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Live streaming commerce and consumers' purchase intention: An uncertainty reduction perspective

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ABSTRACT

The fusion of live streaming and e-commerce is booming. However, it remains unclear how live streaming affects consumers' purchase intention (PI) in online markets of clothes and cosmetics. On the basis of signaling theory and uncertainty literature, we propose broadcasters' physical characteristics conveyed through vicarious product trials and values shared via instant interaction as two signals that can help reduce product uncertainty and cultivate trust for the consumers with similar physical traits and values. The analysis of survey and interview data largely supports the hypotheses. This research contributes to the literature of live streaming commerce, uncertainty literature, and signaling theory.

1. Introduction

The widespread proliferation of live streaming has boosted its fusion with marketing campaigns and driven a boom in e-commerce economies [1-3]. Industrial reports have revealed that the market size of live streaming commerce in China reached 433.8 billion yuan in 2019 and is expected to reach more than 900 billion yuan in 2020 [4, 5]. Live streaming is especially efficient in introducing and selling experience products, such as clothes and cosmetics. For instance, in 2019, the sales volume of clothes and cosmetics accounted for nearly 60% of Taobao's live streaming sales [6].

This phenomenon is in sharp contrast to the relatively low purchase rate of these experience products on traditional e-commerce platforms [6], where consumers perceive high uncertainty [7-9]. For example, consumers may wonder whether they look good in wearing specific clothes, or they may be unsure about the trustworthiness of a seller. On the contrary, in live streaming commerce, broadcasters can achieve huge turnover by eliminating these uncertainties. For example, Jiaqi Li, a famous broadcaster, sold 15,000 lipsticks in five minutes during his live streaming show. Most of the viewers will not hesitate to buy a product as long as it is recommended by Jiaqi Li [6]. Therefore, how broadcasters reduce perceived uncertainty of consumers and largely improve the online purchase of clothes and cosmetics in live streaming commerce is an interesting topic to explore. The research on live streaming commerce is still in its infancy. Extant studies mainly identify predictors of purchase intentions (PIs) from the perspectives of IT platforms and consumers [1, 3, 10, 11]. Only a few studies focus on the role of broadcasters in influencing PI [2]. To extend the latter research line, this study examines how broadcasters' features help to reduce perceived uncertainty and improve PI in live streaming commerce.

Practically speaking, broadcasters influence consumers through two routes. Some consumers purchase because of the quality and features of products per se, whereas others purchase owing to influence created by the broadcasters. The former route is product-centered, in which the broadcasters usually vicariously try products for consumers [3]. The main difference between the trial of broadcasters and that of the models shown on traditional e-commerce websites lies in the term "vicarious." In live streaming commerce, broadcasters' physical characteristics conveyed through vicarious product trials act as key signals to persuade consumers with similar features that the clothes or cosmetics that suit broadcasters will suit them as well. The latter route is social-interaction centered. Broadcasters develop trust with consumers through synchronous social interaction afforded by live streaming [2]. Consumers who trust a broadcaster will be certain that the broadcaster will recommend the right products with good quality for them and tend to purchase. The two routes also evolve into two modes of live streaming commerce in China: live streaming embedded in e-commerce (e.g., Taobao live, JD live, etc.) and e-commerce integrated into live streaming (e.g., Douyin, Kuaishou, etc.) [12, 13].

This study adopts signaling theory to explore the above-mentioned phenomena. Perceived uncertainty is due to a lack of information. Signals convey information that helps reduce uncertainty [14, 15]. Thus,

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Table 1
Comparison between live streaming commerce in China and that in other countries.

Dimensions	Industrial scale	Government support	Degree of specialization	Development of different business modes
Live streaming commerce in China	Large scale with explosive growth	National policies implemented	High degree of specialization	Highly mature
Live streaming commerce in other countries	Initial stage of development	Limited	Low degree of specialization	Less mature

we use signaling theory to examine how broadcasters convey different signals to decrease different types of uncertainty that are well-documented as main inhibitors of PI. Specifically, in the product route, we postulate that broadcasters' physical characteristics act as salient signals released via vicarious product trials. Consumers who feel similar in physical characteristics with the broadcasters experience a low degree of product fit uncertainty, which is expected to improve PI. In the social route, broadcasters' personal values shared via instant interaction are deemed as an efficient signal. Consumers' perceived value similarity helps them judge whether the broadcasters are trustworthy or not, as the principle of similarity attraction states that people trust those who have attitudes similar to theirs [16]. The trust is expected to reduce product quality and fit uncertainty, further increasing PI.

This study makes several contributions to extant literature. First, it focuses on the predictors of purchasing experience products (i.e., clothes and cosmetics) in live streaming commerce, which is a bottleneck in developing e-commerce [6]. Extant live streaming commerce literature focuses on the predictors of purchasing general products and does not consider specific product categories [1-3, 11, 13]. Second, considering the critical role of broadcasters in product recommendation, this study examines the effects of broadcasters' features on purchase intention, while previous research mainly identifies the predictors of purchase intention in live streaming commerce from the perspectives of platforms and consumers [1, 3, 10, 11]. Third, previous research has applied various theories to investigate the antecedents of PI in live streaming commerce, such as IT affordance [1], consumer motivation theory [13], flow theory [10], and so on. Our study is one of the few that adopt signaling theory and uncertainty literature to understand the predictors of consumers' PI. Based on the signaling theory, we identify two different signals (i.e., physical characteristics and values) delivered by broadcasters in live streaming commerce, which help reduce online consumers' uncertainty and improve PI. Last, this study identifies the dual routes in live streaming commerce, namely, product and social routes, through which broadcasters can release signals (i.e., physical characteristics and values) to induce consumers' PI. This supplement is meaningful to live streaming marketing literature.

The remainder of the paper is organized as follows. We provide a review of the literature related to our current research. We then propose the research model and discuss the constructs and hypotheses. The subsequent section elaborates upon our research method and describes the research site for collecting empirical data. We present the statistical analyses and provide the related discussion concerning the results. Finally, we conclude the paper with a summary of our research contributions, limitations, and potential future directions.

2. Related literature

To investigate whether and how live streaming affects consumers' PI considering the product and social routes, we relate this study to three themes in the research literature: (1) live streaming commerce, (2) uncertainty in online markets, and (3) signaling in e-commerce.

2.1. Live streaming commerce

Live streaming is a type of user-generated content [17, 18]. As a special combination of multiple media forms, live streaming involves a broadcaster who uploads real-time video content, which includes games, talent performances, daily life, and so on [17, 18]. During streaming, broadcasters can engage in dialogues and interact with their audience, while the audience can interact with the broadcaster and other viewers in real-time by sending text messages [17, 19].

The academic community has paid growing attention to live streaming. The research efforts have mainly focused on exploring the antecedents of audiences' continuous engagement [18-21]. As live streaming offers a real-time watching experience for audiences and opportunities to communicate and socialize among broadcasters and other audiences, the frequent interactions among different participants are deemed as efficient elements in attracting and maintaining an audience [17, 20, 22].

The rise of live streaming has also boosted its fusion with marketing campaigns [1-3]. The product and social routes are two salient ways to induce consumers' PI, and they evolve into two modes of live streaming commerce in China: live streaming embedded in e-commerce and e-commerce integrated into live streaming [12, 13]. Specifically, live streaming embedded in e-commerce indicates that live streaming is embedded in e-commerce platforms as an alternative approach to fully introduce products. Typical examples include Amazon live, Taobao live, and JD live. By contrast, e-commerce integrated into live streaming means that e-commerce business is embedded in live streaming platforms. For example, Facebook live, Douyin, and Kuaishou have incorporated e-commerce business into their live streaming platforms. Besides product introduction, the social culture embedded in the live streaming platforms enables broadcasters to acquire consumer value by cultivating "broadcaster–consumer" relationships [12].

In reality, with the first-mover advantage of e-commerce, the live streaming commerce in China differs significantly from that in other countries. We summarize these differences in Table 1.

Overall, the live streaming commerce in China is experiencing the development of blowout and is expected to reach more than 900 billion yuan in 2020 [4, 5]. Realizing the huge potential of live streaming commerce in stimulating economic development, the Chinese government has promulgated and implemented various national policies to support it [5, 6]. The most typical example is that live streaming commerce has appeared in the "2020 Chinese Government Work Report" as a national strategy in targeted poverty alleviation [23]. By contrast, live streaming commerce in other countries is still at an initial stage of development, and national policy support is also limited.[1] From the perspective of specialization, live streaming commerce has become a specialized profession in China, and the government and related e-commerce companies, such as Taobao and JD, have implemented customized training service programs for live streaming practitioners [5, 12]. On the contrary, live streaming commerce in other countries is still at a low degree of specialization, and related streaming activities are always broadcaster self-operated without professional training [24]. For the development of different business modes, both modes of live streaming commerce are mature in China [12]. For the live streaming embedded in e-commerce, most of the leading Chinese e-commerce platforms, such as Taobao, Jing Dong (JD), Jumei, and Mogujie have incorporated live streaming into their websites. However, in other countries, only Amazon live stands out as an example. Integration of e-commerce into live streaming has been demonstrated as a very successful practice in China [5, 12]. For example, the broadcaster sellers on

[1] Source: https://www.agriterra.org/Live_stream_e-commerce/

Table 2
Summary of related studies in live streaming commerce.

