Article

How Streamers Foster Consumer Stickiness in Live Streaming Sales

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Abstract: Streamers play a critical role in fostering consumer stickiness in live streaming sales. Thus, it is necessary to make clear the mechanism of how streamers influence consumer stickiness. Based upon the theories of social support, social identification and consumer stickiness, this study investigates the effects of consumers' perceived emotional support, informational support, financial support, affectionate support and social network support from streamers on consumer–streamer identification, which in turn affects consumer–streamer stickiness and consumer–brand stickiness in live streaming sales settings. Based on the structural equation modeling analysis of 280 online questionnaires, using the software of Smart PLS 3.0, the results demonstrate that perceived emotional support, perceived informational support, perceived financial support and perceived affectionate support enhance consumer–streamer identification, thereby enhancing consumer–streamer stickiness and consumer–brand stickiness, and thus, consumer–streamer stickiness also enhances consumer–brand stickiness. This study not only extends the theories of live streaming sales, but also provides practical implications for enterprises' improving consumer–streamer stickiness and consumer–brand stickiness in live streaming sales.

Keywords: live streaming sales; perceived streamer support; consumer–streamer identification; consumer–streamer stickiness; consumer–brand stickiness

1. Introduction

The rapid development of social media, 5G technology and artificial intelligence (AI) has spawned a new business model, live commerce, which provides consumers with a great deal of information and a high degree of interactivity [1,2]. Due to the high popularity of live commerce marketing in China, e-commerce platforms such as Taobao, Tmall, JD.com and Pinduoduo, as well as social media platforms such as WeChat, Douyin, and Kuaishou, have all launched live streaming sales campaigns, which attract huge network traffic. E-commerce platforms, social networking sites, live streaming agencies, manufacturers, intermediaries, and so on, are motivated to invest in live streaming sales because of its strong competitive edge in product sales and brand building, leading to the explosive growth of this sales model [1,3–5]. In order to obtain an advantage in this increasingly competitive market, internet celebrities, who are expected to have a higher capability to promote goods and services, are hired by firms/brands as streamers [4,6–9]. A streamer's challenge is to build and maintain a large enough influence over their followers in the fierce streaming sales competition to obtain substantial network traffic and, ultimately, convert the traffic into sales revenue [10]. For this, they need to first achieve consumer stickiness, which is addressed in this paper.

In traditional e-commerce research, consumer stickiness is considered as a critical determinant for the success of e-commerce websites, a key to profitability, a common indicator of consumer loyalty, and a major strategy for value creation [7,11–13]. Thus, scholars have explored various factors that can attract and retain consumers on the e-commerce websites to delineate the mechanisms behind consumer stickiness [11,14]. However, live streaming sales environments are quite different and more complicated than traditional e-commerce environments. There exists intense competition, not only between e-commerce live streaming platforms and between corporate brands, but also between streamers. In such environments, creating and maintaining consumer stickiness should be considered as a critical determinant for the success of a company's live streaming sales strategy [7,12]. Streamers are in the center of live streaming and consumer attention could be attracted through the streamer's real-time, vivid, diversified, and highly interactive display of products, which in turn stimulates consumers to purchase products, and ultimately realizes the conversion from watching live streaming to product purchase [1,4]. In live streaming sales, how can streamers foster consumer stickiness? Although the literature reveals a relationship between streamer-related factors and consumer purchase intention [9,15], consumer stickiness is overlooked. The current research addresses this void. Taking the interaction between streamers and consumers as the starting point, and building on the theory of social support, we explore how perceived streamer support affects consumer stickiness during the interaction process in live streaming sales.

Live streaming sales is characterized by strong interactivity, and the marketing logic behind it is to achieve marketing purposes through building interpersonal relationships between streamers and consumers [9]. Interpersonal interaction is a universal social phenomenon that can bring various kinds of social support to consumers and can have an important impact on consumer psychology and behavior [16,17]. However, compared with the social support in other situations, the social support perceived by consumers through the interaction with streamers in live streaming sales has its own unique connotation [18,19]. In view of this, our study will conceptualize and measure consumer-perceived social support in accordance with the specific situation of live streaming sales. We argue that consumer stickiness is the result of consumer–streamer identification during the interaction between consumers and streamers in streaming sales. Furthermore, consumer-perceived streamer support during the course of interaction is an important factor affecting consumer–streamer identification [20–23]. Therefore, when exploring the influence mechanism of consumer-perceived social support on consumer stickiness, our study incorporates the construct of consumer–streamer identification.

