,60]
Green Advocacy (GA)	GA1: The mukbang host emphasized the environmentally friendly features of green agri-food products in the live streaming. GA2: The mukbang host described the health benefits of green agri-food products in the live streaming. GA3: Watching the mukbang made me realize the environmental and social values of green agri-food products.	[61]
Audiovisual Experience (AE)	AE1: The display of green agri-food products in the mukbang was visually appealing. AE2: The green agri-food products presented in the mukbang looked fresh. AE3: The sound effects in the mukbang (e.g., chewing, cooking, etc.) made me feel like I was there.	[62]
Social Interaction (SI)	SI1: The real-time interaction in the mukbang gave me a deeper understanding of green agri-food products. SI2: During the mukbang, the host actively answered questions from the viewers. SI3: The mukbang created a friendly community atmosphere for the viewers.	[63,64]
Perceived Utilitarian Value (PUV)	PUV1: I think the green agricultural product is effective in providing nutrition. PUV2: The green agricultural product meets my daily dietary needs. PUV3: I think the green agricultural product has a good taste. PUV4: I am satisfied with the overall quality of the green agricultural product.	[28,65]
Perceived Social Value (PSV)	PSV1: I think supporting this green product demonstrates my commitment to healthy living. PSV2: I think supporting the green agricultural product is a contribution to environmental protection. PSV3: I think supporting the green agricultural product is a sign of social responsibility. PSV4: I believe that supporting the green agricultural product will help build a positive social image of the individual.	[52,66]
Purchase Intention (PI)	PI1: I am willing to buy the green agricultural product. PI2: I would recommend my relatives and friends buy the green agricultural product. PI3: I would prefer this green agricultural product to others.	[64,67]

3.2. Questionnaire Design and Data Collection

The initial questionnaire was compiled by integrating the previously described measurement items. It was divided into three sections: the introductory section outlined the purpose of exploring the behaviors and attitudes of mukbang live streaming viewers and assured respondents of complete confidentiality throughout the survey process. The personal information section collected key demographic characteristics, including gender, age, education, and average monthly disposable income. The main section of the questionnaire focused on measuring variables relevant to the theoretical model. Our research period spanned 24 April–28 July 2024. To enhance the questionnaire’s adaptability and validity, it was pre-tested face-to-face with 20 consumers in Fujian Province, China, who had purchased green agri-food products via mukbang live streaming, leading to adjustments based on feedback. Subsequently, the final questionnaire was distributed for a fee using the Tencent Questionnaire platform’s sample service function. One of China’s largest data

collection platforms, Tencent Questionnaire, has processed over 3 billion questionnaires for 50 million users, enabling targeted distribution to experienced mukbang live streaming viewers. To ensure sample diversity and universality, the questionnaire deployment included demographic constraints, such as maintaining a male-to-female ratio between 0.4 and 0.6. A screening question was included to identify respondents with actual viewing experience: “In the past month, have you watched any live-streaming mukbang showcasing green agri-food products (e.g., organic vegetables, pesticide-free fruits, etc.)?” During the collection process, 614 questionnaires were received. After excluding responses without actual viewing experience and those with obvious similarities, 455 valid questionnaires remained, yielding an effective recovery rate of 74.1%.

Descriptive statistics were performed on the sample data, as detailed in Table 2. Regarding gender distribution, the sample consisted of 47.9% males and 52.1% females, showing a balanced representation. Regarding regional distribution, each economic region has a certain number of samples, with the eastern region having the highest proportion, reaching 55%, while the northeastern region has the lowest, accounting for only 5%. This distribution is fairly similar to China’s population distribution. The age group 20–29 represents the largest segment of respondents, accounting for 40% of the sample. Over 70% of respondents hold a bachelor’s degree or higher. The predominance of young, highly educated respondents may reflect the perception of green consumption as a fashionable and innovative practice. This demographic is typically more inclined to pursue innovative consumption patterns, positioning them as primary participants in green consumption. This observation aligns with the findings of Hume [68] and Chekima et al. [69]. Regarding average monthly disposable income, 39.6% of respondents earn 3000–6000 yuan, aligning with Szczepaniak and Szulc-Obłóza [70] findings that the middle-income group predominantly engages in green consumption.

Table 2. Descriptive analysis of respondents.

Sample	Category	Number	Percentage (%)
Sex	Male	218	47.9
	Female	237	52.1
Region	Northeastern part	23	5.0
	Eastern part	250	55.0
	Central part	95	20.9
	Western part	87	19.1
Age	20–29	182	40.0
	30–39	166	36.5
	40–49	90	19.8
	50 and above	17	3.7
	Secondary vocational school, high school and below	76	16.7
Education	Junior college	110	24.2
	Bachelor’s degree	209	45.9
	Master’s degrees and above	60	13.2
Monthly disposable income	3000 and below	133	29.2
	3000–6000 yuan	180	39.6
	6000–9000 yuan	114	25.1
	9000 yuan and above	28	6.2

3.3. Research Methods

This paper employs smartPLS4.0 to conduct partial least squares structural equation modeling (PLS-SEM), which is structured around two main components: the measurement model and the structural model. The measurement model assesses model quality using indicators such as Cronbach’s alpha, composite reliability (CR), and average variance extracted (AVE). The structural model, on the other hand, comprehensively evaluates the model’s explanatory and predictive power based on R^2 and Q^2 . Through path analysis, we validate 11 proposed hypotheses and innovatively introduce the Importance-Performance

Map Analysis (IPMA) technique to identify key variables for enhancing model performance and areas for improvement. Ultimately, rigorous conclusions are drawn by integrating empirical data with theoretical analysis.

4. Results

4.1. Common Method Bias Tests

Common method bias (CMB) refers to systematic errors due to the same data sources or raters, a consistent measurement environment, and similar item contexts. Severe CMB can distort relationships between variables, undermining the credibility and stability of research outcomes. To assess CMB, we employed Harman's single-factor test, which uses exploratory factor analysis with only one factor extracted. A 50% or more variance explanation by this factor would suggest that CMB significantly affected the data [71]. Results revealed that the question items were aggregated into 4 factors with eigenvalues greater than 1. The first factor before rotation had a variance explained of 47.782%, below the 50% threshold, suggesting acceptable levels of CMB. However, this method has been critiqued [72] for its sensitivity to variable quantity, as an increase in variables can lead to more factors being extracted in exploratory factor analysis, thereby reducing the variance explained by the first factor. Consequently, we also applied the unmeasured common latent factor method proposed by Liang et al. [73] to further test if there is a situation where most of the explained variance is concentrated in one factor. Results (Table 3) showed that the average substantive explained variance was 0.743, whereas the method-based variance was just 0.006, yielding a ratio of approximately 131.201:1. Meanwhile, all substantive explanatory factors were significant, whereas most method-based factor loadings were not. The application of both methods indicated that CMB is not a significant concern in this study.

Table 3. Common method factor analysis.

