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# Does Live Streaming Influencers' Popularity Really Affect Consumer Purchase Intention in China? The Moderating Role of Product **Information Quality**

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#### **Abstract**

China is currently experiencing a significant increase in the live-streaming industry, driven by high profitability and sales. The increasing prevalence of live-stream platforms has also contributed to the rise of influencers who possess larger fan bases and greater bargaining power. In the cosmetic sector, consumers often require firsthand experience with products in order to feel satisfied, which can create uncertainty in their purchase intentions. Live streaming is a recognised marketing strategy that allows firms to leverage the popularity of influencers to convert buying intentions into actual buying behaviour. This study aims to investigate the factors that influence consumer purchase intention in relation to influencer popularity. This study aims to investigate the mediating role of perceived enjoyment and uncertainty, as well as the moderating role of product information, in the relationship between influencer popularity and purchase intention. This study expands the existing knowledge of the S-O-R model by gathering data from Taobao live streaming. The collected data was analysed using SPSS version 26 and structural equation modelling (SEM) with SmartPLS 3.3.9. The study's findings indicate that the impact of influencer popularity on consumer buying intention is partially mediated by perceived uncertainty and perceived enjoyment. Furthermore, studies have demonstrated the significant moderating role of the quality of product information. The results suggest that cosmetic companies should offer comprehensive product information to influencers when showcasing their products during live streaming events. The live streaming industry can enhance product preparation and information dissemination for online marketing.

**Keywords:** Influencer Popularity, Live Streaming e-commerce, Perceived Uncertainty, Perceived Enjoyment, Cosmetic Information Quality, Audiences' Purchase Intention.

#### Introduction

Between 2020 and 2022, COVID-19 movement control (MOC) in China prompted a significant increase in consumer preference for online shopping, leading to a decline in traditional shopping methods. Gao et al. (2018) found that consumers purchase cosmetics and flowers from online platforms. During the movement control period, consumers spent more time online, but they were no longer satisfied with traditional online shopping. Virtual shopping relies on graphical product information, which can be compromised by sellers engaging in fraud or scams, resulting in product information asymmetry (Milan et al., 2015). Live streaming has garnered attention in this context.

The live streaming industry in China has experienced significant growth due to the ability of live streaming platforms and influencers to boost sales and profits within a specific timeframe. Several e-commerce platforms, including Taobao, Mushroom Street, and NetEase Koala, have recently introduced popular "live streaming + e-commerce" services. Taobao live streaming generated around \$65 billion in gross merchandise value between 2019 and 2021 (Bu et al., 2019). The cosmetics industry seems to be the most prosperous in terms of revenue. The cosmetics market is experiencing increased demand as a result of rapid population growth (Mihailovic et al., 2017). According to HKTDC Research (2022), China's cosmetic market held the second largest share of the global market in 2021, accounting for 17.3%, trailing behind the United States with a share of 20%. However, consumer purchase intention is not easily triggered by simply observing cosmetic products being sold through live streaming. Researchers have identified the reason as the lack of specific skills to differentiate products (Wang et al., 2012). Consumers now have a convenient means of comprehending product descriptions due to the significant increase in influencers (Lv, 2020).

Choosing suitable influencers to promote cosmetics can be a difficult task. The selection of influencers is crucial for businesses due to their potential to enhance consumers' purchase intentions (Gupta et al., 2017; Ladhari et al., 2020; Nguyen, 2021); Rao Hill and Qesja (2023). Dwidienawati et al. (2020) emphasised that establishing a link between consumers and influencers creates a sense of familiarity, facilitating easy access to online communities. Popular influencers, who are seen as ambassadors of virtual communities, can serve as influential and opinionated leaders. This argument posits that the concept of influencers' popularity in the context of live streaming commerce is worthy of exploration due to the limited existing literature.

China currently has 660 million live streaming users, engaging in various activities such as live games, live shows, live life sharing, and live e-commerce (IiMedia Research, 2022). According to statistics, approximately 75.5% of the audience for live streaming used the platform for entertainment, while 44.2% watched it for shopping purposes (CNNIC, 2022). Additionally, the average transaction rate for shopping on live streaming platforms is less than 10% (Yoshu, 2021). This indicates a relatively low conversion rate, particularly within the cosmetic industry. Product uncertainty negatively affects consumer purchase intentions. Influencers possess the ability to decrease uncertainty and enhance purchase intention. This study investigates the impact of perceived uncertainty,

influencer popularity, and product information quality on consumers' purchase intentions. To increase sales, cosmetic companies and the live streaming industry can focus on reducing audience uncertainty.

This study provides an overview of the current state of e-commerce and discusses the problems and issues related to online shopping for consumers. The second part of the study provides a review of the relevant literature on live streaming e-commerce and proposes a research framework for live streaming e-commerce based on the S-O-R model. Subsequently, the data is collected and analysed. The fourth and fifth sections of the study involve hypothesis testing, drawing conclusions, and providing recommendations for both cosmetic companies and the live streaming industry.

#### Literature Review

#### S-O-R Model

The Stimulus-Organism-Response (S-O-R) model was initially proposed by Mehrabian and Russell (1974) and later modified by Jacoby in 2002. The model is based on three essential elements: stimuli, organisms, and responses. The stimulus factor plays a role in the development of emotional and cognitive processes in organisms. This process generates an approaching behaviour as a response (Donovan et al., 1994). Chan et al. (2017) analyse stimuli from various perspectives, including external, internal, and situational stimuli. In their study, Liu et al. (2013) found that organisms play a role in mediating stimulus and response. One can view response as a consumer behaviour that involves either purchasing or avoiding risk.