Streamers, as the main actors in live streaming sales, play a critical role in their interaction with consumers, thus directly determining the success of live streaming sales [19,24]. Therefore, our study explores the formation mechanism of consumer stickiness by taking streamers as hubs of live streaming sales, in order to reveal the relationship between "perceived social support, consumer–streamer identification, and consumer stickiness". Not only does our study theoretically expand and enrich the research on e-commerce, especially on live streaming sales, but it also provides managerial implications for enterprises who want to enhance consumer–streamer stickiness and consumer–brand stickiness through live streaming sale campaigns.

2. Theoretical Background

2.1. Live Streaming Sales

Live streaming refers to the e-commerce activities in which streamers provide consumers with product display and purchase services through product trial and experience shared in online live streaming studios [25]. Because live streaming enhances the authenticity, visualization and interactivity of online activities [25], firms make great efforts to launch live streaming sale campaigns, in which streamers recommend products to consumers through real-time, interactive, face-to-face onsite communication in live streaming studios [4,26,27]. Live streaming sales are also referred to "e-commerce live streaming" [25],

"live streaming e-commerce" [26], "live streaming commerce" [9,28], "live commerce" [3], "live social commerce/live social shopping" [19], "live streaming shopping" [7], or "live streaming service" [6]. Judging by these definitions, it is natural to infer that live streaming sales should be a subset of e-commerce, which is considered the advanced and the latest form of e-commerce [4,18,26]. These different definitions reflect two common characteristics of live streaming sales, i.e., interactions between streamers and consumers and the use of live streaming to promote online sales [4]. We consider live streaming sales as a new marketing model that allows streamers to engage in social interactions with consumers via all-around, full-scale product demonstrations in live streaming studios, thus facilitating the consumer shopping experience, and ultimately achieving the goal of a higher sales performance.

Composed of social commerce activities, live streaming sales is considered the advanced and the latest form of e-commerce that emphasizes the prevalent entertaining elements of live streaming to provide a favorable social atmosphere for firms to promote and sell products, and enables consumers to obtain virtual perceptions of commodities, such as smell, taste, and touch, through the alternative experience of the streamers [4,18,26]. Streamers, also termed as live streamers, livestreamers, online streamers, broadcasters, showroom hosts, vloggers, etc. [8], act as a central hub in live streaming sales, closely connecting brands and consumers [26]. In a live streaming sales context, not only do streamer characteristics, such as physical attractiveness, social attractiveness, expertise [28–31], professionalism and public events [26], trustworthiness [15,28], streamer–product fit [15,30], etc., but also viewer characteristics, such as loneliness [29], immersion [31], fear of missing out [32,33], etc., can increase the consumer's trust [1], parasocial interactions and parasocial relationships [10,29–31], which can all effectively increase their purchase intention [1,30,31]. Therefore, when making purchase decisions through live streaming sales, consumers will not only be affected by traditional e-commerce-related factors, but also by streamer-related factors. Our research focuses on the latter, trying to explore how perceived streamer support enhances consumer–streamer identification, and in turn, increases consumer stickiness in live streaming sales settings.

Live streaming sales is highly related to influencer marketing, social media marketing and social media brand communities, showing a high degree of social commerce particularities [5]. Live streaming sales highly overlap with influencer marketing, in which firms select and incentivize online influencers to engage their followers on social media in an effort to leverage these influencers' unique resources to promote a firm's products, with the ultimate goal of enhancing firm performance [34]. Live streaming sales also highly intersects with social media marketing [10], through which firms can promote interactions between consumers and brands, influence consumer behavior, increase the consumer's network traffic, raise sales revenue and enhance brand reputation [35]. Live streaming studios are regarded as special types or subsets of social media brand communities, in which consumers can perceive the social support of streamers via interaction, thus promoting consumer-citizenship behavior and enhancing brand value [17]. In short, though they are different concepts, live streaming sales, influencer marketing, social media marketing and social media brand communities show a high degree of social commerce characteristics by emphasizing interactions between different actors. In live streaming sales, interactions between streamers and consumers are crucial to improving the consumer shopping experience. In view of this, our study aims to explore the consumer-perceived social support of streamers, which arises from interactions in live streaming sales, and to reveal the formation of the consumer stickiness mechanism.