Study	Research focus	Data sources	Theoretical lens	Major findings	Considering clothes and cosmetics as a specific context	Multi-methods analysis	Considering vicarious trial (product route) and value sharing (social route)
Sun et al. [1]	Customers' purchase intentions	Live streaming from Taobao, JD, Mogujie, and Sina Microblog in China.	IT affordance	Live streaming visibility affordance, metavoicing affordance, and guidance shopping affordance can influence customer purchase intention through live streaming engagement.	N.A.	N.A.	N.A.
Wongkitrungrueng and Assarut [24]	Consumers' engagement	Facebook live streaming in Bangkok, Thailand.	Value theory, trust	Symbolic value has a direct and indirect effect via trust in sellers on customer engagement, while utilitarian and hedonic values affect customer engagement indirectly through customer trust in products and trust in sellers sequentially.	N.A.	N.A.	N.A.
Park and Lin [2]	Consumer attitudes	Live streaming from Taobao and Yizhibo in China.	Celebrity endorsement and match-up hypothesis	Product-source fit affects the perceived source attractiveness and trustworthiness, while product content fit affects utilitarian and hedonic attitudes toward the content. Source trustworthiness, hedonic attitude and self-product fit increased the purchase intention.	N.A.	N.A.	N.A.
Cai et al. [13]	Consumers' purchase intention	Live streaming commerce in Facebook, YouTube, Twitch, etc.	Consumer motivation theories, Technology Acceptance Model (TAM)	Hedonic motivation is positively related to celebrity-based intention and utilitarian motivation is positively related to product-based intention.	N.A.	N.A.	N.A.
Li et al. [10]	Consumers' consumption intention of virtual gifts	Live streaming platforms in China.	Flow theory	Flow mediates the effects of interactivity, social presence, curiosity, and social media dependence on the consumption intention of virtual gifts.	N.A.	N.A.	N.A.
Chen et al. [3]	Consumers' purchase intention	Live streaming commerce in China.	Human-computer interaction	Value compatibility, consumption experience transmission and product presentation positively affect consumers' purchase intention during live streaming shopping.	N.A.	N.A.	N.A.
Xu et al. [11]	Consumers' hedonic consumption, impulsive consumption, and social sharing	Live streaming commerce in China	Stimulus–organism–response paradigm	Hedonic consumption and social sharing behavior are determined by emotional energy and cognitive assimilation. These cognitive and emotional states are influenced by information quality, broadcaster attractiveness, and para-social interaction.	N.A.	N.A.	N.A.
This study	Consumers' purchase intention	Live streaming commerce in China.	Signaling theory, uncertainty theory, trust	Consumers' PPCS improves PI by reducing consumers' perceived product fit uncertainty, whereas PVS improves PI by increasing trust between consumers and broadcasters.	Yes	Structural equation modeling analysis, multi-group analysis, qualitative case analysis.	Yes

the Kuaishou platform always call their consumers "Laotie" (similar to "homie"), which is a specialized appellation to indicate the close relationships between broadcasters and consumers. Although Facebook live and Twitch have also set foot in the field of e-commerce [13, 24], the mainstream social gene embedded in these platforms still advocates personal life sharing among peers [19].

Given the development of live streaming commerce, adequate research attention has been paid to this emerging topic (Table 2). Existing studies mainly consider consumers' engagement and PI as the outcomes during live streaming commerce [1, 2, 10, 11, 13]. The potential influencing factors include IT-enabled functions or mechanisms (e.g., visibility [1], guidance shopping [1], interactivity [10]), product-related factors (e.g., product values [24], product uncertainty [25], product presentation [3]), consumer-related factors (e.g., utilitarian and hedonic motivations [13], emotional energy, cognitive assimilation [11]), and broadcaster-related factors (e.g., broadcaster-product match [2]). In sum, although a broadcaster plays an important role in live streaming commerce, broadcaster-related factors gain relatively less attention compared with other factors.

Table 2 shows that our research differs from existing studies in the following aspects: (1) this study specifically focuses on clothes and cosmetic markets. On the one hand, clothes and cosmetics are typical experience products with unstandardized attributes that are usually more uncertain compared with search products in online markets [9]. Although the sales volume of clothes and cosmetics usually accounts for a large proportion of the live streaming commerce sales, the purchase rate of these products on traditional e-commerce websites is relatively low [6]. On the other hand, live streaming provides an efficient approach for broadcasters to fully display and introduce products for consumers, especially for clothes and cosmetics (e.g., vicarious product trials), which may help consumers better evaluate the products. Therefore, investigating whether and how live streaming affects consumers' PI in clothes and cosmetic markets is practically meaningful.

(2) we simultaneously consider the broadcaster's vicarious product trial (product route) and value sharing (social route) in live streaming commerce. The two modes of live streaming commerce present two routes (i.e., product and social routes) that may induce consumers' PI. However, the working of these two processes remains unclear. Focusing on clothes and cosmetic markets, and based on signaling theory and uncertainty literature, we propose that broadcasters' physical characteristics conveyed through vicarious product trials and values shared via instant interaction as two signals in product route and social route, respectively. We also postulate that consumers' perceived physical characteristic similarity (PPCS) and perceived value similarity (PVS) with the broadcasters improve PI through product uncertainty reduction and trust cultivation between broadcasters and consumers.

(3) We use multiple analysis methods to fully excavate and validate the results. Most of the prior studies in this area usually adopted structural equation modeling (SEM) analysis based on survey data [1, 2, 11, 13], which may be insufficient to validate the results. Therefore, we applied structural equation modeling analysis, multi-group analysis, and qualitative case analysis. Specifically, SEM analysis is adopted to test the research hypotheses, multi-group analysis is used to further excavate the results, and qualitative case analysis acts as an efficient complement to validate the hypotheses. We believe that such a multi-method analysis can generate valid and robust results.

In the following sections, we review the related theoretical basis of this study, including uncertainty in online markets and signaling in e-commerce.

2.2. Uncertainty in online markets

Uncertainty refers to the degree to which the future states of the environment cannot be accurately predicted because of imperfect information [26]. In the online marketplace, consumers' perceived uncertainty is generally deemed as the degree to which the outcome of a transaction cannot be predicted by consumers owing to seller and product uncertainty [8].

Seller uncertainty arises when the buyer cannot fully monitor the seller's behaviors, and it is defined as "the buyer's difficulty in assessing the seller's true characteristics and predicting whether the seller will act opportunistically" [8]. Seller-related uncertainty may lead to adverse selection and moral hazards in online markets [27, 28]. Pavlou et al. [7] analyzed uncertainty in online markets from a principal-agent perspective and postulated that consumers' perceived information asymmetry, fear of seller opportunism, and information privacy and security concerns are significant antecedents of seller uncertainty. Trust has been proposed as an efficient factor that can help mitigate seller uncertainty. As the sellers' true quality information is typically private to themselves, buyers can also use different strategies, such as feedback from previous buyers [29] and positive/negative seller rating score [30], to minimize risks in online transactions.

Product uncertainty is closely interrelated with seller uncertainty and is defined as the consumer's difficulty in evaluating product attributes and predicting how a product will perform in the future [8, 9]. Multiple dimensions of product uncertainty have been proposed, including product description uncertainty, performance uncertainty, and fit uncertainty. Product description uncertainty occurs when the seller is unable to represent the product characteristics online, while product performance uncertainty arises from a buyer's concerns about a product's performance [8]. Along this line, Hong and Pavlou [9] further added product fit uncertainty, which originates from a buyer's concerns on whether a product (or its characteristics) matches her/his needs. Product uncertainty is a major impediment to online markets, especially for experience products that cannot be perfectly evaluated before they are purchased. In reducing product uncertainty, Dimoka et al. [8] found that the diagnosticity of product description and third-party product assurances can help reduce a product's description and performance uncertainty in online used car markets. In terms of product fit uncertainty, online media and online product forums can be adopted to attenuate the effects of product type (i.e., experience vs. search goods) on product fit uncertainty [9].

Uncertainty in online markets has a direct influence on price premium [8], product return [9], and consumers' PI [31]. In this study, consumers may have product uncertainty and seller uncertainty during live streaming. Consumers own imperfect knowledge about the product quality and whether the product is fit for them, especially for experience products (e.g., clothes and cosmetics). Moreover, consumers may be unsure about whether a broadcaster is trustworthy during live streaming transactions. Therefore, mitigating product uncertainty and cultivating trust with broadcasters can significantly contribute to the success of live streaming commerce. In this research, we propose broadcasters' physical characteristics conveyed through vicarious product trials and values shared via instant interaction as two signals that can help attenuate product and seller uncertainties, respectively.