In recent years, there has been significant growth in live streaming e-commerce. Scholars have therefore sought to examine the impact of live streaming on consumer behaviour using the S-O-R model. Hu and Chaudhry (2020) conducted a study that examined consumer engagement on live streaming platforms, analysing consumer attributes such as hedonic consumption, social sharing, and impulsive behaviour within the context of live streaming. They analysed these attributes using the S-O-R model. Another study utilised the same model to examine consumers' purchase intentions on live streaming platforms for agricultural products.

Prior literature primarily focused on investigating factors influencing online shopping motivations. However, Xu et al., 2023, have neglected the role of emotion as a mediator. Practitioners can enhance this model by incorporating indirect effects, which help them understand the underlying mechanism that drives customers' purchase intention during live streaming. While live streaming e-commerce can create an exciting atmosphere that enhances consumers' enjoyment, virtual environments also pose risks to consumers. Perceived enjoyment and perceived uncertainty are significant factors influencing consumers' purchase intention, as indicated by studies conducted by Guo et al. (2022) and Ma (2021). This study is grounded in the S-O-R model and aims to investigate the indirect effect of consumers' perceived uncertainty and enjoyment on live purchase intention, going beyond direct influence.

# **Purchase Intention in Live Streaming**

Scholars have extensively researched purchase intention in various contexts within the field of literature. Furthermore, scholars have extensively linked it to perceived values, consumer behavior, attitude, and perceived risk (Adnan, 2014; Al-Nasser et al., 2014; Almousa, 2014; Faqih, 2013; Gatautis et al., 2014; Hidayat & Diwasasri, 2013; Shaharudin et al., 2010). Akar and Nasir (2015) conducted a study on factors influencing online purchase intention and identified 57 variables associated with this phenomenon. However, it is challenging to examine all variables within a unified framework. This study examines the relationship between influencer popularity and consumer purchase intention, as discussed by Djafarova and Rushworth (2017), Jin and Phua (2014), and Park and Lin (2020). Djafarova et al. (2017) discovered that micro-celebrities have a greater influence on the younger generation than traditional celebrities. Jin et al. (2014) argued that positive tweets from influencers can enhance purchase intention. Park et al. (2020) found a positive relationship between the match-up of online influencers and Chinese customers' purchasing intentions in live streaming e-commerce.

### Influencer's Popularity

Traditional influencers, such as actors, musicians, models, sports icons, authors, and others, have historically played a significant role in consumers' lives (Djafarova et

al., 2017). The emergence of social media platforms has introduced consumers to a novel form of influencer marketing (Chae, 2021). They are commonly known as "digital celebrities," "social media influencers," or "internet micro-celebrities." Micro-celebrities are individuals who have a large number of followers on social media platforms. They differ from traditional celebrities in that they actively share their personal lives with their followers, which helps to establish credibility and a stronger connection with consumers (Nouri, 2018). Influencers have the ability to create their own digital personas that appeal to consumers (Chae, 2021). Hwang and Zhang (2018) found that online influencers possess greater power and influence compared to traditional celebrities. Djafarova et al. (2017) discovered that Instagram influencers, such as bloggers and vloggers with a substantial following, exerted a stronger influence on customers' purchase intentions compared to traditional influencers. Zhang et al. (2020) identified eight characteristics that indicate an influencer: popularity, attractiveness, credibility, expertise, interaction, price support, affinity, and responsiveness. They also discovered that among them, popularity is a significant factor for influencers.

This study examines the impact of influencer popularity on purchase intention by referencing previous research conducted by scholars in various contexts. In Vietnam, Nguyen (2021) highlighted the impact of popular influencer advertising on consumers' purchase intentions for smartphones. Jin et al. (2014) examined the impact of short text posts by influencers on Twitter and discovered that celebrities with a large number of followers have a positive influence on consumers' purchasing intentions in the United States. Rao Hill et al. (2023) and Djafarova et al. (2017) have emphasised the impact of influencer popularity on consumers' purchase intentions. They have found that customers tend to imitate influencers' preferences in various areas, including clothing, makeup, restaurants, and vacation destinations, as observed through their Instagram posts. This study supports the findings of Hill et al. (2017) and Ladhari et al. (2020) that there is a positive relationship between the popularity of vloggers (influencers) and viewers' purchase intentions. This study examines cosmetic products in live streaming videos in China, which differs from Hill et al. (2017) research that recorded various product types in vlogs in Australia, and Ladhari et al. (2020) study that recorded beauty product videos on YouTube in the US.

**H1:** Influencer popularity positively increases audiences' purchase intention in live streaming.

Prior studies have primarily focused on the relationship between influencer popularity and trustworthiness. Jin et al. (2014) suggest that endorsements from popular celebrities or influencers with a large number of followers are more trustworthy compared to those from individuals with a limited following. Djafarova et al. (2017) investigated the influence of online celebrities, also known as influencers, on YouTube or Instagram. They discovered that people perceive these influencers as more reliable and trustworthy than traditional celebrities, which in turn leads to greater influence. Therefore, products endorsed by popular influencers are considered reliable. Similarly, Hill et al. (2017) discovered a positive correlation between popularity and the perceived trustworthiness of vloggers. Nevertheless, the impact of influencer popularity on consumers' perceived uncertainty has been overlooked. According to Featherman et al. (2010), online trust significantly reduces perceived uncertainty in the context of online shopping. This study posits that audiences experience less uncertainty when watching live streams by popular influencers because of their trust in them.

**H2:** *Influencer popularity positively reduces perceived uncertainty in live streaming.* 

Zhichao and Qian (2020) found a positive correlation between the popularity of micro-celebrities (influencers) and perceived enjoyment. The authors argue that consumers have a positive experience when influencers share product reviews in a friendly and pleasant manner, but they also have a real-time experience that enhances consumer engagement. The positive atmosphere on live-streaming platforms fosters a sense of joy and connection between consumers and influencers. According to Zhichao et al. (2020), it is important to investigate perceived enjoyment in relation to influencers' popularity, as there is a perceived positive correlation between the two.