2.2. Social Support

Social support refers to the perception or experience that an individual is responded to, loved and cared for, esteemed, valued, and helped by people in that individual's social group [20,24]. There are many forms of social support, so it is often distinguished into a multidimensional construct whose components could differ from context to con-

text [17,20,24,36]. Liang et al. [24] regards social support as a construct of informational support and emotional support in the context of social commerce. Rosenbaum and Massiah [16] explore social support in the service context and measure it in terms of both social-emotional support and instrumental support. Lee and Kim [36] investigate social support in the context of mobile smart device usage, suggesting that social support consists of four components: informational support, emotional support, social network support and affectionate support. Zhu et al. [17] conceptualize social support as a construct of informational support and emotional support in online brand communities.

In the specific situation of live streaming sales, we term the consumer-perceived social support of streamers as perceived streamer support, which is composed of five constructs, namely; perceived emotional support, perceived informational support, perceived financial support, perceived affectionate support and perceived social network support. Perceived emotional support refers to the consumer's perception of emotional concerns, such as caring, understanding, and empathy from streamers, via interaction in live streaming studios [16,20,36,37]. Perceived informational support is defined as the consumer's perception of various information, including the pros and cons of brands and solutions of numerous problems shared by streamers, via interaction in live streaming studios [17,24,36,37]. Perceived financial support is conceptualized as the consumer's perception of the best value for money, including price value, discounts, rebates, refunds, coupons, voucher, tokens, gifts, cumulative points programs, etc., from the brands recommended by streamers, via interaction in live streaming studios [18,38]. Perceived affectionate support refers to the consumer's perception of love and affection from streamers via interaction in live streaming studios [36,37,39]. The difference between perceived affectionate support and perceived emotional support is that the former refers to behavioral manifestations of love and affection (e.g., hugging someone [36,37,39]), while the latter contains exchanging emotions, such as care or feelings and expressing empathetic understanding [16,20,36,37]. Actual behavioral manifestations of love and affection could not occur directly via live streaming sales in virtual environments. However, the communication technology of live streaming sales vividly provides diverse tools such as live demos, live chats, bullet chats, emoticons, comments, or messaging functions to express affection through social software [36,39]. Perceived social network support is defined as the consumer's perception of connections with their peers and other members who have common interests and needs with the help of streamers in live streaming studios [36,40,41].

Extant studies have found that perceived social support can bring about a variety of consequences, such as improving consumer purchase intention [24,26], consumer-citizenship behavior [17,36], consumer-perceived collective efficacy and collective intelligence [36], user mental health [20], consumer voluntary performance behaviors [16], and user identification [20–23]. Considering the specific live streaming sales context, our study investigates the impact of perceived streamer support on consumer–streamer identification and consumer stickiness.

2.3. Social Identification

Social identification refers to an individual's acknowledgment that they belong to a social category or group [40,42,43]. Social identification theorists treat a social category or group as a collective composed of similar individuals, all of whom hold similar views, see themselves and each other in similar ways, are closely related, and identify with each other, and all this is in contrast to members of an out-group [40,44]. Individuals tend to positively associate themselves with groups that value and identify with their self-concept characteristics, meanwhile, they need to distinguish themselves from members of out-groups [45,46].

Identification with a person is similar to identification with a group [45]. In addition to being an assessment of individual-group similarity [40,42,43], social identification is also an assessment of an individual's similarity with other in-group members [46–49]. This being the case, social identification allows an individual to support their group or

other in-group members, and encourage the individual to establish long-term relationships with their group or other in-group members [46,48,49]. In live streaming sales, viewers and streamers coexist within live streaming studios, thus belonging to the same group; a viewer's identification with a streamer takes place when the viewer perceives the streamer's similarity in the live streaming studios [10].