2.3. Signaling in E-commerce

The signaling theory has been widely applied in economics, management, and marketing disciplines, helping explain the influence of information asymmetry in a wide array of research contexts [14]. Signals are usually deemed as the features of an object that can be manipulated or altered according to a signaler's preferences, which can convey the hidden or limited quality information of one object to another [15]. In seller-buyer relationships, signaling theory has been used to understand the types of signals that sellers provide to buyers to reduce information asymmetry and help buyers make more accurate assessments of quality when information about products is limited [15, 32].

In the e-commerce context, information asymmetry becomes more salient due to physical isolation between buyers and sellers [14, 32]. In general, product quality and seller quality are two major sources of information asymmetry in online markets [32]. Signaling theory is applied in situations of uncertainty and it explains how signals can be applied to influence the buyers' attitude toward the signaling party. Traditional market signals include unconditional money-back guarantee [33], branding, and advertising [34]. In e-commerce, the concept of signals is extended. Various types of signals have been introduced, such as online Word of Mouth (WOM [35]), online product description [8], third-party assurances [8], promotion policy, and money-back guarantee [14].

In this study, we propose broadcasters' physical characteristics conveyed through vicarious product trials and values shared via instant interaction as two signals that are useful in alleviating the product uncertainty and cultivating trust with broadcasters in a live streaming commerce context. On the one hand, the broadcaster's vicarious product trial provides consumers an efficient way to better evaluate whether the product is fit for them through comparing physical similarities with the broadcasters. On the other hand, consumers' perceived value similarity with the broadcasters can help cultivate trust between them, that is, reduce consumers' uncertainty about the broadcasters.

3. Research model and hypotheses

Live streaming commerce is reshaping the business environment. The two modes of live streaming commerce present two routes (i.e., product and social routes) to induce consumers' PI. In this study, we propose broadcasters' physical characteristics conveyed through vicarious product trials and values shared via instant interaction with consumers as two signals in product route and social route, respectively. We also postulate that consumers' PPCS and PVS with the broadcasters improve PI through product uncertainty reduction and trust cultivation with broadcasters.

Product route: Live streaming allows broadcasters' vicarious product trial for consumers. For example, a consumer can search for a broadcaster seller who shares the physical similarities (e.g., weight, height, etc.) to try a T-shirt for her/him, then s/he can directly observe the dress on effect of this T-shirt. In such a process, the most salient signal that the broadcaster release is the physical characteristics. Consumers may evaluate the products by comparing the physical characteristic similarity between themselves and the broadcaster. Therefore, we conceptualize and define the concept of consumers' *Perceived Physical Characteristic Similarity* as their perceived similarity between themselves and the broadcasters in terms of related physical characteristics. With respect to PPCS, consumers can evaluate product fit uncertainty through related physical characteristic similarity judgments during a live session. In this study, *Product Fit Uncertainty* refers to a consumer's concerns on whether a product (or its characteristics) matches her/his needs and suitable for her/him [9].

Social route: "Broadcaster–consumer" relationship is important in live streaming commerce. Live streaming allows different broadcasters to share their values with the consumers, such as the "fit and healthy" value shared by a seller of fitness clothes and the "youth is fashion" value conveyed by a seller of fashion wear. These values are the significant signals released by the broadcasters, through which consumers may feel close with the broadcasters if they hold similar values. Therefore, we conceptualize and define the concept of consumers' *Perceived Value Similarity* as the extent to which consumers think that they share similar values with broadcasters. PVS is cultivated through an instant interaction between consumers and broadcasters. Shared values can help build trust between consumers and broadcasters. When a consumer trusts a seller, the trust may directly affect the consumer's PI. The products recommended by the seller are also be treated with less uncertainty in quality and fit, that is, the trust can help reduce consumers' perceived product quality and fit uncertainty. In this study, *Product Quality Uncertainty* refers to a consumer's concerns about a product's performance in the future.[2]

We propose that consumers' perceived product fit uncertainty, quality uncertainty, and trust toward the broadcaster significantly affect consumers' PI. In the following section, we elaborate on the hypotheses.

3.1. Perceived physical characteristic similarity and product fit uncertainty

Product fit uncertainty generally arises when consumers have insufficient information to evaluate whether a product fits them in online contexts [9]. Product fit uncertainty is more salient for experience products (e.g., clothes and cosmetics) [36] because the attributes of these products are not standard compared with search products. For example, a consumer may feel less uncertain regarding whether a smartphone is fit for her/him because the attributes of smartphones (e.g., size, color, storage, pixel, etc.) are standard and consumers can evaluate them in advance. By contrast, a consumer may feel more uncertain about whether clothes or cosmetics fit her/him without a personal trial in advance.

Live streaming provides a useful solution to product fit uncertainty issues by enabling broadcasters' vicarious product trials. Specifically, live broadcasters usually act as models to try the products for the consumers. In this study, we deem the physical characteristics of the broadcasters as salient signals. By releasing such signals, broadcasters convey observable cues for consumers to evaluate whether a product fits them by comparing themselves with the broadcasters. Consumers' PPCS with the broadcasters will show a direct impact on consumers' evaluation of product fit uncertainty. If the consumers perceive that they share similarities with the broadcasters in terms of physical characteristics, they will obtain an accurate comparison target to evaluate the products. For example, a consumer who wants to purchase a dress can easily observe how the dress will look on her and whether it is suitable for her by comparing herself with a similar broadcaster in terms of body shape. Hence, we propose the following hypothesis:

H1: Consumers' perceived physical characteristic similarity with the broadcaster is negatively related to their perceived product fit uncertainty.

3.2. Perceived value similarity and trust

To attract and cultivate intimacy with the consumers, sharing values during live streaming has been a successful practice for broadcasters to establish their personal image [12]. For example, the "fit and healthy" value shared by a seller of fitness clothes advocates that if one wants to be healthy, one should exercise. The "youth is fashion" value conveyed by a seller of fashion wear praises the value of youth. From a signaling perspective, the sharing of these value signals helps broadcasters attract consumers with similar values and cultivate intimacy between them. In this study, we propose that value similarity is positively related to the trust formation between consumers and broadcasters [16].

Prior empirical evidence also suggests that value similarity can enhance feelings of trust [37-40]. Some researchers reported that shared language and vision have positive effects on benevolence- and competence-based trust [40]. Others showed a strong correlation of PVSto social trust [37-39]. In this research, we postulate that consumers' PVS with the broadcasters is positively related to their trust toward the broadcasters. First, consumers' PVS with the broadcasters will trigger their perceptions of the broadcasters as members who understand and share their worldview, which will further facilitate the formation of

[2] According to the definition of product quality uncertainty, consumers' PPCS with the broadcaster cannot help reduce product quality uncertainty. Consumers who perceive physical characteristic similarity with the broadcaster will obtain more accurate information cues to evaluate whether the products are fit for them. However, such physical cues cannot help consumers evaluate the products' future performance (i.e., quality uncertainty).

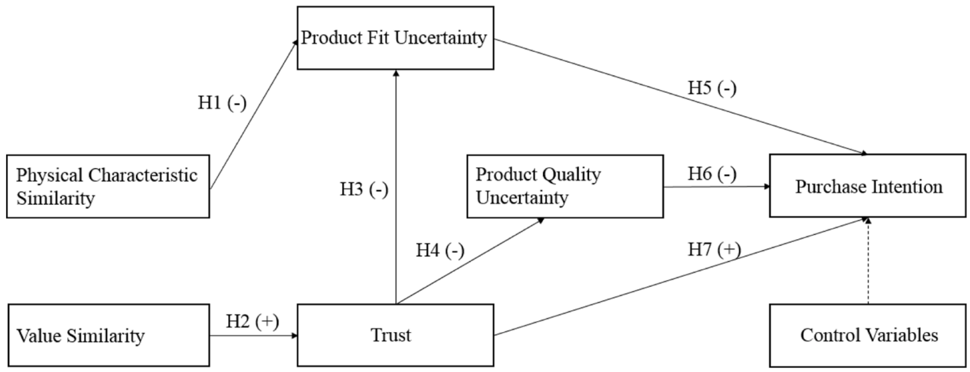

Fig. 1. Research Model.

identification-based trust [40]. Second, consumers' PVS with the broadcasters ensures a high level of shared language and topics [41] between the consumers and broadcasters. Research reveals that people with a shared language may feel a close bond with one another in terms of both competence and benevolence [40]. Third, consumers' PVS with the broadcasters can make interactions more rewarding by improving the interaction quality, efficiently reducing potential uncertainty between consumers and broadcasters [42], thereby contributing to the formation of trust relationships [43]. Therefore, we propose the following hypothesis:

H2: Consumers' perceived value similarity with the broadcaster is positively related to their trust toward the broadcaster.