**H3:** *Influencer popularity positively increases audiences' perceived enjoyment in live streaming.* 

# **Perceived Uncertainty**

Perceived uncertainty refers to the inability of prospective customers to accurately predict the outcome of a transaction (Zhang et al., 2020). Consumers may experience greater uncertainty in the online shopping environment compared to offline shopping due

to information asymmetry. E-retailers may engage in deceptive practices such as misrepresenting product features, using stolen images, and compromising customer privacy (Bock et al., 2012). Additionally, there is a risk of receiving lower quality products or incorrect items (Hong, 2015; Pavlou et al., 2007). Live audiences may experience uncertainty towards e-retailers or the products being sold during live demonstrations, as live streaming shopping falls under the umbrella of online shopping. This study aims to address the perceived uncertainty of audiences by incorporating the perceived uncertainty related to both sellers and products, following the approach used by Zhang et al. (2020).

Past research indicates that perceived uncertainty has a significant impact on purchase intention (Amirtha et al., 2020; Islam & Hussain, 2022; Milan et al., 2015; Pavlou et al., 2007; Wang, 2017; Wu et al., 2021; Yang et al., 2016). Pavlou et al. (2007) and Milan et al. (2015) discovered that consumers' perceived uncertainty negatively impacted their purchase intentions in virtual stores. Wang (2017) and Wu et al. (2021) found that perceived uncertainty has a negative impact on consumer purchase intentions for food. Yang et al. (2016) and Amirtha et al. (2020) examined perceived uncertainty in the context of online shopping. The study found that several dimensions of perceived uncertainty, such as social, psychological, performance, and financial factors, negatively impacted online purchase intention.

Product uncertainty strongly influences consumer purchase intention in live streaming, according to the literature (Guo et al., 2022; Lu & Chen, 2021; Zhang et al., 2020). According to Lu et al. (2021), perceived product fit and product quality uncertainty had a negative impact on live purchase intention. Zhang et al. (2020) discovered a negative relationship between perceived uncertainty from e-retailers, product aspects, and customers' live purchase intention. Guo et al. (2022) found that the audience's perceived risk negatively affected the purchase of fresh agricultural products during live streaming. The uncertainty level for cosmetic products may be significantly higher than that of other products. Consumers may have concerns regarding the waterproof properties of mascara or eyeliner. Therefore, this study suggests conducting additional research to explore the impact of perceived uncertainty on consumers' behavioural intentions towards cosmetics in live streaming.

**H4:** Audiences' perceived uncertainty negatively affects purchase intention in live streaming.

Several scholars have investigated the association between purchase intention and perceived uncertainty, both directly and indirectly (Guo et al., 2022; Islam et al., 2022; Lu et al., 2021; Wu et al., 2021; Zhang et al., 2020). Wu et al. (2021) emphasised that perceived uncertainty partially mediates the relationship between perceived quality of traceability information and organic food purchase intention. Lu et al. (2021) investigated the role of perceived uncertainty as a partial mediator between streamers' physical characteristics and purchase intention. Zhang et al. (2020) found that perceived uncertainty partially mediated the relationship between live video streaming and customers' live purchase intention. Guo et al. (2022) examined how live streaming features of fresh agricultural products can enhance consumer purchase intention by reducing perceived risk among audiences. They applied the S-O-R model and found that perceived risk serves as a significant mediator in this relationship. Islam et al. (2022) investigated how consumers' perceptions of the country of origin influence their purchasing intentions. They found that these perceptions have a negative impact, both directly and indirectly.

**H5:** Perceived uncertainty mediates the relationship between influencer popularity and purchase intention of consumers.

### **Perceived Enjoyment**

Prior research has demonstrated a positive relationship between perceived enjoyment and consumers' purchase intention (Kasinphila et al., 2023; Ma, 2021; Park et al., 2020; Sawmong, 2022; Wagner et al., 2017; Xu et al., 2020; Zhichao et al., 2020). Kasinphila et al. (2023) investigated the correlation between customers' purchase intention and perceived enjoyment on Sephora's global website, sephora.com. In terms of visitor traffic, this website is Thailand's top-ranked beauty and cosmetic business. Additionally, Wagner et al. (2017) found that enjoyment positively influenced audiences' intentions to purchase Internet-enabled television. Park et al. (2020) highlighted the importance of aligning the image of online celebrities (influencers) with their live streaming content in order to enhance audience enjoyment and subsequently increase purchasing intention. Several studies (Ma, 2021; Sawmong, 2022; Xu et al., 2020; Zhichao et al., 2020) have shown that audiences derive enjoyment from streamer characteristics, influencer

effects, and interactions. Wongkitrungrueng et al. (2020) and Cai et al. (2018) have both identified enjoyment as a significant factor influencing consumers' continued engagement with live streaming.

**H6:** Audiences' perceived enjoyment positively increases purchase intention in live streaming.

This study examines the mediating effect of perceived enjoyment, drawing on previous research that has identified perceived enjoyment as a mediator. In offline stores in Cairo, Saad and Metawie (2015) investigated the relationship between shopping enjoyment, store environment factors (music and layout), and consumers' impulsive purchase behaviour. Hasim et al. (2020) examined the relationship between online environment and online impulse purchase, as well as online promotion and online impulse purchase, in a Malaysian online retail store. They found that perceived enjoyment partially mediated these relationships. Floh and Madlberger (2013) found that perceived enjoyment mediated the relationship between atmospheric cues (content, design, and navigation) and impulse purchase intention in the context of online bookstores. However, there is a lack of research on the relationship between influencer popularity, perceived enjoyment, and live purchase intention.

**H7:** Audiences' perceived enjoyment mediates the relationship between influencer popularity and purchase intention in live streaming.