Social identification theory has been applied to different fields of research. In the field of marketing, the identification mechanism of an individual consumer and a group expresses the degree of the perception of self, both as an individual and as a member of the group, in relation to other in-group members and the firm/brand [49]. Consumers need to feel psychologically linked to the destiny of the group and find distinctiveness of the brand values and specific group practices to achieve identification [48,49]. In view of different objects that an individual consumer can identify with, consumer identification can be categorized into consumer–firm identification, consumer–brand identification, consumer–community identification, consumer–employee identification, and consumer–consumer identification, and so forth [46–50]). Similarly, in the context of live streaming sales, there are different objects that consumers can identify with, and accordingly, consumer identification can be divided into consumer–firm identification, consumer–brand identification, consumer–streamer identification, consumer live streaming studio identification, consumer–platform identification, consumer–consumer identification, and so on. In view of the fact that streamers play a pivotal role in interacting with consumers in the context of live streaming sales [4,10,26,27], we herein investigate the role of consumer–streamer identification in the influence of consumer-perceived streamer support on consumer stickiness.

2.4. Consumer Stickiness

In earlier traditional studies, consumer stickiness is the equivalent to loyalty, meaning that consumers will repeat purchases at stores [7]. With the development of the Internet, consumer stickiness refers to the time spent on the network platform during the visit session or a specific time [7], or indicates that users are willing to revisit their favorite websites [7,51,52]. In the fierce competition of online marketing, consumers are easy to switch back and forth between different websites due to the comparison of goods and prices; therefore, e-commerce companies have been making a great effort to improve consumer stickiness to their websites [11,51,53]. In the academic research field, consumer stickiness is considered as a critical determinant for the success of e-commerce websites [14], a key to profitability [14], a common indicator of consumer loyalty [7,11–13], and a major strategy for value creation [11].

In the e-commerce and online marketing literature, the definitions of consumer stickiness can broadly be made from two different perspectives, i.e., either from a business perspective or from a consumer perspective. From a business perspective, consumer stickiness is defined as the ability of websites to draw and retain consumers, such as the consumers' amount of time spent and interaction while using websites [7,11,52,53]. In contrast, from a consumer perspective, consumer stickiness is defined as the consumer's intention to consistently reuse a website in the future [7,14,51,52,54]. We argue that the attraction and retention of consumers depends on the consumer's experience, evaluation, approval, and psychological feelings of the websites [14,51,52,54], and therefore, consumer stickiness needs to be defined from a consumer perspective.

The existing literature has verified that consumer stickiness is critically influenced by factors such as sharing behavior [55,56], persistent motivation [55], emotional experience [57], information/content quality [13,51,52,58], system quality [13,58], service quality [51,54,58], consumer value [58,59], satisfaction [51,54,58], trust [11,51,52,56,58], commitment [51,58], interaction [7,10,13,56], identification [7,10,12], emotion attachment [7], participation [10,13], consumer engagement [59], and social support [56].

For the specific live streaming sales scenario, our study regards consumer stickiness as a concept of two constructs, namely, consumer–streamer stickiness and consumer–brand stickiness. The former refers to the consumer's willingness to return to and prolong

their duration of stay in watching live streaming contents hosted by streamers, and the latter refers to the consumer's intention to consistently reuse the brands recommended by streamers. Considering this, we try to reveal the mechanisms of consumer–streamer stickiness and consumer–brand stickiness.