Constructs	Indicator	Substantive Factor Loading (R1)	R1 ²	Method Factor Loading (R2)	R2 ²
PR	PR1	0.876 *	0.767	0.063	0.004
	PR2	0.869 *	0.755	−0.026	0.001
	PR3	0.818 *	0.669	−0.041	0.002
GA	GA1	0.870 *	0.757	−0.02	0.000
	GA2	0.787 *	0.619	−0.024	0.001
	GA3	0.850 *	0.723	0.043	0.002
AE	AE1	0.872 *	0.760	−0.041	0.002
	AE2	0.819 *	0.671	−0.08	0.006
	AE3	0.820 *	0.672	0.12	0.014 *
SI	SI1	0.845 *	0.714	0.068	0.005 *
	SI2	0.794 *	0.630	−0.201	0.040 *
	SI3	0.862 *	0.743	0.111	0.012 *
PUV	PUV1	0.852 *	0.726	0.047	0.002
	PUV2	0.876 *	0.767	0.02	0.000
	PUV3	0.871 *	0.759	−0.08	0.006
	PUV4	0.877 *	0.769	0.013	0.000
PSV	PSV1	0.870 *	0.757	0.135	0.018 *
	PSV2	0.882 *	0.778	0.004	0.000
	PSV3	0.894	0.799	−0.096	0.009 *
	PSV4	0.88	0.774	−0.043	0.002
PI	PI1	0.934	0.872	−0.015	0.000
	PI2	0.904	0.817	−0.027	0.001
	PI3	0.889	0.790	0.043	0.002
average			0.743		0.006

Note: * The level of significance is 0.05.

4.2. Assessment of Measurement Model

Measurement models assess whether Observed Indicators effectively measure corresponding latent variables. To comprehensively evaluate the quality of the measurement model, we assessed factor loadings, Cronbach's alpha coefficients, AVE, and CR—common indicators of model quality. Assessment results, detailed in Table 4, show the lowest factor loading at 0.777, surpassing the conventional benchmark of 0.7 and indicating good factor structure validity. Cronbach's alpha coefficients of the variables ranged from 0.781 to 0.904, exceeding the 0.7 threshold recommended by Nunnally [74] and demonstrating the model's good internal consistency. Meanwhile, CR values ranged from 0.872 to 0.935, surpassing the 0.7 baseline proposed by Gefen et al. [75], thus confirming the model's stability and reliability. Furthermore, AVE values from 0.695 to 0.827 exceeded the 0.50 threshold set by Black et al. [76], demonstrating robust convergent validity for all latent variables.

Table 4. Measurement model analysis results.

Constructs	Items	Loadings	α	CR	AVE
PR	PR1	0.884	0.815	0.890	0.755
	PR2	0.869			
	PR3	0.808			
GA	GA1	0.869	0.784	0.874	0.730
	GA2	0.781			
	GA3	0.856			
AE	AE1	0.867	0.787	0.875	0.701
	AE2	0.806			
	AE3	0.836			
SI	SI1	0.850	0.781	0.872	0.695
	SI2	0.777			
	SI3	0.871			
PUV	PUV1	0.853	0.892	0.925	0.755
	PUV2	0.877			
	PUV3	0.868			
PSV	PSV1	0.878	0.904	0.933	0.777
	PSV2	0.875			
	PSV3	0.883			
PI	PI1	0.891	0.895	0.935	0.827
	PI2	0.933			
	PI3	0.903			

4.3. Assessment of Structural Model

Structural models describe the interrelationships among latent variables, primarily measuring the model's overall explanatory power for the phenomenon under study. Common metrics include variance explained Q^2 , predictive relevance Q^2 , R^2 , and goodness of fit (GOF). Variance explained Q^2 assesses how well the model explains the variance of the observed variables, with values closer to 1 indicating better explanatory power. Predictive relevance Q^2 evaluates the predictive power of exogenous latent variables on endogenous latent variables, with values closer to 1 indicating stronger predictive power [77]. R^2 measures the explanatory power of exogenous variables on endogenous latent variables, with values above 26% indicating strong explanatory power [78]. The GOF measures the agreement between the statistical model and the observed variables. Higher GOF values signify better explanation and prediction. Specifically, GOF values of 0.100, 0.250, and 0.360 correspond to low, medium, and high model fit, respectively [79].

Detailed data presented in Table 5 indicate that all indicators fall within the ranges suggested by researchers. Specifically, R^2 values range from 0.497 to 0.586, substantially exceeding the threshold of 0.260, which confirms the structural model's strong explanatory

power. Additionally, a GOF value of 0.512, surpassing the 0.360 benchmark, signifies a high level of fit for the structural model.

Table 5. Results of structural model analysis.

Constructs	Variance Explained Q ²	Predictive Relevance Q ²	R ²	GOF
PR	0.392			0.512
GA	0.392			
AE	0.616			
SI	0.448			
PUV	0.613	0.393	0.525	
PSV	0.579	0.384	0.497	
PI	0.386	0.481	0.586	

Discriminant validity is a critical criterion for evaluating the validity of models, assessing whether different latent variables are distinctly distinguishable from one another. This study employed two methods to assess discriminant validity among variables: the Heterotrait–Monotrait ratio (HTMT) and the Fornell–Larcker criterion. Table 6 presents the results of the HTMT, with the highest HTMT value at 0.802, below the threshold of 0.85 [80]. This indicates that the variables maintain relative independence in measurement and are distinguishable. Table 7 shows the results of the Fornell–Larcker criterion. The square root of the AVE for each latent variable exceeds its respective two-by-two correlation coefficients [81]. This further confirms the strong discriminant validity of the structural model.

Table 6. Discriminant validity: Heterotrait–Monotrait ratio (HTMT).

	PR	GA	AE	SI	PUV	PSV	PI
PR							
GA	0.726						
AE	0.607	0.667					
SI	0.796	0.775	0.802				
PUV	0.702	0.619	0.701	0.79			
PSV	0.57	0.729	0.651	0.732	0.605		
PI	0.598	0.624	0.611	0.691	0.741	0.761	

Table 7. Discriminant validity: Fornell–Larcker criterion.

	PR	GA	AE	SI	PUV	PSV	PI
PR	0.854						
GA	0.579	0.836					
AE	0.491	0.52	0.837				
SI	0.635	0.615	0.641	0.834			
PUV	0.599	0.519	0.588	0.666	0.869		
PSV	0.494	0.617	0.554	0.619	0.545	0.882	
PI	0.514	0.523	0.514	0.582	0.662	0.685	0.909

Note: The diagonal of the matrix (boldface) is the square root of AVE.

4.4. Hypothesis Test

Path coefficients were analyzed using bootstrapping in SmartPLS 4.0. Figure 2 illustrates the results of the model path analysis. Concurrently, the regression coefficients of the structural equation model were obtained, with detailed data presented in Table 8.