### **Product Information Quality**

Xu et al. (2020) defined high information quality as providing comprehensive, accurate, and reliable descriptions of live streaming products. Furthermore, the researchers discovered that the quality of information had an impact on the emotional states of audiences. Popular influencers in live streaming e-commerce are believed to have the ability to assist consumers by providing accurate product information. Customers tend to have a more positive attitude towards brands and products that popular influencers endorse, according to research (Smith et al., 2018). Live streaming audiences may experience reduced uncertainty if the live streaming industry provides

comprehensive product information and professional training to influencers. For instance, influencers provide detailed descriptions of cosmetics while simultaneously instructing their audience on how to apply makeup and addressing their questions in real-time. The influencer can provide insights into her experience using cosmetics for sensitive skin. Milan et al. (2015) found that qualitative product information can decrease consumer uncertainty. Further, Sawmong (2022) suggested that audiences are more inclined to make purchasing decisions when influencers in live streaming provide immediate and detailed information about the products. Therefore, it is reasonable to propose that the delivery of high-quality product information by popular influencers can decrease the level of uncertainty on live streaming platforms.

**H8:** *Product information quality delivered by popular influencer decreases uncertainty.* 

Online influencers are believed to be more accessible, allowing for the establishment of virtual intimacy with followers, in contrast to traditional celebrities. This close connection also elicits positive emotions, enhancing the level of enjoyment on live streaming platforms. Furthermore, influencers' effective delivery of high-quality and credible information about specific products enhances audience satisfaction. The argument aligns with Gao et al. (2012) study, which asserts a significant relationship between information quality and perceived enjoyment in the context of online shopping. In addition, when influencers with a larger fan base promote something, it automatically increases the level of interaction among consumers, resulting in a higher level of enjoyment. Therefore, it can be inferred that exchanging high-quality production information can establish a positive relationship between the popularity of influencers and the perceived enjoyment of the audience. Hence, we propose that:

**H9:** Quality production information mediates the positive relationship of influencer popularity with perceived enjoyment.

Figure 1 illustrates the research model and hypothesised relationships based on the S-O-R model. This study examines the impact of influencer popularity (S) on audiences' purchase intention (R) during live streaming. It specifically focuses on the roles of perceived uncertainty (O) and perceived enjoyment (O). This study aims to examine the moderating

effect of product information quality on audiences' perceived uncertainty and enjoyment. It is hypothesised that the current live streaming technology, with its high-quality real-time product description, can reduce uncertainty and enhance enjoyment.

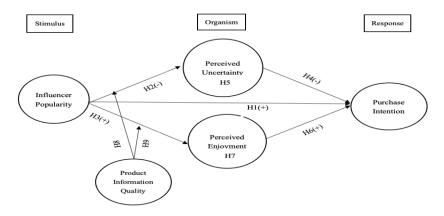


Figure 1: Quality Product Information Influencer-Support Model for Live Streaming E-Commerce.

# Methodology

# Sample

The questionnaire was translated into Chinese for use in a survey conducted in China. A backward translation was conducted to verify the consistency between the Chinese and English versions (Sun et al., 2019). Pandemic-related movement control measures have led to the collection of data through virtual platforms, particularly the Wenjuanxing platform. Researchers commonly use the Wenjuanxing platform for participant recruitment, questionnaire distribution, and to demonstrate the platform's advantages over in-person data collection (Sun et al., 2019; Teng et al., 2020). The inclusion of screening questions at the beginning of the survey is intended to ensure the reliability of the data. Only respondents who meet specific criteria, such as gender and shopping experience on a live streaming platform, were permitted to proceed further. The study employed purposive and snowball sampling methods to collect the data. From September to November 2022, we collected a total of 230 valid questionnaires. The data indicates that the majority of the sample population falls within the 19–29 age bracket. Moreover, the majority of respondents consisted of university students, who are more likely to have the time to observe and embrace fashion trends. Regarding

consumption, the majority of respondents spent less than 500 yuan. University students typically rely on their parents for financial support, which accounts for this. Moreover, over 50% of the participants in the sample engage in live streaming sessions 3–4 times per month. Table 1 presents the demographic information of the samples.

Table 1: Respondents' Demographic Profile (N=230).

Demographics' characteristics	Frequency	0/0						
Age								
18-29	206	89.6						
30-39	22	9.6						
40-49	1	0.4						
More than 50 years	1	0.4						
	Occupation							
Students	171	74.3						
Institutional Staff	32	13.9						
Self-employed	2	0.9						
Corporate staff	24	10.4						
Other	1	0.4						
	Monthly spending							
Less than 500 CNY	126	54.7						
500-1000	64	27.8						
1000- 2000	27	11.7						
2000- 4000	10	4.3						
More than 4000 CYN	3	1.3						
	Watching Frequency							
Frequently throughout a day	22	9.5						
Once or twice a day	29	12.6						
Twice or thrice a week	64	27.8						
3-4 times a month	115	50						
Number of Followers of Favourite Influencer								
Less than 1k	19	8.2						
1K-10K	16	6.9						
10K-100K	34	14.8						
100K-1M	53	23.0						
More than 1M	108	46.9						

## **Scales**

This study has five variables, "influencers' popularity (IP), product information quality (PIQ), perceived uncertainty (PU), perceived enjoyment (PE) and purchase intention (PI)". All the measurements were adopted and adapted appropriately from the mature scale. This study uses a five-point Likert scale, which ranged from "1 = Strongly Agree" to "5 = Strongly Agree". Three professors from UPM (Universiti Putra Malaysia) were invited to review and modify the questionnaire in order to enhance its surface validity and content validity (Liu et al., 2013). The questionnaire was modified in

response to participant feedback in this study. Park et al. (2020) conducted a pre-test using a sample of 30 females who had experience with watching or shopping on Taobao live streaming. Finally, the final questionnaire is presented in the appendix.