3. Conceptual Model and Hypotheses

By integrating the theories of social support, social identification and consumer stickiness into the specific context of live streaming sales, we develop a conceptual model which demonstrates how perceived emotional support, perceived informational support, perceived financial support, perceived affectionate support and perceived social network support separately impacts consumer–streamer identification, and in turn, how consumer–streamer identification impacts consumer–streamer stickiness and consumer–brand stickiness, respectively (Figure 1).
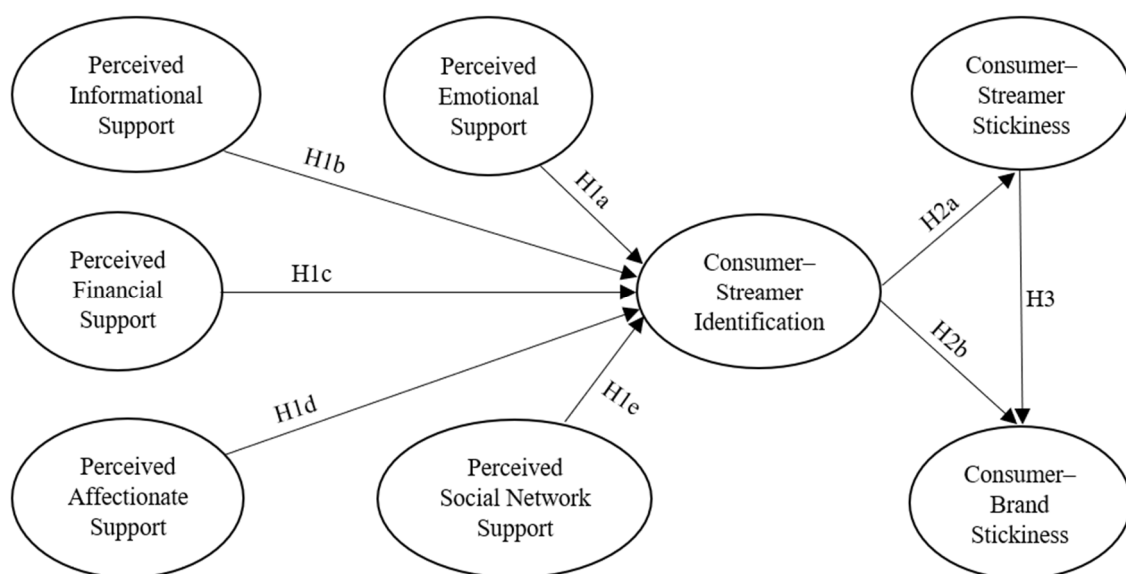
Figure 1. Conceptual Model.

3.1. The Impact of Perceived Streamer Support on Consumer–Streamer Identification

Scholars from different fields have studied the impact of social support on social identification in different contexts. Graupensperger et al. [20] found that student athletes who perceived more social support have a greater extent of identification with their collegiate sports teams in the United States during the COVID-19 pandemic. Hagiwara et al. [21] found a significant correlation between perceived social support from teammates and student–athlete identification in Japanese universities during the COVID-19 pandemic. Shehadeh et al. [22] demonstrated that social support is a significant predictor of ethnic identification among migrant workers in Florida. Toyoshima and Nakahara [23] validated that social support between family members, promoting role identification in family relationships. In the course of interaction during live streaming sales, streamers can provide consumer assistance by addressing various issues while consumers may regard streamers as intimate friends who care for the consumer's suggestions and feelings, thereby increasing consumers' identification with streamers through financial bonds, social bonds and structural bonds, which can enhance the consumer's affective commitment to streamers [10]. Hu et al. [12] certified that on social commerce/media platforms, the follower's parasocial relationships with digital influencers have a positive impact on their wishful identification with the digital influencers.

Based on the aforementioned analysis, we assert that the consumer's perception of social support from streamers can strengthen their identification with streamers. First, consumers can obtain emotional understanding, care and resonance from streamers [16,20,36],

thus enhancing their identification with streamers. Additionally, consumers can obtain detailed and useful information through a streamer's sharing [36,37], hence increasing their identification with streamers. Moreover, consumers can enjoy the best-value-for-money preference of the brands provided by streamers [18,38], which consequently boosts consumer–streamer identification. In addition, consumers can feel the sense of love and affection manifested by streamers [36,39], and as such, consumers will identify more with streamers. Lastly, consumers can perceive the contact they have with their peers, regarding common interests and needs from streamers [36,40,41], which will subsequently augment the consumer's identification with streamers. Therefore, we can infer the following hypotheses:

H1. *Perceived streamer support has a positive impact on consumer–streamer identification;*

H1a. *Perceived emotional support has a positive impact on consumer–streamer identification;*

H1b. *Perceived informational support has a positive impact on consumer–streamer identification;*

H1c. *Perceived financial support has a positive impact on consumer–streamer identification;*

H1d. *Perceived affectionate support has a positive impact on consumer–streamer identification;*

H1e. *Perceived social network support has a positive impact on consumer–streamer identification.*