3.3. Trust and product uncertainty

In online markets, product uncertainty is directly related to sellers [8, 44]. For example, due to sellers' inability to provide concrete information, consumers cannot fully evaluate whether the products have been fully described and whether they can perform consistently well in the future as described by the seller [8]. Meanwhile, consumers are also concerned about whether the seller has fully considered their personal needs and recommended a product that matches their preferences [9]. Therefore, the reduction of seller uncertainty may significantly contribute to the reduction of product uncertainty. Numerous studies have shown that building an intimate relationship and cultivating trust toward the seller is an efficient way to reduce seller uncertainty and that trust in online markets is based on beliefs in the seller's trustworthiness, which includes three dimensions: integrity, ability, and benevolence [45, 46].

During live streaming, all products are introduced and recommended by the broadcasters, and the consumers' trust toward the broadcaster plays a salient role in reducing product uncertainty. When consumers cultivate trustworthiness toward broadcasters, they will believe that the broadcasters can fully describe and evaluate the products and reveal the real quality of the products. Meanwhile, with their trust in the broadcasters, consumers will tend to believe that the broadcasters will have their personal needs and preferences in mind and recommend products specifically suitable for them [45, 46]. The consumers' trust toward broadcasters will efficiently help reduce product fit and quality uncertainty during live streaming. Based on the notion, we propose the following hypotheses:

H3: Consumer's perceived trust toward broadcasters is negatively related to their perceived product fit uncertainty.

H4: Consumer's perceived trust toward broadcasters is negatively related to their perceived product quality uncertainty.

3.4. Product uncertainty and purchase intention

In this study, PI is defined as the consumer's intention to purchase from a broadcaster. PI is a direct determining factor of actual purchase behaviors [47]. Product uncertainty (i.e., product fit and quality uncertainty) is one of the most important utilitarian aspects that consumers consider during the online shopping process. Specifically, product fit uncertainty generally arises when consumers have insufficient information to evaluate whether a product suits them, which is especially a salient issue for experience products in online contexts, such as clothes and cosmetics [9]. Product quality uncertainty refers to a consumer's concerns about a product's future performance [8]. The effects of product uncertainty have been extended from price premium [8] to buyer satisfaction, product return, and PI [9]. Therefore, if consumers feel a high degree of product fit and quality uncertainty, they may have a low intention to buy these products. Hence, we propose the following hypotheses:

H5: Consumer's perceived product fit uncertainty is negatively related to their purchase intention;

H6: Consumer's perceived product quality uncertainty is negatively related to their purchase intention.

3.5. Trust and purchase intention

In addition to product uncertainty, we propose that consumers' trust toward the broadcasters can also directly affect their PI. In online transactions, trust can be viewed as a significant antecedent belief that creates a positive attitude toward the transaction behavior [48, 49], which leads to purchase intentions. Prior studies have revealed that trust is related to purchase intentions [50, 51]. Gefen and Heart [52] revealed that integrity affects consumers' intention to engage in a purchase, and the ability affects intentions to inquire about the product without actual purchase. The consumers' trust toward broadcasters can help reduce the social complexity and vulnerability that consumers perceive in the e-commerce context. Consumers can subjectively rule out any undesirable, yet potential, behaviors of broadcaster sellers. As such, trust can help consumers reduce their risk perceptions when dealing with online broadcaster sellers, thus encouraging them to engage with broadcasters, such as sharing information or making purchases [64]. Therefore, we propose the following hypothesis:

H7: Consumer's perceived trust toward broadcasters is positively related to their purchase intention.

The proposed research model is depicted in Fig. 1. We also control the potential effects of consumers' gender, age, education, income, online shopping experiences, and live streaming watching frequency.

4. Data and measurement

4.1. Data collection

In this study, we consider live streaming commerce platforms in China as the research targets, specifically live streaming embedded in e-

Table 3
Demographics of respondents ($N = 535$).

Items		Live Streaming Embedded in E-commerce ($N = 241$)		E-commerce Integrated into Live Streaming ($N = 294$)	
		Frequency	Percentage	Frequency	Percentage
Gender	Male	15	6.22%	23	7.82%
	Female	226	93.78%	271	92.18%
Age	Under 25	21	8.71%	47	15.99%
	25–34	189	78.42%	199	67.69%
	35–44	29	12.03%	43	14.63%
	45 or older	2	0.83%	5	1.70%
Education Level	Second school	3	1.24%	0	0
	Junior college	16	6.64%	28	9.52%
	Bachelor	203	84.23%	109	37.07%
	Master	19	7.88%	151	51.36%
	PhD	0	0	6	2.04%
Income Level (Yuan)	Under 5000	41	17.01%	50	17.01%
	5000–9999	132	54.77%	185	62.93%
	10,000–14,999	42	17.43%	38	12.93%
	15,000–19,999	20	8.30%	13	4.42%
	20,000 or higher	6	2.49%	8	2.72%
Online Shopping Experience (Year)	Under 1	3	1.24%	0	0
	1–2	9	3.73%	12	4.08%
	2–3	19	7.88%	42	14.29%
	3–4	44	18.26%	42	14.29%
	4 or higher	166	68.88%	198	67.35%
Live Streaming Watching Frequency	Very low	16	6.64%	31	10.54%
	Slightly low	167	69.29%	28	9.52%
	Medium	35	14.52%	206	70.07%
	Slightly high	13	5.39%	12	4.08%
	Very high	10	4.15%	17	5.78%

Table 4
Constructs and items.

Constructs	Items	Constructs	Items
Perceived physical characteristic similarity	I find that the broadcaster shares similar physical characteristics with me; There are similarities between the broadcaster and me with respect to physical characteristics; I can hardly find any physical characteristic similarities between the broadcaster and me (reverse).	Perceived value similarity [37-39]	I find that the broadcaster thinks in a similar way as I do; I find that the broadcaster has the similar goals as me.
Perceived product quality uncertainty [8]	Broadcaster's recommendation helped to represent the products' characteristics (reverse); I am concerned that the products will look different in real life from how it looks on broadcaster; Based on the broadcaster's recommendations, I am not sure that the products will look good on me as I expect.	Perceived product fit uncertainty [9]	I'm concerned that the products broadcaster recommended would not match my tastes; I feel that the products broadcaster recommended would fit my preference (reverse); Broadcaster's product recommendations cannot reduce my concerns about whether the products fit for me or not.
Trust [45]	The broadcaster is like a real expert in assessing the products; The broadcaster keeps my interests in mind; I consider this broadcaster to possess integrity.	Purchase Intention [54]	I am very likely to buy the products from the broadcaster; I would consider buying the products from the broadcaster in the future; I intend to buy the products from the broadcaster.

commerce platforms (e.g., Taobao live, JD live, etc.) and e-commerce integrated into live streaming platforms (e.g., Douyin, Kuaishou, etc.) are considered. Taobao and JD are the two largest e-commerce companies in China, which have incorporated live streaming functions into their platforms. Douyin and Kuaishou are the two leading live streaming platforms in China and they have embedded e-commerce business in their platforms. We consider these two modes of live streaming commerce for the following reasons: 1) Both modes of live streaming commerce enable consumers to get access to detailed and vivid product information and conduct transactions via live streaming. 2) Despite the similarity, live streaming embedded in e-commerce usually focuses on the introduction of products, whereas e-commerce integrated into live streaming emphasizes relationships between broadcasters and consumers. The difference between these two modes of live streaming commerce will engender further insights regarding how live streaming affects consumers' PI via product and social routes.

We adopted the survey method to obtain sample data. Our questionnaire includes 17 self-report items. In addition to the main constructs, we included consumers' gender, age, income level, education level, experience in online shopping, and live streaming watching frequency in the survey. Since the survey was conducted in China, the questionnaire was translated into Chinese first, and then a backward translation was conducted to ensure consistency between the Chinese and English versions [1].

During data collection, we put the questionnaire on the Wenjuanxing website (https://www.wjx.cn/). Wenjuanxing is one of the largest data collection websites in China [1]. We chose the professional data collection service offered by Wenjuanxing, which helped us randomly select live streaming shopping users and remove invalid questionnaire responses. To ensure the suitability of potential respondents, we included pre-screening questions that ask consumers if they had watched live streaming commerce for clothes or cosmetics in the past three days and which platform(s) they had watched from. Only those who reported "yes" were given access to the questionnaire. These consumers were then instructed to answer questions by recalling their latest experience of live streaming commerce watching experience for clothes or cosmetics in the past three days. We also included three questions to identify invalid responses: they were similarly expressed to their genuine counterparts in the questionnaire but had opposite meanings. If respondents gave the same answers to these three questions as to their

Table 5
Descriptive analysis of the constructs.

Variables	V1	V2	V3	V4	V5	V6
Mean	5.026	5.279	5.527	2.432	2.464	5.597
Standard Deviation	1.321	1.133	0.916	0.859	0.837	0.966
Cronbach's alpha	0.930	0.842	0.835	0.781	0.850	0.909
rho_A	0.936	0.843	0.835	0.797	0.854	0.911
VIF	1.168	1.000	1.333	1.768	1.689	–
V1: PPCS	0.937					
V2: PVS	0.381	0.929				
V3: PT	0.380	0.559	0.867			
V4: PPQU	−0.333	−0.446	−0.595	0.833		
V5: PPFU	−0.347	−0.441	−0.568	0.552	0.877	
V6: PI	0.280	0.379	0.529	−0.500	−0.473	0.920

Table 6
Factor cross loadings.