#### **Data Assessment**

Harman's single factor analysis was used to evaluate common method variance before conducting exploratory factor analysis (Podsakoff & Organ, 1986). This technique assumes the presence of a common method variance if one component explains the majority of the covariance between all dependent and independent variables. The study revealed that 5 factors were identified with eigenvalues greater than 1.00, and the first component explained 33.2% of the total variance. Therefore, CMV can be dismissed as no single factor explains the majority of the variance.

#### Results

### Reliability and Validity

This study employed Cronbach's Alpha, the widely recognised and commonly utilised method for assessing reliability, to test trustworthiness. The study utilised SPSS 26.0 to assess Cronbach's alpha. All Cronbach's alpha values exceeded 0.9, indicating a high level of reliability. Hair et al. (2014) recommends the use of composite reliability (CR) to assess reliability. In this study, CR values ranged from 0.925 to 0.937, all of which exceeded the threshold of 0.7 (see Table 2). The results indicate that all the constructs demonstrate high reliability. Convergence validity was assessed by conducting confirmatory factor analysis using Smart PLS 3.3.9. Fornell and Larcker (1981) say that good convergent validity is shown by a composite reliability (CR) value above 0.9 and an average variance extract (AVE) value above 0.6. Table 2 shows these values. Discriminant validity is the statistical verification of whether the correlation between two distinct constructs is significantly different. It is important to avoid high correlations between items in different constructs. When the correlation coefficient exceeds 0.85, it signifies a high degree of similarity between the items under measurement, usually because of significant overlap in the definitions of the constructs. The study employed a more

rigorous AVE method to assess the discriminant validity. Fornell et al. (1981) emphasized the requirement that the square root of the AVE for each factor exceed the correlation coefficient between each pair of variables, indicating discriminant validity. The square root of the AVE for each construct in Table 3 is greater than its correlation coefficient, indicating strong discriminant validity (Sitgreaves, 1979).

Table 2: Mean and Standard Deviation of the Variables.