3.2. The Impact of Consumer–Streamer Identification on Consumer Stickiness

Consumer stickiness has different manifestations, such as product utilization and extra-role behavior, long-term consumer relationship, consumer emotional attachment, consumer loyalty, consumer commitment, and consumer reputation [11,14,51–53], and is examined to be affected by consumer identification in different contexts. In consumer–brand relationship settings, consumer identification encourages consumers to develop long-term relationships with brands [46,48,49], thus revealing a positive impact on consumer brand loyalty and brand emotional commitment [60]. Consumer dentification is shown to have a positive impact on consumer stickiness in consultative services [50], e-commerce [51–53], and social commerce [11,14]. In the context of e-commerce live streaming, it has been demonstrated that consumer–streamer identification is positively related to the consumer's continuous watching intention [10], long-term relationship between consumers and streamers [25], consumer's emotional attachment to streamers [7], and consumer–streamer stickiness [12].

In a live streaming sales scenario, we argue that consumer–streamer identification can improve both consumer–streamer stickiness and consumer–brand stickiness. The consumer's identification with a streamer may trigger the intention to maintain a longer relationship with and loyalty to them, as a result of the role model effect, i.e., consumers may admire and worship a streamer because of their attitudes and values, special talents, or even personal charisma, which enhance the consumer's stickiness to the streamer [10,12,61]. Furthermore, the streamer's authenticity perception and communal relationships with consumers can convince consumers to try a recommended brand, and later to maintain that initial brand trust, and finally to convert the trust into brand loyalty [12,34,61]. Therefore, the following hypotheses can be inferred:

H2. *Consumer–streamer identification has a positive impact on consumer stickiness;*

H2a. *Consumer–streamer identification has a positive impact on consumer–streamer stickiness;*

H2b. *Consumer–streamer identification has a positive impact on consumer–brand stickiness.*

3.3. The Impact of Consumer–Streamer Stickiness on Consumer–Brand Stickiness

A high degree of consumer stickiness to a shopping website means that the website can attract more attention from consumers and enhance consumer involvement so that consumers will learn more brand information and are more likely to buy brands from the website [52,56]. In addition, a high degree of consumer stickiness to a website indicates

that the website has the ability to attract and maintain consumers so that consumers will not readily switch to competing websites, and that consumers will consider buying brands from the website more often [7,14], thereby enhancing consumer–brand stickiness. Li et al. [7] verified that the consumer's emotional attachment to streamers positively influences their attachment to live streaming platforms. Hu and Chaudhry [25] testified that an affective commitment to streamers positively influences affective commitment to online marketplaces. In the same vein, in the specific live streaming sales scenario, as streamers can exert vital influence on the consumer's commitment and loyalty to brands [7,12,25,61], the consumer's streamer preference is then transferred to the endorsed brands, which enhances the brand preference and increases the chance of a purchase decision [12,34,61]. In other words, consumer–streamer stickiness will promote the consumer's intention to consistently purchase and share the recommended brands. Therefore, we infer the following hypothesis:

H3. *Consumer–streamer stickiness has a positive impact on consumer–brand stickiness.*

4. Research Methodology

4.1. Sample and Data Collection Procedure

The respondents of our study are consumers who have live streaming shopping experiences. The online survey was conducted through the reputable professional survey platform called Wenjuanxing (wjx.cn, accessed on 1 May 2022) in China, which has been proved to be an appropriate means to collect data [7,25]. In the introduction of the questionnaire, a clear explanation is provided of live streaming sales, emphasizing that the respondents must have experience of live streaming sales to ensure the quality of the collected data. In order to screen out appropriate respondents, three leading filter questions are placed at the beginning of the questionnaire: (1) do you often watch live streaming sales?; (2) which streamer's/streamers' channel(s) do you often watch in live streaming sales?; and (3) which brand(s) is/are recommended by streamer(s) you often watch? The online survey was conducted from 1 May 2022 to 31 May 2022, lasting for one month. A total of 302 questionnaires were collected; 12 questionnaires were deleted because of inaccurate answers to the first two leading filter questions; and 10 other questionnaires were removed for the lack of authenticity; thus, a total of 280 valid questionnaires were reserved for further analysis. The descriptive statistical results demonstrate that 132 of the respondents watched the live streaming sales hosted by Jiaqi Li (47.1%), 87 of the respondents watched the live streaming sales hosted by Viya (31.1%), and 61 of the respondents watched the live streaming sales hosted by other streamers (21.8%). As reported by the descriptive statistics, 222 of the respondents watched the live streaming sales on the Taobao platform (79.3%), 23 of the respondents watched the live streaming sales on the Douyin platform (8.2%), and 35 of the respondents watched the live streaming sales on other platforms (12.5%). Based on the descriptive statistics, the majority of the respondents are highly educated (96.8%) women (71.1%) in their 20s (68.9%), and more than half have a monthly income of less than 5000 CNY (51.8%). However, 139 of the respondents are students (49.6%). Table 1 shows the demographic characteristics of the respondents.