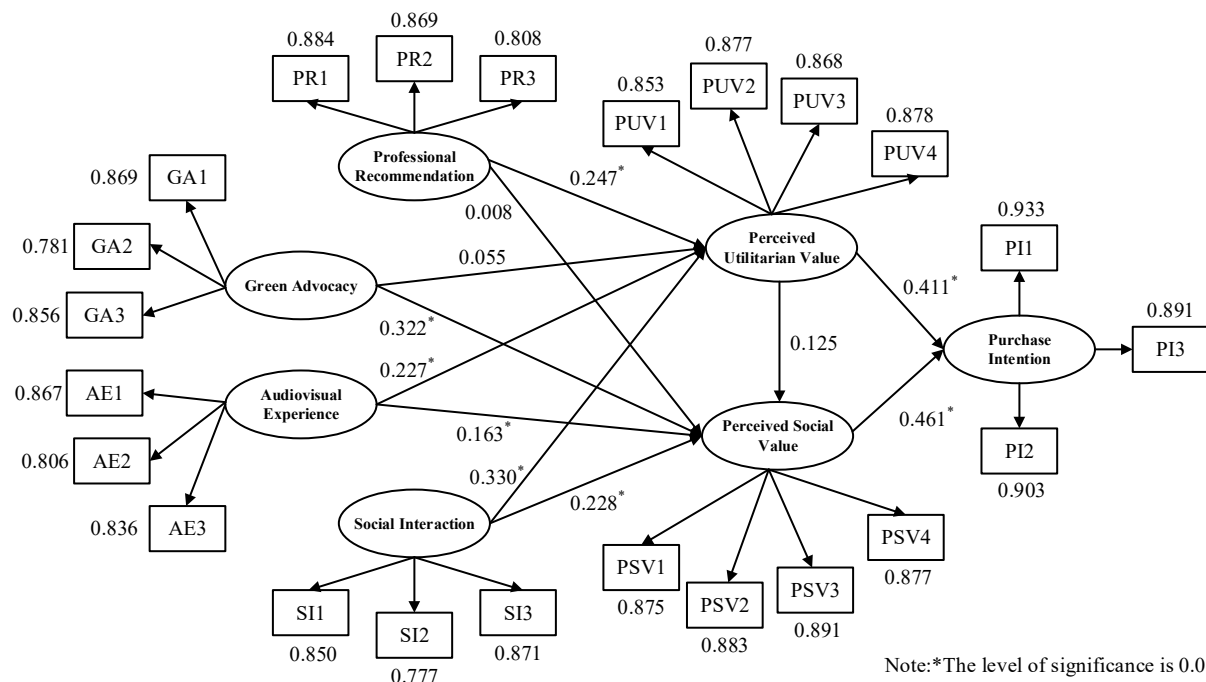


Figure 2. Analysis results of hypothesized model.

Table 8. Results of the path analysis test.

Hypothesis	Path	Std Beta	p-Value	VIF	Results
H1	PR → PUV	0.247 *	0	1.865	Support
H2	GA → PUV	0.055	0.381	1.836	No Support
H3	AE → PUV	0.227 *	0	1.788	Support
H4	SI → PUV	0.330 *	0	2.392	Support
H5	PR → PSV	0.008	0.911	1.994	No Support
H6	GA → PSV	0.322 *	0	1.842	Support
H7	AE → PSV	0.163 *	0.002	1.897	Support
H8	SI → PSV	0.228 *	0.001	2.623	Support
H9	PUV → PSV	0.125	0.081	2.125	No Support
H10	PUV → PI	0.411 *	0	1.422	Support
H11	PSV → PI	0.461 *	0	1.422	Support

Note: * The level of significance is 0.05.

We initially examined the effect of stimulating factors on PUV and PSV in mukbang live streaming shopping. PR, AE, and SI significantly and positively influenced the PUV ($\beta = 0.247, p < 0.001$; $\beta = 0.227, p < 0.001$; $\beta = 0.330, p < 0.001$), confirming hypotheses H1, H3, and H4. However, GA's effect on PUV was insignificant ($\beta = 0.055, p > 0.05$), invalidating hypothesis H2. GA, AE, and SI significantly enhanced PSV ($\beta = 0.322, p < 0.001$; $\beta = 0.163, p < 0.01$; $\beta = 0.228, p < 0.01$), supporting hypotheses H6, H7, and H8. However, PR's effect on PSV was not significant ($\beta = 0.008, p > 0.05$), invalidating hypothesis H5.

We also tested the effect of PUV on PSV. Although the regression coefficient was positive ($\beta = 0.125$), the p -value was 0.081, exceeding the significance threshold of 0.05. Therefore, the relationship was not statistically significant, and Hypothesis H9 was unsupported.

Finally, we tested the effect of consumers' perceived values on their PI for green agri-food products. The results revealed that PUV and PSV significantly and positively affect the PI for green agri-food products. Specifically, the regression coefficient for PUV was $\beta = 0.411$ with a p -value of < 0.001 , and the regression coefficient for PSV was $\beta = 0.461$ with a p -value of < 0.001 . Consequently, both Hypotheses H10 and H11 were supported. Eight of the eleven hypotheses were supported, validating the critical path hypotheses. This confirms that the S-O-R theory provides an effective analytical framework for green

agricultural product consumption in mukbang live streaming shopping. Additionally, we calculated the VIF values for each path to address potential covariance issues. As detailed in Table 8, all path VIF values were below the common threshold of 5 [82], indicating no multicollinearity issues in our analysis.

4.5. Importance–Performance Map Analysis

IPMA is a method used to assess the importance and actual performance of the target dimension. It complements path analysis results by visualizing target dimensions' importance and actual performance scores on a two-dimensional chart [83]. On the IPMA chart, the vertical axis represents the average performance score (APS) of the target dimension, ranging from 0 to 100, while the horizontal axis represents the average importance score (AIS), indicating the extent to which the dimension affects the overall goal or outcome. By analyzing these two dimensions, IPMA identifies areas requiring improvement in management activities or areas that the model should specifically focus on, thus offering decision-makers intuitive guidance for optimizing management strategies [84].

Figure 3 displays the IPMA results for green agri-food products' PI, indicating that the APS for PUV is 71.793 with an AIS of 0.469, and for PSV, the APS is 73.789 with an AIS of 0.461. Both measures are comparable in importance and actual performance, underscoring their critical roles in affecting customer PI for green agri-food products, and they are quite close to each other in terms of actual performance. Figure 4 presents the IPMA for PUV, where PR and SI emerge as more significant, with AIS values of 0.247 and 0.33, respectively, compared to GA (AIS = 0.055) and AE (AIS = 0.227); however, their actual performance does not meet expectations. Specifically, the APS for PR and SI were 64.504 and 67.126, respectively, lower than those for GA (APS = 72.366) and AE (APS = 72.903). This suggests that although PR and SI are regarded as key stimulating factors, their performance needs to be further optimized to enhance consumers' PSV and ensure that their significance can be fully reflected. Figure 5 details the IPMA of PSV, in which the performance scores of PUV, PR, AE, and SI are 71.793, 64.504, 72.366, 72.903, and 67.126, respectively, with corresponding AIS of 0.125, 0.039, 0.329, 0.191, and 0.269. Although AE, SI and GA are significant in improving consumers' PSV, their actual performance does not form a clear advantage, so the focus of improvement should be on AE, SI and GA for social value-perceiving consumers.