	PPCS	PVS	PT	PPQU	PPFU	PI
PPCS_1	0.906	0.345	0.371	−0.312	−0.326	0.255
PPCS_2	0.956	0.377	0.372	−0.336	−0.353	0.287
PPCS_3	0.947	0.346	0.319	−0.282	−0.289	0.240
PVS_1	0.359	0.931	0.513	−0.372	−0.371	0.350
PVS_2	0.350	0.928	0.525	−0.456	−0.447	0.355
PT_1	0.347	0.499	0.869	−0.501	−0.489	0.447
PT_2	0.320	0.508	0.861	−0.520	−0.479	0.479
PT_3	0.320	0.446	0.872	−0.526	−0.511	0.451
PPQU_1	−0.326	−0.444	−0.514	0.861	0.497	−0.437
PPQU_2	−0.302	−0.376	−0.504	0.895	0.419	−0.446
PPQU_3	−0.281	−0.333	−0.476	0.841	0.458	−0.356
PPFU_1	−0.275	−0.390	−0.552	0.499	0.885	−0.487
PPFU_2	−0.250	−0.269	−0.409	0.486	0.883	−0.338
PPFU_3	−0.304	−0.438	−0.507	0.468	0.862	−0.405
PI_1	0.244	0.376	0.493	−0.471	−0.460	0.923
PI_2	0.242	0.323	0.460	−0.444	−0.410	0.918
PI_3	0.286	0.346	0.507	−0.464	−0.434	0.920

Table 7
Heterotrait-Monotrait (HTMT) ratio.

	PPCS	PVS	PT	PPQU	PPFU	PI
PPCS						
PVS	0.430					
PT	0.429	0.666				
PPQU	0.387	0.540	0.727			
PPFU	0.387	0.517	0.674	0.673		
PI	0.302	0.433	0.606	0.583	0.535	

answers to the genuine items, their questionnaire was classified as invalid. In total, 535 valid questionnaires were received from June 18, 2020 to July 5, 2020. Table 3 provides the basic description of samples.

4.2. Measurement items

In this study, measurement items for PPCS were developed according to the process proposed by Moore and Benbasat [53] (Appendix A). Items for PVS were adapted from Earle and Cvetkovich [37-39]. Items for PPQU were adapted from Dimoka et al. [8], who focused on the description and performance uncertainty of specific products. Items for PPFU were adapted from Hong and Pavlou [9]. Items for perceived trust (PT) were adapted from Benbasat and Wang [45], and the items for consumers' PI were adapted from Liao et al. [54]. The concrete measurement items for each construct are listed in Table 4.

5. Results and discussion

5.1. Measurement model

As self-reported data were collected in a cross-sectional survey, common method bias may exist [55]. According to Liang et al. [56] and Loh et al. [57], Harmon one-factor test was conducted on the six constructs in our theoretical model including PPCS, PVS, PPFU, PPQU, PT, and PI. Results showed that six factors are present and the most covariance explained by one factor is 21.47%, indicating that common method biases are not a likely threat to our results. In addition, we added a common method factor whose indicators included all the principal constructs' indicators in the model and calculated each indicator's variances substantively explained by the principal construct and by the method. The results revealed that the ratio of substantive variance to method variance was about 58:1. Therefore, common method bias is not a risk in this study.

Following Liang et al. [58] and Armstrong and Overton [59], we compared the demographic variables between the first 100 and last 100 respondents. T-tests show that the two groups do not differ in age ($p = 0.102$), online shopping experience ($p = 0.129$), income ($p = 0.937$), and live streaming watching frequency ($p = 0.878$). Chi-square tests show that the two groups do not differ in gender ($p = 0.239$) and education ($p = 0.342$). These results suggest that nonresponse bias is not likely an issue in this study.

We assessed the convergent validity of the constructs by examining the average variance extracted (AVE) and the internal consistency of the indicators using the Dijkstra-Henseler's rho (rho_A). As shown in Table 5, all rho_A and AVE values fulfilled the recommended threshold values. To evaluate the discriminant validity, the AVE should be compared with the square of the correlation among the latent variables [60]. The diagonal elements of Table 5 contain the square root of the AVE. All AVEs are greater than the off-diagonal elements in the corresponding rows and columns, demonstrating the discriminant validity. Another way to evaluate the convergent and discriminant validity is to examine the factor loadings of each indicator. Each indicator should load higher on the construct of interest than on any other factor [60]. Factor loadings and cross-loadings for the multi-item measures were calculated and are shown in Table 6. Inspection of loadings and cross-loadings confirms that the observed indicators have adequate discriminant and convergent validity. Finally, the discriminant validity was examined with the heterotrait-monotrait ratio of correlations (HTMT). Table 7 showed that the HTMT values ranged from 0.302 to 0.727 as they were all below 0.850, thereby reconfirming discriminant validity [61].

5.2. Structural equation model

The proposed hypotheses were tested using the structural equation modeling with the SmartPLS software. The goodness of fitness using the Kolmogorov–Smirnov test for all the measurement items was less than 0.05, indicating the non-normal distribution of data in this research [57]. SmartPLS is commonly used for structural equation modeling and can handle small-sample and non-normal data [62]. The test results are listed in Table 8. For control variables, such as consumers' gender, age, educational level, income level, frequency of watching live streaming, and online shopping experience have no significant effect on consumers' PI in live streaming shopping. Moreover, all hypotheses are significantly supported. The consumers' PPCS with the broadcaster shows a significant negative influence on their PPFU ($\beta = -0.153$, $p < 0.001$), whereas their PVS has a significant positive effect on consumers' PT toward broadcasters ($\beta = 0.559$, $p < 0.001$). Consumers' PT toward broadcasters negatively affects their PPFU ($\beta = -0.510$, $p < 0.001$) and PPQU ($\beta = -0.595$, $p < 0.001$). Finally, consumers' PPFU ($\beta = -0.188$, $p < 0.01$) and PPQU ($\beta = -0.217$, $p < 0.01$) show significant negative influence on consumers' PI, whereas consumers' PT toward broadcasters has a significant positive effect on PI ($\beta = 0.289$, $p < 0.001$). The variances explained for trust, product fit uncertainty, product quality uncertainty, and PI were 0.311, 0.341, 0.353, and 0.353, respectively. The model fitness indexes, including SRMR (Standardized Root Mean Square Residual) =0.052, RMS Theta=0.100, and NFI (Normed Fit Index) =0.911

Table 8
The results of structural equation modeling analysis ($N = 535$).

Hypotheses	Path	Bias-corrected Confidence Intervals (95%)	STDVE	β
–	Gender -> PI	[−0.134, −0.011]	0.031	−0.072
–	Age ->PI	[−0.079, 0.059]	0.035	−0.009
–	Education ->PI	[−0.131, 0.003]	0.034	−0.062
–	Income ->PI	[−0.043, 0.090]	0.033	0.022
–	Frequency -> PI	[−0.120, 0.047]	0.042	−0.038
–	Experience -> PI	[−0.072, 0.071]	0.036	−0.003
H1	PPCS -> PPFU	[−0.228, −0.078]	0.038	−0.153***
H2	PVS ->PT	[0.483, 0.626]	0.037	0.559***
H3	PT -> PPFU	[−0.604, −0.415]	0.049	−0.510***
H4	PT -> PPQU	[−0.658, −0.521]	0.035	−0.595***
H5	PPFU -> PI	[−0.302, −0.078]	0.058	−0.188**
H6	PPQU -> PI	[−0.346, −0.090]	0.066	−0.217**
H7	PT -> PI	[0.151, 0.415]	0.068	0.289***

* $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$.

were obtained. These indices reflect an appropriate model fit according to some generally accepted criteria (SRMR<0.100; NFI>0.900; RMS Theta<0.120) [63].

5.2.1. Importance-performance map analysis

Importance–Performance Map Analysis (IPMA) is conducted to extend the PLS-SEM results by considering the performance of each construct [64]. The computation of performance values is carried out by rescaling the latent variable scores to a range between 0 and 100 [65]. For a specific criterion construct, the IPMA contrasts the structural model total effects (importance) and the average values of the latent variable scores (performance) to highlight significant areas to improve management activities [66]. To increase the analyzed endogenous latent variables' performance level in the future, actions should be taken along lines that have relatively high importance and relatively low performance [64].