Popularity	Constructs	Items	Mean	Stand Deviation	Factor Loading	Cronbach's Alpha	CR	AVE
Influencer		IP1	3.84	1.07	.785	-		
Influencer		IP2	3.94	1.02	.843			
Influencer Popularity   IP5		IP3	3.60	.98	.829			
Popularity	Influencer	IP4	4.16	.84	.779			
IP7		IP5	3.79	.91	.763	.924	.937	.624
IP8	горианту	IP6	3.95	.91	.794			
IP9		IP7	4.10	.88	.785			
PIQ1 3.95 8.88 .775 PIQ2 3.92 .87 8.03 PIQ3 3.99 .88 .770  Product PIQ4 4.00 .84 .759  Information PIQ5 3.85 .88 826 .923 .936 .62  Quality PIQ6 3.96 .83 .767 PIQ7 4.10 .81 .785 PIQ8 4.00 .83 804 PIQ9 3.83 .88 .788 PU1 3.77 .89 .808 PU2 3.58 .98 .821 PU3 3.60 1.00 .804  Received PU4 3.70 .88 804 Uncertainty PU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PU8 3.59 .96 .788 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 Perceived PE4 3.79 .81 .832 .906 .925 .63 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PU2 3.23 .99 .797 Purchase PI3 3.50 .94 .821 PU2 3.23 .99 .797 Purchase PI4 3.48 .94 .819 .910 .929 .65		IP8	3.81	.95	.773			
PIQ2 3.92 .87 .803 PIQ3 3.99 .88 .770 Product PIQ4 4.00 .84 .759 Information PIQ5 3.85 .88 .826 .923 .936 .66 Quality PIQ6 3.96 .83 .767 PIQ9 4.10 .81 .785 PIQ9 3.83 .88 .788 PU1 3.77 .89 .808 PU2 3.58 .98 .821 PU3 3.60 1.00 .804 Received PU4 3.70 .88 .804 PIU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE2 3.63 .89 .763 PE3 3.59 .96 .788 PE4 3.79 .81 .832 .906 .925 .66 PIH 3.50 .94 .821 PIH 3.50 .99 .797 PIH 3.48 .99 .819 .910 .929 .66		IP9	3.94	.95	.754			
Product         PIQ3         3.99         .88         .770           Information         PIQ4         4.00         .84         .759           Information         PIQ5         3.85         .88         .826         .923         .936         .63           Quality         PIQ6         3.96         .83         .767         .785         .785         .785         .785         .788         .804         .785         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .789         .808         .789         .780         .780         .777         .774         .776         .778         .778		PIQ1	3.95	.88	.775			
Product         PIQ4         4.00         .84         .759           Information         PIQ5         3.85         .88         .826         .923         .936         .67           Quality         PIQ6         3.96         .83         .767         .767         .77         .77         .77         .77         .785         .7767         .77         .77         .789         .808         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .788         .777         .778         .7763         .778         .7763         .778 <td< td=""><td></td><td>PIQ2</td><td>3.92</td><td>.87</td><td>.803</td><td></td><td></td><td></td></td<>		PIQ2	3.92	.87	.803			
Information		PIQ3	3.99	.88	.770			
Quality       PIQ6 PIQ7 PIQ7 PIQ7 PIQ7 PIQ8       4.00 PIQ8 PIQ9 PIQ8       8.81 PIQ8 PIQ9 PIQ9 PIQ9       3.83 PIQ9 PIQ9 PIQ9 PIQ9 PIQ9 PIQ9 PIQ9 PIQ9	Product	PIQ4	4.00	.84	.759			.619
PIQ7 4.10 .81 .785 PIQ8 4.00 .83 .804 PIQ9 3.83 .88 .788 PU1 3.77 .89 .808 PU2 3.58 .98 .821 PU3 3.60 1.00 .804  Received PU4 3.70 .88 .804 Uncertainty PU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE2 3.63 .89 .763 PE3 3.59 .96 .788 Perceived PE4 3.79 .81 .832 .906 .925 .63 Pight 3.50 .94 .821 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI4 3.48 .94 .819 .910 .929 .63	Information	PIQ5	3.85	.88	.826	.923	.936	
PIQ8 4.00 .83 .804 PIQ9 3.83 .88 .788 PU1 3.77 .89 .808 PU2 3.58 .98 .821 PU3 3.60 1.00 .804  Received PU4 3.70 .88 .804 Uncertainty PU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 Perceived PE4 3.79 .81 .832 .906 .925 .63 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI3 3.50 .94 .819 PI4 3.48 .94 .819 .910 .929 .63	Quality	PIQ6	3.96	.83	.767			
PIQ9 3.83 .88 .788 PU1 3.77 .89 .808 PU2 3.58 .98 .821 PU3 3.60 1.00 .804 Received PU4 3.70 .88 .804 Uncertainty PU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 Perceived PE4 3.79 .81 .832 .906 .925 .63 Pin 3.50 .94 .821 Pin 3.50 .94 .821 Pin 3.50 .94 .821 Pin 3.50 .94 .821 Pin 3.50 .94 .819 Pin 3.50 .929 .63 Purchase Intention Pin 3.73 .81 .774	•	PIQ7	4.10	.81	.785			
PU1 3.77 8.89 8.808 PU2 3.58 .98 .821 PU3 3.60 1.00 .804 Received PU4 3.70 .88 .804 Uncertainty PU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.57 .92 .804 PE2 3.63 .89 .763 PE2 3.63 .89 .763 PE3 3.59 .96 .788 PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI3 3.50 .94 .819 .910 .929 .63		PIQ8	4.00	.83	.804			
Received PU4 3.70 8.8 .804 Uncertainty PU5 3.73 .85 .777 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI3 3.50 .94 .767 PI4 3.48 .94 .819 .910 .929 .63		PIQ9	3.83	.88	.788			
Received PU4 3.70 .88 .804 .916 .931 .662		PU1	3.77	.89	.808			
Received Uncertainty         PU4         3.70         .88         .804         916         .931         .62           Uncertainty         PU5         3.73         .85         .777         916         .931         .62           PU6         3.61         .96         .780         .783         .783         .783         .783         .783         .788         .788         .788         .788         .788         .832         .906         .925         .632         .632         .788         .788         .81         .832         .906         .925         .632         .632         .794         .794         .794         .792         .792         .792         .792         .792         .793         .81         .821         .794         .821         .794         .783         .783         .91         .994         .767         .792         .797         .792		PU2	3.58	.98	.821	916	021	.629
Uncertainty PU5 3.73 8.5 .777 916 .931 .62 PU6 3.61 .96 .780 PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 Perceived PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI5 3.73 .81 .774		PU3	3.60	1.00	.804			
Purchase Intention  PUS 3.73	Received	PU4	3.70	.88	.804			
PU7 3.50 1.08 .801 PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PU8 3.50 1.08 .801 PU9 3.50 .94 .819 PI3 3.50 .94 .819 PI4 3.48 .94 .819 .910 .929 .63	Uncertainty	PU5	3.73	.85	.777		.931	
PU8 3.50 1.03 .750 PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI3 3.50 .94 .819 .910 .929 .63 PI4 3.48 .94 .819 .910 .929 .63	·	PU6	3.61	.96	.780			
PE1 3.57 .92 .804 PE2 3.63 .89 .763 PE3 3.59 .96 .788 PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI3 3.50 .94 .819 .910 .929 .63 PI4 3.48 .94 .819 .910 .929 .63		PU7	3.50	1.08	.801			
Perceived PE3 3.59 .96 .788 Perceived Enjoyment PE5 3.89 .81 .832 .906 .925 .63 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI5 3.73 .81 .774		PU8	3.50	1.03	.750			
Perceived Enjoyment         PE3         3.59         .96         .788           Enjoyment         PE4         3.79         .81         .832         .906         .925         .63           PE5         3.89         .84         .794           PE6         3.78         .91         .792           PE7         3.70         .99         .820           PI1         3.50         .94         .821           PI2         3.23         .99         .797           Purchase Intention         PI4         3.48         .94         .819         .910         .929         .65           Intention         PI5         3.73         .81         .774         .774         .774		PE1	3.57	.92	.804			
Perceived Enjoyment PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI5 3.73 .81 .774		PE2	3.63	.89	.763			
Enjoyment PE4 3.79 .81 .832 .906 .925 .63 PE5 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI4 3.48 .94 .819 .910 .929 .65	D 1	PE3	3.59	.96	.788			
PES 3.89 .84 .794 PE6 3.78 .91 .792 PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 PI3 3.50 .94 .767 Purchase Intention PI4 3.48 .94 .819 .910 .929 .68		PE4	3.79	.81	.832	.906	.925	.639
PE7 3.70 .99 .820 PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI4 3.48 .94 .819 .910 .929 .65	Enjoyment	PE5	3.89	.84	.794			
PI1 3.50 .94 .821 PI2 3.23 .99 .797 Purchase Intention PI4 3.48 .94 .819 .910 .929 .65 PI5 3.73 .81 .774		PE6	3.78	.91	.792	792		
PI2 3.23 .99 .797 Purchase PI4 3.48 .94 .819 .910 .929 .65 PI5 3.73 .81 .774		PE7	3.70	.99	.820			
PI2 3.23 .99 .797 Purchase PI4 3.48 .94 .819 .910 .929 .65 PI5 3.73 .81 .774		PI1	3.50	.94	.821			
Purchase Intention       PI3       3.50       .94       .767         PI4       3.48       .94       .819       .910       .929       .65         PI5       3.73       .81       .774								
Purchase PI4 3.48 .94 .819 .910 .929 .65 Intention PI5 3.73 .81 .774	D 1			.94				
Intention PI5 3.73 .81 .774				.94		.910	.929	.651
	Intention							
110 0,10 ,/1 ,011		PI6	3.46	.94	.844			
PI7 3.62 .95 .822								

<sup>\*</sup>Scales used: 1- Strongly Disagree, 2-Disagree, 3-Neutral, 4-Agree, 5-Strongly Agree.