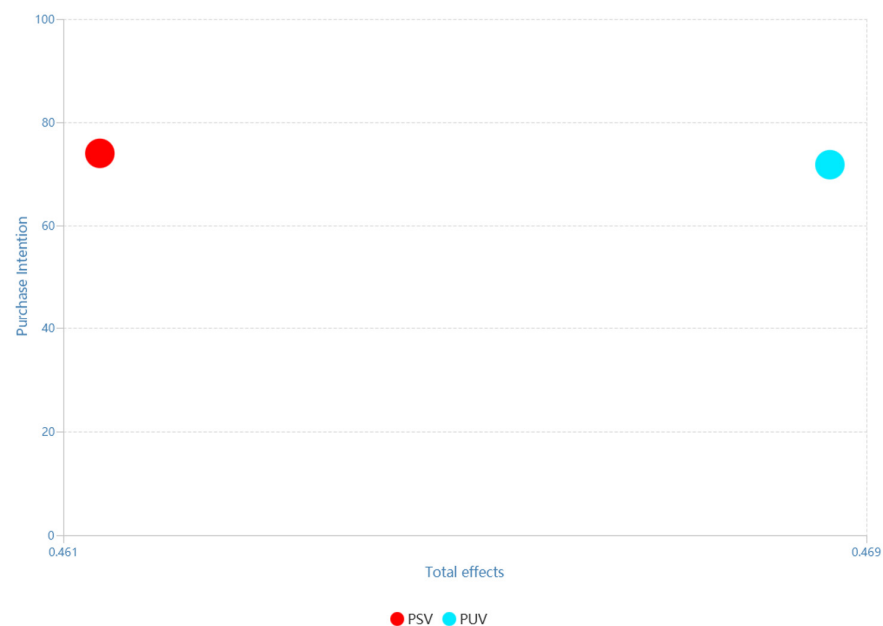


Figure 3. Importance–performance map analysis of PI.

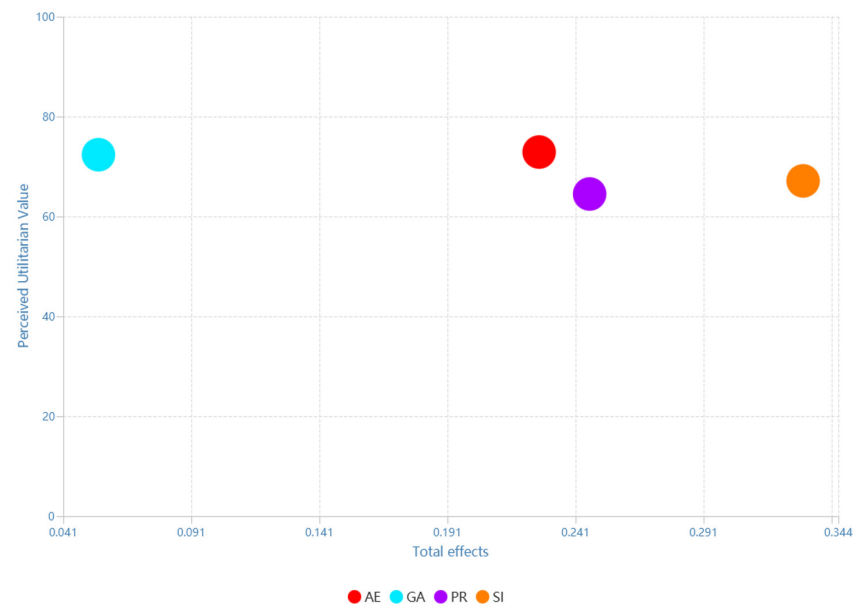


Figure 4. Importance–performance map analysis of PUV.

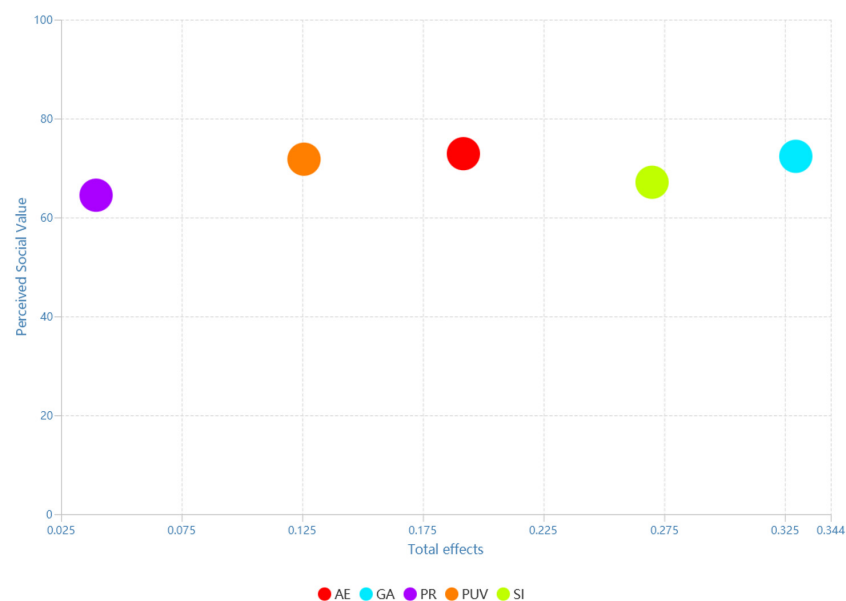


Figure 5. Importance–performance map analysis of PSV.

5. Conclusions and Implications

5.1. Discussions

This study examines the stimulating factors and individual factors that influence the purchasing intention of green agri-food products in the context of mukbang live streaming shopping, with detailed discussions as follows:

Regarding the relationship between stimulating and organismic factors, this study reveals that PR, AE, and SI significantly enhance consumers' PUV, whereas GA does not have a significant effect. This finding resonates with previous research, such as that by Gaberamos and Pasaribu [33], Moreira, Fortes and Santiago [38], and Chang and Yu [40], which underscores the importance of effective product information presentation, engaging AE, and positive SI in enhancing consumers' PUV of green agri-food products within the mukbang live streaming context. Conversely, while our study finds that GA, AE, and SI significantly enhance consumers' PSV, PR does not exert a significant effect, highlighting the efficacy of GA, high-quality AE, and SI in shaping consumers' social value perceptions

of green agri-food products. Notably, unlike prior research that primarily focused on traditional live streaming, this study extends these insights to the mukbang live streaming shopping context. By doing so, it contributes to the understanding of how stimulating factors influence consumers' perceived value of green agri-food products in this emerging shopping mode, thereby enriching the existing discourse.

This study reveals two important findings regarding the relationship among organismic factors and the relationship between organismic factors and consumers' PI. Firstly, contrary to Choi and Kim [48] and Ariffin, Yusof, Putit and Shah [49], the effect of PUV on PSV was insignificant in the mukbang live streaming context. This indicates that in this context, the PUV of green agri-food products does not directly affect PSV, potentially due to other contextual factors or individual differences. Secondly, PUV and PSV significantly affect consumers' PI for green agri-food products, aligning with findings by Lavuri, Jindal and Akram [55], Cao, Zheng, Liu, Yao and Chen [58]. The lack of a significant correlation between PUV and PSV suggests the existence of two distinct consumer segments for green agri-food products: those prioritizing utilitarian values and those focusing on social values.