Fig. 2 illustrates that the construct total effects of perceived product fit uncertainty, quality uncertainty, and trust on PI are −0.188, −0.217, and 0.514, respectively. The construct performances of perceived product fit uncertainty, quality uncertainty, and trust in affecting PI are 28.632, 28.958, and 72.013, respectively. Trust is highly relevant for increasing PI owing to its major impact. However, this area already has a high performance, so the potential for further increase is relatively minor. In addition, product fit uncertainty is relatively more important than product quality uncertainty in affecting PI. Nevertheless, the performance of both factors is low, suggesting major improvement potential.

Table 9
The analysis of alternative paths ($N = 535$).

Hypotheses	Path	Bias-corrected Confidence Intervals (95%)	STDVE	β
H1	PPCS -> PPFU	[−0.231, −0.077]	0.039	−0.153***
H2	PVS -> PT	[0.485, 0.624]	0.036	0.559***
H3	PT -> PPFU	[−0.597, −0.409]	0.048	−0.510***
H4	PT -> PPQU	[−0.659, −0.525]	0.035	−0.595***
H5	PPFU -> PI	[−0.290, −0.067]	0.058	−0.178**
H6	PPQU -> PI	[−0.338, −0.069]	0.069	−0.206**
H7	PT -> PI	[0.124, 0.400]	0.071	0.264***
–	PPCS -> PI	[−0.043, 0.122]	0.042	0.037
–	PVS -> PI	[−0.058, 0.150]	0.053	0.045

* $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$.

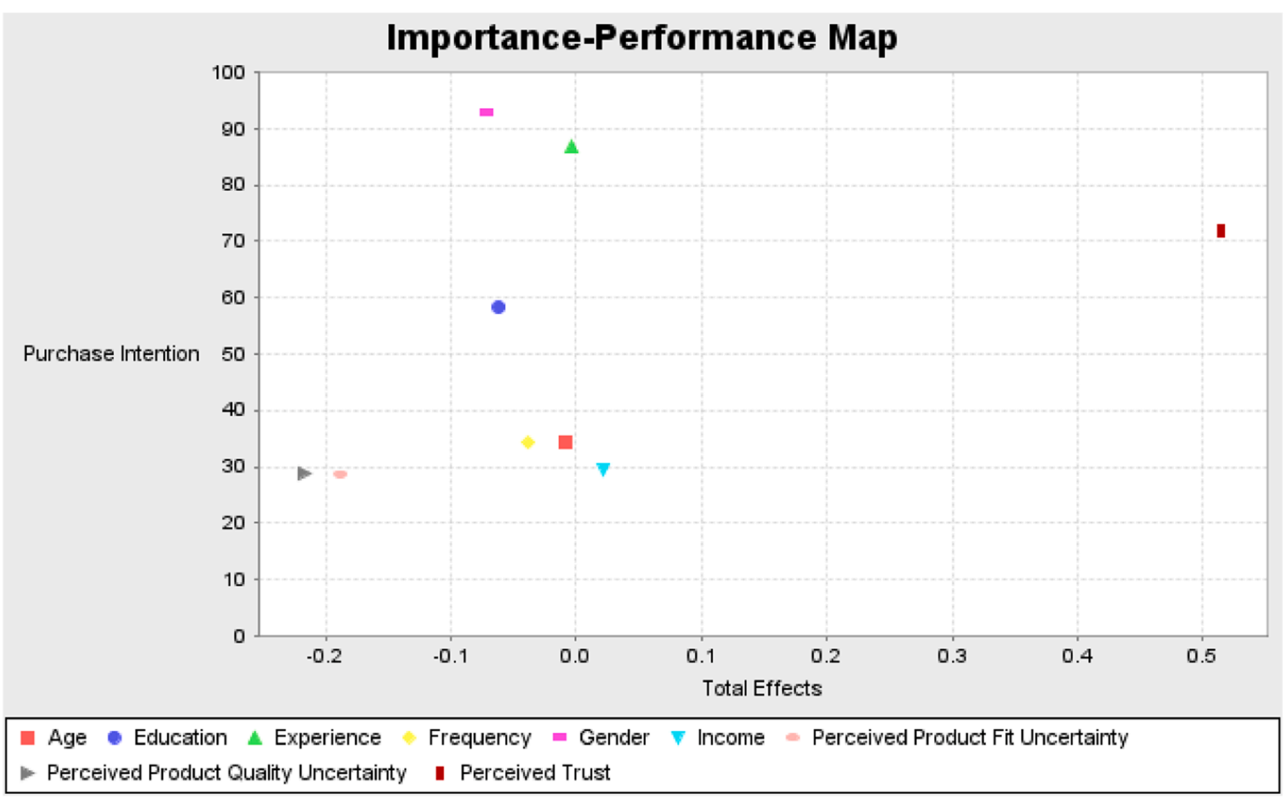

Fig. 2. Importance-Performance Map Analysis of PI.

Table 10
Measurement invariance for clothes and cosmetics groups.

Composite	Correlation c value (=1)	Bias-corrected 95% confidence interval	Permutation p-value	Compositional invariance?
Compositional invariance				
PPCS	1.000	[0.999, 1.000]	0.297	Yes
PVS	1.000	[0.999, 1.000]	0.982	Yes
PPFU	1.000	[0.999, 1.000]	0.777	Yes
PPQU	1.000	[0.998, 1.000]	0.142	Yes
PT	1.000	[1.000, 1.000]	0.102	Yes
PI	1.000	[1.000, 1.000]	0.764	Yes
Composite	Mean difference between the two groups	Bias-corrected 95% confidence interval	Permutation p-value	Equal mean values?
Scalar invariance				
PPCS	0.016	[−0.164, 0.161]	0.867	Yes
PVS	−0.024	[−0.169, 0.173]	0.765	Yes
PPFU	−0.046	[−0.173, 0.182]	0.613	Yes
PPQU	−0.138	[−0.180, 0.173]	0.115	Yes
PT	0.096	[−0.166, 0.170]	0.290	Yes
PI	−0.026	[−0.169, 0.169]	0.759	Yes
Composite	Variance difference between the two groups	Bias-corrected 95% confidence interval	Permutation p-value	Equal variance?
PPCS	−0.063	[−0.226, 0.202]	0.561	Yes
PVS	−0.007	[−0.261, 0.251]	0.970	Yes
PPFU	−0.148	[−0.384, 0.362]	0.428	Yes
PPQU	−0.294	[−0.401, 0.399]	0.169	Yes
PT	−0.294	[−0.372, 0.357]	0.132	Yes
PI	−0.266	[−0.464, 0.443]	0.258	Yes

5.3. *Additional analysis*

5.3.1. *Alternative model*

To exclude other possible explanations, alternative model paths were also tested (Table 9), including the direct path from PPCS to PI and from PVS to PI. We found that the influence of these two paths was insignificant, while the influences of the remaining paths were consistent with those in the original research model. These findings indicated that the mechanisms underlying consumers' perceived similarity with the

Table 12
Measurement invariance for the two modes of live streaming commerce.

Composite	Correlation c value (=1)	Bias-corrected 95% confidence interval	Permutation p-value	Compositional invariance?
Compositional invariance				
PPCS	1.000	[0.999, 1.000]	0.680	Yes
PVS	1.000	[0.999, 1.000]	0.654	Yes
PPFU	1.000	[0.999, 1.000]	0.430	Yes
PPQU	1.000	[0.998, 1.000]	0.652	Yes
PT	1.000	[1.000, 1.000]	0.394	Yes
PI	1.000	[1.000, 1.000]	0.680	Yes
Composite	Mean difference between the two groups	Bias-corrected 95% confidence interval	Permutation p-value	Equal mean values?
Scalar invariance				
PPCS	0.001	[−0.185, 0.166]	0.992	Yes
PVS	0.128	[−0.176, 0.165]	0.129	Yes
PPFU	0.095	[−0.162, 0.163]	0.265	Yes
PPQU	−0.010	[−0.175, 0.174]	0.909	Yes
PT	−0.035	[−0.178, 0.168]	0.680	Yes
PI	0.056	[−0.176, 0.166]	0.544	Yes
Composite	Variance difference between the two groups	Bias-corrected 95% confidence interval	Permutation p-value	Equal variance?
PPCS	0.024	[−0.222, 0.225]	0.827	Yes
PVS	−0.150	[−0.269, 0.280]	0.283	Yes
PPFU	−0.160	[−0.353, 0.358]	0.424	Yes
PPQU	0.028	[−0.406, 0.408]	0.876	Yes
PT	−0.010	[−0.370, 0.369]	0.961	Yes
PI	−0.151	[−0.432, 0.458]	0.516	Yes

Table 11
The results of Multi-Group Analysis between different types of products (N_Cosmetics=229, N_Clothes=306).