Table 3: Discriminant validity. (HTMT Criterion).

Constructs	1-IP	2-PIQ	3-PU	4-PE	5-PI
1.Influencer Popularity	0.790				
2.Product Information Quality	0.298	0.787			
3. Perceived Uncertainty	-0.532	-0.452	0.793		
4. Perceived Enjoyment	0.525	0.389	-0.427	0.799	
5.Purchase Intention	0.578	0.328	-0.639	0.539	0.807

**Note:** The Diagonal Values (in Bold) are square root of AVE of Each Construct.

#### **Structural Model Test**

Smart PLS 3.3.9 was applied in this study to evaluate the hypotheses. The outcomes of the structural model are displayed in Figure 2. The findings indicate that influencer popularity has a negative impact on perceived uncertainty ( $\beta$  = -.315\*\*\*, p < 0.001) but a positive impact on perceived enjoyment ( $\beta$  = .453\*\*\*, p < 0.001) and purchase intention ( $\beta$  = .242\*\*\*, p < 0.001). As a result, H1, H2, and H3 are all supported. Additionally, both perceived uncertainty ( $\beta$  = -. 361\*\*\*, p < 0.001) and perceived enjoyment ( $\beta$  = .239\*\*\*, p < 0.001) have significant effect on purchase intention, thus H4, H6 are supported. The mediation effect was then investigated in this study using the bootstrapping method.

Table 4: The Mediating Effects.

No.	Hypothesis	β	SD	P-value	95% LLCI	95% ULCI	Result
H5	IP -> PU -> LPI	.113***	.029	.000	.064	.178	Supported
H7	IP -> PE -> LPI	.108***	.031	.000	.055	.179	Supported
	Total effect	0.464***	0.053	.000			
	Direct effect	.222***	.043	.000			Partial Mediation

The total effect of influencer popularity on purchase intention is significant ( $\beta$  = 0.464\*\*\*, p < 0.001), the indirect effect  $\beta$  = .113\*\*\* (LLCI = .064, ULCI = .178), and the confidence interval of the indirect effect does not include 0, indicating that perceived uncertainty plays a partial mediating role between influencer popularity and purchase intention (Preacher & Hayes, 2008). As well as perceived enjoyment ( $\beta$  = .108\*\*\*, LLCI = .055, ULCI = 0.179) partially mediates the relationship between influencer popularity and purchase intention. Thus, H5, H7 are supported, see Table 4. Product information quality ( $\beta$  = -.219\*\*\*, p < 0.001) significantly moderate the relationship of influencer popularity to perceived uncertainty. Thus, H8 is supported. Meanwhile, Product information quality ( $\beta$  = .201\*\*, p < 0.01) also significantly

moderate the relationship of influencer popularity to perceived enjoyment. Thus, H9 is supported, see Table 5.

No.	Hypothesis	β	SD	P-value	Result
H2	IP -> PU	-0.315***	0.049	0.000	Supported
H3	IP -> PE	0.453***	0.055	0.000	Supported
H18	PIQ*IP-> PU	-0.219***	0.042	0.000	Supported
H19	PIO*IP-> PE	0.201**	0.059	0.001	Supported

Table 5: The Moderating Effects.

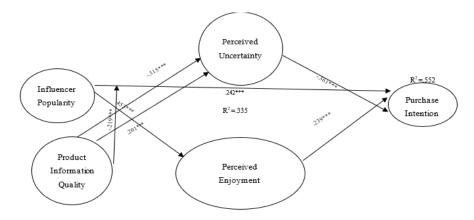


Figure 2: Structural Model Results.

#### Conclusion

This study examined the impact of perceived uncertainty, perceived enjoyment, and product information quality on the popularity of live streaming influencers and its influence on audiences' purchase intention. The study yielded intriguing results. The results offer additional evidence regarding the impact of influencer popularity. The popularity of influencers plays a crucial role in live streaming shopping by reducing audience perceived uncertainty and increasing their perceived enjoyment. Consistent with previous studies (Hill et al., 2017; Ladhari et al., 2020; Nguyen, 2021), this research also observed a positive correlation between influencer popularity and purchase intention. This study investigated the mediators of perceived uncertainty and enjoyment on audiences' purchase intention. The results aligned with the S-O-R theory, indicating that the association between influencer popularity and purchase intention was partially influenced by perceived uncertainty and perceived enjoyment, respectively. This study supports the notion that high-quality information is crucial in determining the connection between influencer

popularity, perceived uncertainty, and perceived enjoyment.

# **Contribution of the Study**

This study has two theoretical contributions. This study contributes to the existing S-O-R literature by examining the impact of influencer popularity on purchase intention, both directly and indirectly through perceived uncertainty, in the context of live streaming. Additionally, existing literature has highlighted the significant influence of information quality on consumer purchase intention. However, this study further identifies the potential moderating role of product information quality. Previous research has shown that the quality of product information influences purchase intention (Xu et al., 2020). This study introduces product information quality as a novel moderator. The findings indicate that the quality of product information plays a significant role in moderating the relationship between influencer popularity and audiences' perceived uncertainty and enjoyment. This finding further contributes to recognizing the quality of product information.