This study's IPMA analysis of PUV and PSV revealed several key insights. For PUV, while PR and SI are deemed more important than GA and AE, their actual performance is weaker. This suggests that despite the theoretical importance of PR and SI in enhancing PUV, practical implementations require more innovative strategies to achieve desired performance improvements. Furthermore, although AE, SI, and GA are considered important for PSV, they do not demonstrate a clear actual performance advantage. Therefore, to truly leverage these factors, particularly for social value-perceiving consumers, focused improvements are essential to meet consumer needs and enhance the overall shopping experience through strategic optimization and better implementation. Comparing prior research, we note that while previous studies emphasized the theoretical importance of PR and SI for PUV [34–36], and AE, SI, and GA for PSV [27,44,45], our IPMA analysis reveals a disparity between theoretical significance and actual performance. This underscores the need for innovative strategies to bridge this gap and for focused improvements tailored to social value-perceiving consumers. Our study thus contributes to the existing discourse by highlighting these practical challenges and extending the scope of understanding to enhance both PUV and PSV.

5.2. Theoretical Contributions

First, a theoretical contribution was made to understanding consumers' PI for green agri-food products within the mukbang live streaming context. Previous research primarily examined purchasing behaviors in traditional live streaming e-commerce contexts, with a limited exploration into the emerging mukbang live streaming shopping model. Specifically, there has been a notable deficiency in in-depth analysis concerning the purchase motivations for green agri-food products. This study addresses this gap by exploring in-depth consumers' PI for green agri-food products. It offers substantial theoretical support for consumer behavior in this novel shopping mode.

Second, this study extends the application of the S–O–R theory in two aspects. It identifies four core stimulating factors—PR, GA, AE, and SI—that influence consumer PI for green agri-food products in mukbang live streaming shopping. This enrichment of the 'stimuli' component of the S–O–R theory offers a fresh perspective for future research. Moreover, from the 'organism' perspective, this study examines how PUV and PSV affect the PI for green agri-food products, thereby deepening our understanding of the internal psychological processes of consumers.

Thirdly, this study utilizes the IPMA to dissect the importance and performance of various stimulating factors in consumers' purchasing decisions. This analysis offers precise insights into the specific effects of each stimulating factor on consumers' PI. More importantly, this analysis delivers innovative ideas and methodological support for the evaluation and optimization of marketing strategies, thereby enriching theoretical frameworks within consumer behavior and marketing.

5.3. Practical Implications

First, mukbang live streaming platforms and hosts should emphasize three stimulating factors: PR, AE, and SI. As these factors can significantly affect consumers' PUV, platforms and hosts can enhance consumers' perception of the utilitarian value of green agri-food products by improving the professionalism of the live streaming content, optimizing the audiovisual effect, and enhancing the interaction with viewers, which, in turn, promotes PI. For instance, hosts might detail the cultivation process and nutritional benefits of products, employ high-definition cameras to showcase products' appearance and quality, and engage viewers through quizzes, polls, games, and shared experiences to enhance the viewers' sense of participation and stickiness, thus improving their perception of the utilitarian value of green agri-food products.

Second, to enhance consumers' PSV, platforms and hosts should equally focus on GA, AE, and SI. It involves highlighting the environmental and social responsibility aspects of green agri-food products, delivering high-quality AE, and fostering active SI among viewers. For instance, hosts could discuss the environmental benefits of green agri-food products and visually showcase sustainable production practices like eco-friendly planting technology and resource recycling through real-scene filming or virtual reality technology. Additionally, encouraging viewers to share their purchase and usage experiences on social media—including cooking and eating—can enhance SI, boosting awareness and PI for green agri-food products.

Further, this study reveals that the effects of PUV and PSV on PI are independent, suggesting the presence of two distinct consumer segments. Consequently, platforms and hosts must tailor their marketing strategies to cater to the distinct needs of these two consumer segments. For consumers prioritizing utilitarian values, strategies should emphasize green agri-food products' practicality, cost-effectiveness, and quality. For those valuing social aspects, marketing should highlight environmental sustainability, social responsibility, and the brand's ethical image.

Finally, the IPMA analysis suggests that distinct improvement strategies are necessary for consumers who prioritize utilitarian value versus those who emphasize social value. On one hand, the research reveals that while PR and SI are deemed crucial factors influencing PUV, their actual performance scores lag behind those of other factors. This indicates that platforms and hosts must concentrate on refining the implementation of PR and SI strategies to better cater to the expectations of utilitarian-minded consumers. On the other hand, regarding PSV, the research underscores that although AE, SI and GA are acknowledged as significant factors, their current performance does not offer a distinct advantage. This signifies that there is room for enhancement in how these elements are communicated. Consequently, for this consumer segment, platforms and hosts need to focus on optimizing the execution of AE, SI, and GA strategies.

5.4. Limitations and Future Directions

Although this study provides useful insights, it also presents limitations requiring further exploration. In data collection, we predominantly utilized questionnaires, a method that enables the collection of rich information from a broad audience. However, questionnaires have inherent limitations, such as potential biases from respondents' subjective feelings or difficulties in accurately recalling specific experiences during mukbang live streaming. In the future, we plan to integrate experimental methods into our data collection approach. Experimental methods, with their precise variable control and the use of control and experimental groups, allow for an intuitive observation of how different stimulating factors affect PI [85]. Our research model incorporates core stimulating factors—PR, GA advocacy, PSV, and SI—as well as organismic factors like PUV and SI. Nevertheless, it is crucial to acknowledge that PI is a complex psychological process influenced by various factors. In future studies, we will include additional variables like product information, personal consumption habits, and cultural background to enrich our understanding of PI for green agri-food products. Regarding statistical analysis methods, we currently use

PLS-SEM to consider the effects of different single stimulating factors on the PI of green agri-food products. The advantage of this method is its ability to handle complex causal relationships and quantify the path coefficients among factors. However, in the mukbang context, where multiple simultaneous stimulating factors influence consumers, PLS-SEM cannot account for the effects of these combinations. To address this limitation, we intend to implement fuzzy-set qualitative comparative analysis (fsQCA) in future research. This approach will elucidate how various combinations of conditions collectively affect purchase intentions [86], offering valuable insights for developing scientifically grounded marketing strategies for green agri-food products.

5.5. Conclusions

Grounded in the S–O–R theory, this study explores consumers' PI for green agri-food products within the mukbang live streaming shopping context, focusing on the relevant stimulating and organismic factors. After empirically analyzing data from 455 live streaming platform users in China, we present the following research conclusions:

Firstly, PR, AE, and SI contribute to the enhancement of consumers' PUV. Secondly, GA, AE, and SI positively affect consumers' PSV. Lastly, both PUV and PSV positively affect the intention to buy green agri-food products. Furthermore, the IPMA results of this study indicate that both PUV and PSV play equally significant roles with comparable performance in enhancing consumers' purchase intention towards green agri-food products. Nevertheless, while PR and SI are deemed crucial for improving PUV, they necessitate optimization. Additionally, AE, SI, and GA exhibit potential in elevating PSV but lack a distinct performance edge.

The findings of this study provide practical guidance for mukbang live streaming hosts and green agri-food product providers in developing effective agri-food marketing strategies and offer new insights for understanding the sustainable development of mukbang e-commerce.