Path	Group (cosmetics)			Group (clothes)			β-difference
	Bias-corrected 95% confidence interval	STDVE	β	Bias-corrected 95% confidence interval	STDEV	β	
PPCS -> PPFU	[−0.236, −0.013]	0.058	−0.127*	[−0.260, −0.060]	0.051	−0.162*	0.035
PVS ->PT	[0.509, 0.693]	0.047	0.610***	[0.419, 0.625]	0.051	0.531***	0.078
PT -> PPFU	[−0.665, −0.435]	0.059	−0.553***	[−0.613, −0.348]	0.068	−0.491***	−0.062
PT -> PPQU	[−0.672, −0.459]	0.054	−0.580***	[−0.684, −0.504]	0.045	−0.605***	0.025
PPFU -> PI	[−0.380, 0.017]	0.092	−0.193*	[−0.319, −0.056]	0.067	−0.189**	−0.003
PPQU -> PI	[−0.303, −0.021]	0.084	−0.148*	[−0.416, −0.087]	0.086	−0.247**	0.100
PT -> PI	[0.147, 0.482]	0.085	0.319***	[0.073, 0.432]	0.093	0.262**	0.056

* $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$.

Table 13
The results of Multi-Group Analysis between different modes of live streaming commerce (N_ e-commerce integrated into live streaming =294, N_ live streaming embedded in e-commerce =241).

Path	Group (e-commerce integrated into live streaming) Bias-corrected 95% confidence interval	STDVE	B	Group (live streaming embedded in e-commerce) Bias-corrected 95% confidence interval	STDEV	β	β-difference
PPCS -> PPFU	[−0.212, −0.003]	0.053	−0.106*	[−0.316, −0.100]	0.056	−0.209*	0.103
PVS ->PT	[0.532, 0.706]	0.043	0.631***	[0.359, 0.589]	0.059	0.482***	0.148*
PT -> PPFU	[−0.587, −0.336]	0.063	−0.472***	[−0.686, −0.412]	0.070	−0.555***	0.083
PT -> PPQU	[−0.646, −0.467]	0.046	−0.569***	[−0.718, −0.516]	0.051	−0.629***	0.060
PPFU -> PI	[−0.353, −0.040]	0.079	−0.198*	[−0.329, −0.034]	0.077	−0.181*	−0.017
PPQU -> PI	[−0.310, −0.010]	0.077	−0.164*	[−0.462, −0.068]	0.102	−0.273*	0.109
PT -> PI	[0.117, 0.514]	0.100	0.315**	[0.098, 0.443]	0.090	0.273**	0.042

* $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$.

broadcaster to their final PI were consistent and reasonable as we have elaborated. In addition, a direct link between perceived value similarity and product fit uncertainty isn't significant in our model. Having similar value by the broadcaster and consumers does not imply that the consumers would deliver the same image as the broadcasters do when wearing the same clothes. The fit between the product and consumer still depends on the similarity between the perceived physical characteristics.

5.3.2. *Product type*

The samples in this research comprised clothes and cosmetics, both of which are typical experience products. To verify whether product type (i.e., clothes and cosmetics) affect the results, we further conducted a PLS Multi-Group analysis (PLS-MGA). PLS-MGA was used to analyze the difference and significance of group-specific PLS path model estimations. Before conducting multi-group analysis, measurement invariance needs to be established. For this purpose, we conducted the Measurement Invariance for Composite Models (MICOM), described by Henseler, Ringle, and Sarstedt [67], to test measurement invariance based on the permutation algorithm. MICOM is used to determine whether significant intergroup differences are due to inter-group differences in constructs when assessing composite models. The values of Table 10 corroborate the configural,[3] compositional and scalar invariance assuring "full measurement invariance" [68].

Based on the establishment of measurement invariance, we conducted PLS-MGA analysis. The results are listed in Table 11. We found that the results on both groups are consistent with that on the whole sample, meanwhile, no significant differences appeared between the two groups, indicating that our research model has good robustness across different types of products.

5.3.3. *Platform type*

The two typical modes of live streaming commerce in China are live streaming embedded in e-commerce (e.g., Taobao live, JD live, etc.) and e-commerce integrated into live streaming (e.g., Douyin, Kuaishou, etc.). To verify whether the effects on whole samples still exist on different modes of live streaming commerce platforms, we further conducted a PLS-MGA. Measurement invariance was also established according to the applicable procedure in clothes and cosmetics sub-group analysis (Table 12). The PLS-MGA analysis results shown in Table 13 indicates that most of the effects of two different modes remain consistent with that on the whole sample. An exception is that the positive effect of consumers' PVS on trust is more salient on the samples from e-commerce integrated into live streaming platforms compared with that from live streaming embedded in e-commerce platforms.

5.4. *Post hoc analysis*

To complement the survey data analysis, we conducted a follow-up interview with a selected group of 15 active users of live streaming commerce. The criterion for selecting users was whether they purchased clothes or cosmetics at least once from live streaming commerce platforms over the past three days. Only those participants who answered "yes" were given access to the interview. All the users were presented with two examples in terms of live streaming commerce for clothes and cosmetics, with the objective to evoke their impression about the specific context.

In the formal interview, the first question was:

What are the product-related and broadcaster-related factors that affect your purchase?

For the product-related factors, 12 respondents mentioned that if the products recommended by the broadcaster matched their needs and preferences, that is, the products recommended by the broadcaster nicely fit them (i.e., low product fit uncertainty), they would purchase. Meanwhile, 10 respondents mentioned that if the products recommended by the broadcasters were good in quality (i.e., low product quality uncertainty), they would purchase. For example, one of the respondents recalled that "*I'm always troubled with dry skin issues, the reason that I want to buy this skin care cosmetic is that it is very suitable for dry skin protection, which just meets my needs*" (product fit). Another respondent also said that "*the fashion wear jacket I bought is good in quality, and the size and color fit me as well*" (product quality and fit).

Along with the product-related factors, we asked the following question:

How do you evaluate the product fit and quality uncertainty during live streaming shopping? For product fit uncertainty, 12 respondents admitted that broadcasters' vicarious product trial provides them opportunities to evaluate the products, and physical characteristic similarity between the consumers and broadcasters plays a significant role in product fit uncertainty evaluation. As one respondent recalled, "*when I tell the broadcaster the measurement information of my body, she just invites another broadcaster with a similar figure to try the clothes for me. Therefore, I can directly evaluate whether the clothes suit me through comparing myself and the broadcaster regarding related physical traits.*"

Evaluating product quality uncertainty is closely related to broadcaster-related factors. Specifically, 13 respondents indicated that the broadcaster was professional in live streaming (i.e., competence-based trust), 10 respondents postulated that the broadcasters will consider their preferences (i.e., benevolence-based trust), and nine respondents believed that the broadcasters are honest and will not cheat during live streaming shows (i.e., integrity-based trust). For example, one respondent said that "*I believe in the broadcaster, she is very professional in introducing, evaluating, and recommending lipsticks, she knows what I need*" (competence-based and benevolence-based trust). Another one recalled that "*I think the broadcaster has a clear idea of what kind of cosmetics suits me, and the quality of the products she recommends are guaranteed*" (benevolence-based and integrity-based trust). In sum, consumers' multi-dimensional trust toward the broadcaster affects their

[3] Running MICOM in SmartPLS usually automatically establishes configural invariance. The statistical output does not apply to this step and is not shown.

product evaluation (e.g., quality and fit uncertainty) and purchase decisions.

Similarly, we further asked another question as given below:

What affects your trust toward the broadcaster?

Ten respondents confirmed that value similarity between themselves and broadcasters is important in increasing their trust toward broadcasters. For example, one respondent said that "*the broadcaster always advocates that 'buy the right one instead of the expensive one' during the live streaming, which is similar with my consumption value. Therefore, I think that we are similar and trust her.*"

Overall, the above qualitative analysis further supported our proposed hypotheses. In addition, we selected the persons who have purchase behavior during live streaming commerce shows of clothes or cosmetics over the past three days as the interviewees. All questions were based on the purchase experience. Thus, the results of the qualitative study also established a link between consumers' PI and behavior.

6. Discussion

This study examines how live streaming affects consumers' PI by considering product uncertainty reduction and trust cultivation between consumers and broadcasters. Our analysis is based on a structured survey data set and unstructured interview data set from live streaming commerce users in China. We used structural equation modeling and qualitative analyses to verify the research model. Specifically, H1 is supported, indicating that consumers' PPCS shows a significant negative effect on product fit uncertainty. Consumers usually have product uncertainties online. Different from prior research identifying Internet-enabled systems as solutions to relieve product fit uncertainty [9], broadcasters showed efficient physical characteristic signals through vicarious product trials for consumers in the current study. Consumers can then evaluate product fit uncertainty by comparing similarities between their physical characteristics and the broadcasters'. H2 is supported, indicating that consumers' PVS shows a significant positive impact on consumers' trust toward the broadcasters. In live streaming commerce, broadcasters often release value signals by sharing their values with consumers in real-time two-way communications. According to the principle of similarity-attraction [16, 42], consumers may evaluate whether the broadcaster is trustworthy by comparing value similarity between themselves and the broadcasters. Hypotheses H3 and H4 are also supported, suggesting that consumers' trust toward the broadcasters shows significant negative influences on product quality and fit uncertainty. As suggested, product uncertainty is always closely related to seller uncertainty [7, 8]. If a consumer trusts a broadcaster, then the consumer will believe that the broadcaster is competent in introducing and evaluating the products and considers consumers' preferences and needs when recommending products. In this case, the product fit and quality uncertainty are significantly reduced. H5 and H6 are also supported, this demonstrates that consumers' perceived product fit and quality uncertainty negatively affect consumers' PI. Consistent with prior studies [8, 9], when consumers feel uncertain regarding product quality and fit, their PI will be weakened. Finally, consumers' trust toward the broadcaster shows a significant positive effect on PI, supporting H7. By uncovering the significant impacts of product fit uncertainty, product quality uncertainty, and trust on PI, the IPMA results further revealed that trust is more important compared with product fit and quality uncertainty in affecting PI. By contrast, the performance of product fit uncertainty and quality uncertainty is relatively low compared with trust in affecting PI, suggesting major improvement in these two areas.