This study has two managerial implications. Cosmetic companies can recruit popular influencers from the live streaming industry to leverage their large following and positive public image. These influencers have the ability to influence their followers' purchasing intentions by recommending products. Audiences exhibit less uncertainty towards influencers compared to cosmetic companies. These platforms are considered authentic due to their provision of valuable content creation and various benefits, such as advice and tutorials, in live streaming. Audiences express uncertainty towards cosmetics due to the inability to try them on in an online environment. However, live streaming influencers have the opportunity to personally test the products. The influencer's demonstration of different lipstick colours can reduce audiences' uncertainty. Influencers who demonstrate the application of cosmetics to enhance their appearance can enhance audiences' perceived enjoyment. As a result, their intention to purchase will increase. Furthermore, it is imperative for the live streaming sector to deliver high-quality information to influencers. Providing accurate and complete information enables the audience to evaluate products effectively. Live streaming sessions collect detailed information that can enhance the

shopping experience, reduce uncertainty, and increase purchase intention.

#### **Limitations and Future Research**

The study also has a few limitations. This study included only female respondents, while live streaming sessions can have both male and female audience members. Therefore, future studies should consider including male respondents. Additionally, it is recommended to expand the scope of the study beyond cosmetic products to include other product categories. This is because influencers utilise live streaming sessions to promote and sell various types of products. Furthermore, the study focused exclusively on the Taobao live streaming platform for its investigation. Taobao and Douyin are popular Chinese live streaming retail platforms. However, there are other emerging platforms that warrant further investigation.

# **Data Availability**

Data will be made available on request. Please contact <u>gs58063@student.</u> <u>upm.edu.my</u>.

#### **Conflict of Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

# **Ethical Approval**

The right forms were obtained on the website (<a href="http://www.tncpi.upm.edu.my/faildokumen">http://www.tncpi.upm.edu.my/faildokumen</a>) in order to obtain the required approval from the UPM ethical committee. The research was authorized by the university's ethics committee on 25th September 2022.

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# Appendix

Construct	Items	Sources					
	The live streaming influencer I like:	Г					
Inf	has a big fan club.						
Influencer Popularity	2. has a lot of followers.	har					
one	3. has a non-controversial image.	i e					
er	4. is likable.	(EI) t al (20)					
$\mathbf{Po}_{\mathbf{j}}$	5. is good-looking and charming.	NGUYEN (2020); hari et al. (2020); (2021)					
рul	6. has a lot of likes under each published video.	202					
lari	7. has high appeal and influence.	9, 0,					
ty	8. is a role and ideal model for others.	NGUYEN (2020); Ladhari et al. (2020); Ma (2021)					
	9. is well-known in social media such as Douyin and Weibo.	•					
_	I feel that the live streaming demonstration presented by my favorite	N 1					
Perceived Uncertainty	influencer has reduced my uncertainty about:	Zhang et al. (2019); Lu and Chen (2021); Dimoka et al. (2012)					
cei	1. the cosmetics' quality.	ind					
veo	2. the product will look different in real life from how it looks in the live streaming.	hang et al. (2019); L and Chen (2021); Dimoka et al. (2012)					
7.	3. the cosmetics will not perform as I expect it to perform.	al. her					
nc	4. whether the cosmetics fit my physical appearance.	) (2 al.					
ert	5. whether the lipsticks would match my tastes.	019					
ain	6. the influencer has not fully disclosed this cosmetics defects.	1); 1); 012					
र्म्	7. the influencer will not deriver the product as promised in a timery martier.	) lu					
	8. the influencer will not follow through on all of her promises and guarantees.						
	The live streaming demonstration presented by my favourite influencer is						
Pe	enjoyable where it is:	Ma (2021); Wagner et al. (2017)					
erco	1. the influencer makes me feel comfortable like a friend.	(2)					
eiv	2. the influencer makes me exciting by very positive in responding to questions	021					
Perceived Enjoyment	from our audiences.	(20					
En	3. the cosmetics recommended by the influencer make me happy.	<i>N</i> a )17					
joy	4. the words of the influencer describing cosmetics are very funny.	) 9110					
Ħ H	5. the influencer's teaching session about makeup is very appealing.	er e					
ent	6. the activities (such as, give small gifts, limited time promotion, etc.) in the live	<u>a</u>					
	streams are very interesting.						
	7. a good approach for relieving boredom.  The demonstration performed by my favourite influences on Tachae live streaming.						
	The demonstration performed by my favourite influencer on Taobao live streaming	$\odot$ $\overset{\sim}{\times}$					
Produc	platform is providing excellent Fashion (such as cosmetics) information:  1. Policible ingredient information for cosmetic products.	Xu et al. (2022);					
du	1. Reliable ingredient information for cosmetic products.  2. Complete information about the function of this face mask (For example, can	t al (2);					
-	2. Complete information about the function of this face mask (For example, can remove your acne and wrinkles).	$\circ$					
[nf	3. Live video accurately shows different color of lipsticks.	.02(					
orn	4. Various usage of the lipstick (For example, show you how to use lipstick as	)); an					
nat	blush and eye shadow).	d C					
Information Quality	5. Real information of influencer's use experience on cosmetics.	. (2020); Zhang and Cho Chen and Chang (2018)					
Õ	6. Detailed teaching information of makeup steps.	ing					
ua	7. Clear product information about price.	(2) hd					
lity	8. Professional product test information, such as mascara, or eyeliner waterproof test.	Ch 018					
~	9. The right product information to solve my skin problem.	· 😊 2.					
Purchase Intention	I have high intention to purchase from live streaming:  1. as soon as possible.						
rch		Ma (2021); Lu and Chen (2021); Sun et al. (2020)					
las(	3. with extra amount of spending.	(2021); Lu 1 (2021); Su al. (2020)					
ıI ë	4. as my preferred mode of shopping in the future.	1); )21 (20)					
ıte	5. is worth buying.	Lu ); S 20)					
nti	6. as the first choice for future purchase.	un l					
on	7. as I would recommend live streaming shopping to friends.	rd et					
	7. as I would recommend five streaming snopping to mends.						