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

Funding: This research was supported by the Special Project on the Social science research Fund of Xiamen University of Technology (grant YSK24004R).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: We also thank the anonymous reviewers who provided valuable comments on the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Song, H.G.; Kim, Y.-S.; Hwang, E. How attitude and para-social interaction influence purchase intentions of Mukbang users: A mixed-method study. *Behav. Sci.* **2023**, *13*, 214. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Shen, S. Commercialising potential as a critical factor of differential media management: A cultural zoning study of China's regulation of mukbang and online eating disorder communities. *Media Cult. Soc.* **2023**, *45*, 373–387. [\[CrossRef\]](#)
3. Kang, E.; Lee, J.; Kim, K.H.; Yun, Y.H. The popularity of eating broadcast: Content analysis of “mukbang” YouTube videos, media coverage, and the health impact of “mukbang” on public. *Health Inform. J.* **2020**, *26*, 2237–2248. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Lee, D.; Wan, C. The impact of mukbang live streaming commerce on consumers' overconsumption behavior. *J. Interact. Mark.* **2023**, *58*, 198–221. [\[CrossRef\]](#)
5. Kircaburun, K.; Yurdagül, C.; Kuss, D.; Emirtekin, E.; Griffiths, M.D. Problematic mukbang watching and its relationship to disordered eating and internet addiction: A pilot study among emerging adult mukbang watchers. *Int. J. Ment. Health Addict.* **2021**, *19*, 2160–2169. [\[CrossRef\]](#)

6. Stein, J.P.; Yeo, J. Investigating meal-concurrent media use: Social and dispositional predictors, intercultural differences, and the novel media phenomenon of “mukbang” eating broadcasts. *Hum. Behav. Emerg. Technol.* **2021**, *3*, 956–968. [\[CrossRef\]](#)
7. Zhou, Z.; Ding, X.; Tang, X.; Chen, Y. “I Prefer an Everyday Style and Dislike Big Food Fighters”: Integrating Foodshow into Everyday Life. In Proceedings of the HICSS, Maui, HI, USA, 4–7 January 2022; pp. 1–10.
8. Wang, Y.; Lan, J.; Pan, J.; Fang, L. How do consumers’ attitudes differ across their basic characteristics toward live-streaming commerce of green agricultural products: A preliminary exploration based on correspondence analysis, logistic regression and decision tree. *J. Retail. Consum. Serv.* **2024**, *80*, 103922. [\[CrossRef\]](#)
9. Liu, Y.; Sun, D.; Wang, H.; Wang, X.; Yu, G.; Zhao, X. An evaluation of China’s agricultural green production: 1978–2017. *J. Clean. Prod.* **2020**, *243*, 118483. [\[CrossRef\]](#)
10. Mehrabian, A.; Russell, J.A. A measure of arousal seeking tendency. *Environ. Behav.* **1973**, *5*, 315.
11. Su, L.; Swanson, S.R. The effect of destination social responsibility on tourist environmentally responsible behavior: Compared analysis of first-time and repeat tourists. *Tour. Manag.* **2017**, *60*, 308–321. [\[CrossRef\]](#)
12. Xu, X.; Wu, J.-H.; Li, Q. What drives consumer shopping behavior in live streaming commerce? *J. Electron. Commer. Res.* **2020**, *21*, 144–167.
13. Ye, C.; Zheng, R.; Li, L. The effect of visual and interactive features of tourism live streaming on tourism consumers’ willingness to participate. *Asia Pac. J. Tour. Res.* **2022**, *27*, 506–525. [\[CrossRef\]](#)
14. Tan, S. How to interact with consumers to enhance their purchase intention? Evidence from China’s agricultural products live streaming commerce. *Br. Food J.* **2024**, *126*, 2500–2521. [\[CrossRef\]](#)
15. Chen, Y.; Lu, F.; Zheng, S. A study on the influence of e-commerce live streaming on consumer repurchase intentions. *Int. J. Mark. Stud.* **2020**, *12*, 48. [\[CrossRef\]](#)
16. Wang, X.; Aisihaer, N.; Aihemaiti, A. Research on the impact of live streaming marketing by online influencers on consumer purchasing intentions. *Front. Psychol.* **2022**, *13*, 1021256. [\[CrossRef\]](#)
17. Thakkar, R. Green marketing and sustainable development challenges and opportunities. *Int. J. Manag. Public Policy Res.* **2021**, *1*, 15–23.
18. Zheng, S.; Lyu, X.; Wang, J.; Wachenheim, C. Enhancing sales of green agricultural products through live streaming in China: What affects purchase intention? *Sustainability* **2023**, *15*, 5858. [\[CrossRef\]](#)
19. Anjani, L.; Mok, T.; Tang, A.; Oehlberg, L.; Goh, W.B. Why do people watch others eat food? An Empirical Study on the Motivations and Practices of Mukbang Viewers. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, Honolulu, HI, USA, 25–30 April 2020; pp. 1–13.
20. Zhou, J.; Zhou, J.; Ding, Y.; Wang, H. The magic of danmaku: A social interaction perspective of gift sending on live streaming platforms. *Electron. Commer. Res. Appl.* **2019**, *34*, 100815. [\[CrossRef\]](#)
21. Ma, X.; Zou, X.; Lv, J. Why do consumers hesitate to purchase in live streaming? A perspective of interaction between participants. *Electron. Commer. Res. Appl.* **2022**, *55*, 101193. [\[CrossRef\]](#)
22. Zhang, Y.; Li, K.; Qian, C.; Li, X.; Yuan, Q. How real-time interaction and sentiment influence online sales? Understanding the role of live streaming danmaku. *J. Retail. Consum. Serv.* **2024**, *78*, 103793. [\[CrossRef\]](#)
23. Zheng, R.; Li, Z.; Na, S. How customer engagement in the live-streaming affects purchase intention and customer acquisition, E-tailer’s perspective. *J. Retail. Consum. Serv.* **2022**, *68*, 103015. [\[CrossRef\]](#)
24. Edward, M.; Sahadev, S. Role of switching costs in the service quality, perceived value, customer satisfaction and customer retention linkage. *Asia Pac. J. Mark. Logist.* **2011**, *23*, 327–345. [\[CrossRef\]](#)
25. Ham, J.; Lee, K.; Kim, T.; Koo, C. Subjective perception patterns of online reviews: A comparison of utilitarian and hedonic values. *Inf. Process. Manag.* **2019**, *56*, 1439–1456. [\[CrossRef\]](#)
26. Joshi, Y.; Uniyal, D.P.; Sangroya, D. Investigating consumers’ green purchase intention: Examining the role of economic value, emotional value and perceived marketplace influence. *J. Clean. Prod.* **2021**, *328*, 129638. [\[CrossRef\]](#)
27. Wongkitrungrueng, A.; Assarut, N. The role of live streaming in building consumer trust and engagement with social commerce sellers. *J. Bus. Res.* **2020**, *117*, 543–556. [\[CrossRef\]](#)
28. Joo, E.; Yang, J. How perceived interactivity affects consumers’ shopping intentions in live stream commerce: Roles of immersion, user gratification and product involvement. *J. Res. Interact. Mark.* **2023**, *17*, 754–772. [\[CrossRef\]](#)
29. Zhang, H.; Zheng, S.; Zhu, P. Why are Indonesian consumers buying on live streaming platforms? Research on consumer perceived value theory. *Heliyon* **2024**, *10*, e33518. [\[CrossRef\]](#)
30. Sultan, P.; Wong, H.Y.; Azam, M.S. How perceived communication source and food value stimulate purchase intention of organic food: An examination of the stimulus-organism-response (SOR) model. *J. Clean. Prod.* **2021**, *312*, 127807. [\[CrossRef\]](#)
31. Boksberger, P.E.; Melsen, L. Perceived value: A critical examination of definitions, concepts and measures for the service industry. *J. Serv. Mark.* **2011**, *25*, 229–240. [\[CrossRef\]](#)
32. Guo, J.; Li, Y.; Xu, Y.; Zeng, K. How live streaming features impact consumers’ purchase intention in the context of cross-border E-commerce? A research based on SOR theory. *Front. Psychol.* **2021**, *12*, 767876. [\[CrossRef\]](#)
33. Gaberamos, O.; Pasaribu, L.H. The effect of information quality, customer experience, price, and service quality on purchase intention by using customer perceived value as mediation variables (Study On Gofood Applications On The Millenial Generation). *J. Mantik* **2022**, *5*, 2470–2480.