In addition, the PLS-MGA analysis for different modes of live streaming commerce reveals that the positive effect of consumers' perceived value similarity on trust is more salient on the samples from e-commerce integrated into live streaming platforms compared with that from live streaming embedded in e-commerce. Such a result is reasonable considering the characteristics of e-commerce integrated into live streaming. Besides product introduction, e-commerce integrated into live streaming emphasizes the relationships between consumers and broadcasters [12]. Therefore, the effect of consumers' perceived value similarity on trust is more salient in the samples from this group.

7. Theoretical and practical implications

This research provides several theoretical contributions. First, it contributes to the literature of live streaming commerce by developing a theoretical model that uncovers how live streaming affects consumers' PI through product uncertainty reduction and trust cultivation in the context of clothes and cosmetic markets. Although prior studies direct attention to explore related factors that may affect consumers' PI or engagement in live streaming commerce, few of them consider specific product categories [1-3, 11, 13], such as clothes and cosmetics. Clothes and cosmetics account for a large proportion of live streaming commerce markets. The special characteristics of these products make it meaningful to explore how live streaming affects consumers' PI toward these products. Second, this study examines the effects of broadcasters' features on purchase intention, while previous research mainly identifies the predictors of purchase intention in live streaming commerce from the perspectives of IT platforms and consumers [1, 3, 10, 11]. Considering that live streaming enables broadcasters' vicarious product trial and instant interaction, broadcasters' physical characteristics conveyed through vicarious product trial and values shared via instant interaction are postulated as two signals that may induce consumers' PI. Third, this research contributes to the uncertainty literature by identifying two kinds of similarities as antecedents. In the earlier e-commerce literature, various factors were proposed which demonstrated efficiency in reducing uncertainties [7-9]. This study further complements this area by postulating consumers' PPCS and PVS as two factors that may help reduce product uncertainty and trust cultivation. Fourth, this research contributes to signaling literature in the e-commerce context. Specifically, by identifying the dual routes in live streaming commerce, we propose that broadcasters' physical characteristics and values as two signals in product route and social route, respectively. In e-commerce literature, various signals have been proposed and investigated [14, 15, 32]. However, considering the novel context of live streaming commerce, to the best of our knowledge, this study is the first one to consider broadcasters' physical characteristics and values as useful signals. Meanwhile, we conceptualized and developed a preliminary scale for consumers' PPCS and applied it to live streaming commerce. Although it was restricted in a specific context in this study, with the rapid development of social media-enabled marketing campaigns, PPCS can be also applied to a broader range of contexts, for example, user-generated images on traditional e-commerce websites.

This study generated several practical implications. The results derived from this study suggest that consumers' PPCS and PVS are efficient in reducing product uncertainty and trust cultivation. However, the IPMA results further showed that the efforts devoted to trust cultivation will bring in less benefit. This is because trust already has a high performance so that there is relatively minor potential for further increase. By contrast, although product fit and quality uncertainty is less important in affecting PI compared with trust, the low performance of these two factors suggests major improvement potential, especially for "product fit uncertainty." Therefore, a practical implication for the broadcaster is to "create" more physical characteristic similarities with the consumers. For example, one can arrange other models with various body shapes to try the clothes for consumers during a live session. Similarly, for the platforms, designing and embedding certain functions that may help consumers evaluate product fit uncertainty are welcomed. For example, the platforms can add virtual product trial models whose physical characteristics can be changed by parameters. Thus, broadcasters can flexibly adjust the physical characteristics of virtual models to attempt different products for consumers. In addition, efforts should be directed at maintaining the performance level of trust or even expanding it. This will be especially meaningful for live streaming embedded in e-commerce platforms because the effect of PVS on trust is less salient for live streaming embedded in e-commerce than for e-commerce integrated into live streaming. Therefore, actively communicating with consumers and sharing appropriate personal values during a live session is important for broadcasters as the strategies can help stimulate consumers' emotional resonance with them. Platforms can also encourage broadcasters to set up positive social images by sharing personal values.

8. Limitations and future directions

This study suffers from few limitations. First, the research context was restricted to the market for clothes and cosmetics. Although clothes and cosmetics account for a large proportion of the live streaming commerce market, other kinds of products exist. Future research should adjust and modify the current research model and apply it to other scenarios. Second, our sample was from Chinese live streaming commerce participants, which may potentially restrict the external validity of the research findings. The live streaming commerce in China is more developed compared with that in other countries, and most prior studies in this area also focus on the Chinese context. Nonetheless, future research can consider live streaming users in other countries to validate whether the current research model has good external validity. Along this line, future research may integrate the cultural difference within the model, as the current samples are generally Chinese culture oriented. A comparative investigation between Chinese culture and western culture may provide further insights.

9. Conclusion

Live streaming commerce has emerged as a novel form of online marketing. Based on signaling and uncertainty literature, we conceptualized and postulated consumers' PPCS and PVS with broadcasters as two facets that can reduce product uncertainty and cultivate trust. The two routes linking PPCS, PVS, and PI were verified through structured survey data and unstructured interview data.

Overall, this research contributes to live streaming commerce literature by uncovering the potential mechanisms of how live streaming affects consumers' PI. The research also provided useful practical implications for broadcasters and platforms on how to enhance consumers' PI by leveraging related live streaming characteristics.

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Appendix A

Measurement items for perceived physical characteristic similarity (PPCS) were developed according to the rigorous process proposed by Moore and Benbasat [53]. Specifically, there are three stages: item pool generation, scale development, and scale testing. Item pool generation is the creation of pools of items for an instrument by identifying items from existing scales or making items that fit the definition of that construct. Scale development involves panels of judges to sort the items from the first stage into separate categories based on the similarities and differences among items. Any inappropriately worded or ambiguous items will be eliminated during this stage. Testing is the evaluation of the reliability of the scale.

Item pool generation

In the study, consumers' perceived similarity includes both PPCS and PVS; hence, we simultaneously consider PPCS and PVS in the whole development process. We originally generated 5 items for PPCS. Through dropping some conceptually overlapped items, 3 items remaining. Meanwhile, 2 items of PVS were adapted from previous studies [37-39]. In total, 5 items were generated for the sorting procedure (Table A.1).

Table A.1
Item pool.

Items
I find that the broadcaster shares similar physical characteristics with me.
I find that the broadcaster thinks similarly as I do.
There are similarities between the broadcaster and me with respect to physical characteristics.
I find that the broadcaster has similar goals as me.
I can hardly find any physical characteristic similarities between the broadcaster and me.

Item Sorting

Round 1:

In the first round, we did not provide the definitions of initial categories (i.e., PPCS, PVS), and the judges were allowed to classify the items into different categories and label these categories according to their comprehension. Specifically, four judges were involved, and they were two PhD students from the marketing and IS discipline, one professor, and one business employee. This range of backgrounds was chosen to ensure that a range of perceptions would be included in the analysis.

All four judges classified the items into two categories and independently labeled and defined each of their categories. The independent judges' category labels and definitions were very closely matched with those of the original constructs (i.e., PPCS, PVS), demonstrating good content validity. The inter-judge raw agreement scores averaged 1, Kappa scores averaged 1, and the initial overall placement ratio of items within the target constructs was 100% (Table A.2).

Table A.2
First-round item placement ratios.

Theoretical Categories	Actual Categories	TOT	TGT		
	Perceived Physical Characteristic Similarity	Perceived Value Similarity	N/A		
Perceived Physical Characteristic Similarity	12			12	100%
Perceived Value Similarity		8		8	100%
Total Item Placements: 20	Hits: 20	Overall Hit Ratio: 100%			

Round 2:

In the second round, four new judges were invited to sort the items based on the initial construct definitions given (i.e., PPCS, PVS). A "too ambiguous/doesn't fit" category was also included to ensure that the judges did not feel compelled to fit any item into a particular category. Examination of the sorting showed high agreement among the judges. The inter-judge raw agreement scores averaged 1, Kappa scores averaged 1, and the initial overall placement ratio of items within the target constructs was 100%. The above sorting process demonstrated that the items for PPCS and PVS had good content validity and could be applied in the research model for further testing.

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