34. Nuttavuthisit, K.; Thøgersen, J. The importance of consumer trust for the emergence of a market for green products: The case of organic food. *J. Bus. Ethics* **2017**, *140*, 323–337. [\[CrossRef\]](#)
35. Currás-Pérez, R.; Dolz-Dolz, C.; Miquel-Romero, M.J.; Sánchez-García, I. How social, environmental, and economic CSR affects consumer-perceived value: Does perceived consumer effectiveness make a difference? *Corp. Soc. Responsib. Environ. Manag.* **2018**, *25*, 733–747. [\[CrossRef\]](#)
36. Zhang, B.; Fu, Z.; Huang, J.; Wang, J.; Xu, S.; Zhang, L. Consumers' perceptions, purchase intention, and willingness to pay a premium price for safe vegetables: A case study of Beijing, China. *J. Clean. Prod.* **2018**, *197*, 1498–1507. [\[CrossRef\]](#)
37. Yee, F.M.; Yazdanifard, R. How Consumer behaviours Affected by "Sight" and "Hearing" in Terms of Promotion. *Glob. J. Manag. Bus. Res. E Mark.* **2015**, *15*, 17–22.
38. Moreira, A.C.; Fortes, N.; Santiago, R. Influence of sensory stimuli on brand experience, brand equity and purchase intention. *J. Bus. Econ. Manag.* **2017**, *18*, 68–83. [\[CrossRef\]](#)
39. Zhang, H.; Liu, C. Research on The Impact of Reviews on Consumer Perceived Value in Live Streaming. In Proceedings of the 2021 5th International Seminar on Education, Management and Social Sciences (ISEMSS 2021), Chengdu, China, 9–11 July 2021; pp. 487–494.
40. Chang, S.E.; Yu, C. Exploring gamification for live-streaming shopping—Influence of reward, competition, presence and immersion on purchase intention. *IEEE Access* **2023**, *11*, 57503–57513. [\[CrossRef\]](#)
41. Meng, F.; Wei, J. What factors of online opinion leader influence consumer purchase intention. *Int. J. Simul. Syst. Sci. Technol.* **2015**, *16*, 1–8.
42. Liao, Y.-K.; Wu, W.-Y.; Pham, T.-T. Examining the moderating effects of green marketing and green psychological benefits on customers' green attitude, value and purchase intention. *Sustainability* **2020**, *12*, 7461. [\[CrossRef\]](#)
43. Yang, S.; Liu, L.; Jiang, J.; Ren, S. Purchase Intention in Agricultural Products Live-Streaming Commerce: A SOR Model. In Proceedings of the International Conference on Human-Computer Interaction, Virtual Event, 26 June–1 July 2022; pp. 268–279.
44. Ji, G.; Fu, T.; Choi, T.-M.; Kumar, A.; Tan, K.H. Price and quality strategy in live streaming e-commerce with consumers' social interaction and celebrity sales agents. *IEEE Trans. Eng. Manag.* **2022**, *71*, 4063–4075. [\[CrossRef\]](#)
45. He, D.; Yao, Z.; Tang, P.; Ma, Y. Impacts of different interactions on viewers' sense of virtual community: An empirical study of live streaming platform. *Behav. Inf. Technol.* **2023**, *42*, 940–960. [\[CrossRef\]](#)
46. Chiu, C.M.; Wang, E.T.; Fang, Y.H.; Huang, H.Y. Understanding customers' repeat purchase intentions in B2C e-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Inf. Syst. J.* **2014**, *24*, 85–114. [\[CrossRef\]](#)
47. Nkaabu, C.G.; Saina, E.; Bonuke, R. The moderating effect of store image on the indirect relationship between socio-sensory experience and the purchase intention via social value. *Int. J. Econ. Commer. Manag.* **2017**, *5*, 68–81.
48. Choi, E.J.; Kim, S.-H. The study of the impact of perceived quality and value of social enterprises on customer satisfaction and re-purchase intention. *Int. J. Smart Home* **2013**, *7*, 239–252.
49. Ariffin, S.; Yusof, J.M.; Putit, L.; Shah, M.I.A. Factors influencing perceived quality and repurchase intention towards green products. *Procedia Econ. Financ.* **2016**, *37*, 391–396. [\[CrossRef\]](#)
50. De Medeiros, J.F.; Ribeiro, J.L.D.; Cortimiglia, M.N. Influence of perceived value on purchasing decisions of green products in Brazil. *J. Clean. Prod.* **2016**, *110*, 158–169. [\[CrossRef\]](#)
51. Lee, C.-H.; Wu, J.J. Consumer online flow experience: The relationship between utilitarian and hedonic value, satisfaction and unplanned purchase. *Ind. Manag. Data Syst.* **2017**, *117*, 2452–2467. [\[CrossRef\]](#)
52. Gan, C.; Wang, W. The influence of perceived value on purchase intention in social commerce context. *Internet Res.* **2017**, *27*, 772–785. [\[CrossRef\]](#)
53. Escobar-Rodríguez, T.; Bonsón-Fernández, R. Analysing online purchase intention in Spain: Fashion e-commerce. *Inf. Syst. E-Bus. Manag.* **2017**, *15*, 599–622. [\[CrossRef\]](#)
54. Watanabe, E.A.d.M.; Alfinito, S.; Curvelo, I.C.G.; Hamza, K.M. Perceived value, trust and purchase intention of organic food: A study with Brazilian consumers. *Br. Food J.* **2020**, *122*, 1070–1184. [\[CrossRef\]](#)
55. Lavuri, R.; Jindal, A.; Akram, U. How perceived utilitarian and hedonic value influence online impulse shopping in India? Moderating role of perceived trust and perceived risk. *Int. J. Qual. Serv. Sci.* **2022**, *14*, 615–634. [\[CrossRef\]](#)
56. Khan, S.N.; Mohsin, M. The power of emotional value: Exploring the effects of values on green product consumer choice behavior. *J. Clean. Prod.* **2017**, *150*, 65–74. [\[CrossRef\]](#)
57. Cheung, M.F.; To, W.M. An extended model of value-attitude-behavior to explain Chinese consumers' green purchase behavior. *J. Retail. Consum. Serv.* **2019**, *50*, 145–153. [\[CrossRef\]](#)
58. Cao, D.; Zheng, Y.; Liu, C.; Yao, X.; Chen, S. Consumption values, anxiety and organic food purchasing behaviour considering the moderating role of sustainable consumption attitude. *Br. Food J.* **2022**, *124*, 3540–3562. [\[CrossRef\]](#)
59. Zhou, Y.; Huang, W. The influence of network anchor traits on shopping intentions in a live streaming marketing context: The mediating role of value perception and the moderating role of consumer involvement. *Econ. Anal. Policy* **2023**, *78*, 332–342. [\[CrossRef\]](#)
60. Li, L.; Chen, X.; Zhu, P. How do e-commerce anchors' characteristics influence consumers' impulse buying? An emotional contagion perspective. *J. Retail. Consum. Serv.* **2024**, *76*, 103587. [\[CrossRef\]](#)
61. Stockheim, I.; Tevet, D.; Fenig, N. Keen to advocate green: How green attributes drive product recommendations. *J. Clean. Prod.* **2024**, *434*, 140157. [\[CrossRef\]](#)

62. Yoganathan, V.; Osburg, V.-S.; Akhtar, P. Sensory stimulation for sensible consumption: Multisensory marketing for e-tailing of ethical brands. *J. Bus. Res.* **2019**, *96*, 386–396. [\[CrossRef\]](#)
63. Chen, C.-C.; Lin, Y.-C. What drives live-stream usage intention? The perspectives of flow, entertainment, social interaction, and endorsement. *Telemat. Inform.* **2018**, *35*, 293–303. [\[CrossRef\]](#)
64. Shiu, J.Y.; Liao, S.T.; Tzeng, S.-Y. How does online streaming reform e-commerce? An empirical assessment of immersive experience and social interaction in China. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 224. [\[CrossRef\]](#)
65. Fu, J.-R.; Hsu, C.-W. Live-streaming shopping: The impacts of para-social interaction and local presence on impulse buying through shopping value. *Ind. Manag. Data Syst.* **2023**, *123*, 1861–1886. [\[CrossRef\]](#)
66. Alshibly, H.H. Customer perceived value in social commerce: An exploration of its antecedents and consequences. *J. Manag. Res.* **2015**, *7*, 17–37. [\[CrossRef\]](#)
67. Wasaya, A.; Saleem, M.A.; Ahmad, J.; Nazam, M.; Khan, M.M.A.; Ishfaq, M. Impact of green trust and green perceived quality on green purchase intentions: A moderation study. *Environ. Dev. Sustain.* **2021**, *23*, 13418–13435. [\[CrossRef\]](#)
68. Hume, M. Compassion without action: Examining the young consumers consumption and attitude to sustainable consumption. *J. World Bus.* **2010**, *45*, 385–394. [\[CrossRef\]](#)
69. Chekima, B.; Wafa, S.A.W.S.K.; Igau, O.A.; Chekima, S.; Sondoh, S.L., Jr. Examining green consumerism motivational drivers: Does premium price and demographics matter to green purchasing? *J. Clean. Prod.* **2016**, *112*, 3436–3450. [\[CrossRef\]](#)
70. Szczepaniak, M.; Szulc-Obłóza, A. Sustainable Consumption Consciousness and Middle-Income Class Affiliation: Theory and Evidence from Poland. *East Eur. Politics Soc.* **2024**, 08883254231212486. [\[CrossRef\]](#)
71. Podsakoff, P.M.; Organ, D.W. Self-reports in organizational research: Problems and prospects. *J. Manag.* **1986**, *12*, 531–544. [\[CrossRef\]](#)
72. Howard, M.C.; Henderson, J. A review of exploratory factor analysis in tourism and hospitality research: Identifying current practices and avenues for improvement. *J. Bus. Res.* **2023**, *154*, 113328. [\[CrossRef\]](#)
73. Liang, H.; Saraf, N.; Hu, Q.; Xue, Y. Assimilation of enterprise systems: The effect of institutional pressures and the mediating role of top management. *MIS Q.* **2007**, *31*, 59–87. [\[CrossRef\]](#)
74. Nunnally, J.C. Psychometric theory—25 years ago and now. *Educ. Res.* **1975**, *4*, 7–21.
75. Gefen, D.; Straub, D.; Boudreau, M.-C. Structural equation modeling and regression: Guidelines for research practice. *Commun. Assoc. Inf. Syst.* **2000**, *4*, 7. [\[CrossRef\]](#)
76. Black, W.C.; Babin, B.J.; Anderson, R. *Multivariate Data Analysis: A Global Perspective*; Pearson: London, UK, 2010; Volume 7.
77. Hair, J.; Sarstedt, M.; Hopkins, L.; Kuppelwieser, V. Partial least squares structural equation modeling (PLS-SEM) An emerging tool in business research. *Eur. Bus. Rev.* **2014**, *26*, 106–121. [\[CrossRef\]](#)
78. Hair, J.F.; Sarstedt, M.; Ringle, C.M.; Mena, J.A. An assessment of the use of partial least squares structural equation modeling in marketing research. *J. Acad. Mark. Sci.* **2012**, *40*, 414–433. [\[CrossRef\]](#)
79. Marsh, H.W.; Hau, K.-T.; Grayson, D. Goodness of Fit in Structural Equation. In *Contemporary Psychometrics*; Lawrence Erlbaum Associates: Mahwah, NJ, USA, 2005.
80. Awang, Z. *Structural Equation Modeling Using AMOS Graphic*; Penerbit Universiti Teknologi MARA: Shah Alam, Malaysia, 2012.
81. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [\[CrossRef\]](#)
82. Akinwande, M.O.; Dikko, H.G.; Samson, A. Variance inflation factor: As a condition for the inclusion of suppressor variable (s) in regression analysis. *Open J. Stat.* **2015**, *5*, 754. [\[CrossRef\]](#)
83. Carranza, R.; Díaz, E.; Martín-Consuegra, D. The influence of quality on satisfaction and customer loyalty with an importance-performance map analysis: Exploring the mediating role of trust. *J. Hosp. Tour. Technol.* **2018**, *9*, 380–396. [\[CrossRef\]](#)
84. Ringle, C.M.; Sarstedt, M. Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Ind. Manag. Data Syst.* **2016**, *116*, 1865–1886. [\[CrossRef\]](#)
85. Zhong, L.; Sun, S.; Law, R.; Zhang, X. Impact of robot hotel service on consumers' purchase intention: A control experiment. *Asia Pac. J. Tour. Res.* **2020**, *25*, 780–798. [\[CrossRef\]](#)
86. Chen, W.-K.; Chen, C.-W.; Silalahi, A.D.K. Understanding consumers' purchase intention and gift-giving in live streaming commerce: Findings from SEM and fsQCA. *Emerg. Sci. J.* **2022**, *6*, 460–481. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.