Table 1. The descriptive demographic characteristics of the respondents (n = 280).

Constructs	Items	Respondents	Percentages
	Jiaqi Li	132	47.1
Streamer	Viya	87	31.1
	Others	61	21.8
	Taobao	222	79.3
Platform	Douyin	23	8.2
	Others	35	12.5

Table 1. *Cont.*

Constructs	Items	Respondents	Percentages
Gander	Male	81	28.9
	Female	199	71.1
Age (Years)	<20	18	6.4
	20–29	193	68.9
	30–39	60	21.4
	>39	9	3.2
Educational Background	≤Middle school degree	9	3.2
	Graduate	169	60.4
	≥Masters	102	36.4
Monthly Income (CNY)	<5000	145	51.8
	5000–10,000	80	28.6
	10,001–15,000	36	12.9
	15,001–20,000	17	6.1
	>20,000	2	0.7
Occupation	Students	139	49.6
	Others	141	50.4

4.2. Measure Operationalization

Our study aims to explore the impact of consumer-perceived streamer support on consumer–streamer identification, and in turn, the impact of consumer–streamer identification on consumer stickiness in the context of live streaming sales. Our conceptual model incorporates eight constructs, namely: perceived emotional support, perceived informational support, perceived financial support, perceived affectionate support, perceived social network support, consumer–streamer identification, consumer–streamer stickiness, and consumer–brand stickiness. In developing the scales of all the multi-item constructs, we drew upon the existing literature and made appropriate adaptations for the specific scenario of live streaming sales to ensure the content validity of all the constructs. Perceived emotional support and perceived informational support were measured with four items, respectively, which are adapted from Lee and Kim [36], Liang et al. [24], and Zhu et al. [17]. Perceived financial support was gauged with four items, which are compiled according to Hu and Chaudhry [25], Wohn et al. [38], and Wongkitrungrueng and Assarut [18]. Perceived affectionate support was measured with four items, which are adapted from Ladhari et al. [61] and Lee and Kim [36]. Perceived social network support was measured with three items, which are adapted from Hu et al. [10] and Lee and Kim [36]. We measured consumer–streamer identification with 11 items which are compiled from Black et al. [47], Hu et al. [10], Hu et al. [12] and Li et al. [7]. The constructs of consumer–streamer stickiness and consumer–brand stickiness were gauged with six items, respectively, which are adapted from Hu et al. [12], Li et al. [7] and Lien et al. [54]. Table 2 shows the scale items of the eight constructs with their sources from the previous literature. We measured the scales of all the multi-item constructs with a seven-point Likert scale (1 = "strongly disagree", and 7 = "strongly agree").

Table 2. Scale items of constructs with their sources.

Constructs	Codes	Items	Sources
Perceived Emotional Support	PES1	The streamer would be on my side when I encountered difficulties	[17,24,36]
	PES2	The streamer would comfort and encourage me when I encountered difficulties	
	PES3	The streamer would listen to me talk about my private feelings when I encountered difficulties	
	PES4	The streamer would express their concerns for me when I encountered difficulties	
Perceived Informational Support	PIS1	The streamer would offer me suggestions to solve them when I encountered problems	[3,17,24]
	PIS2	The streamer would give me information on how to deal with them when I encountered problems	
	PIS3	The streamer would help me discover the reasons and provide me with proposals when I encountered problems	
	PIS4	The streamer would give me information to help me overcome them when I encountered problems	
Perceived Financial Support	PFS1	The streamers would help me save money when I intended to buy the recommended brands	[18,25,38]
	PFS2	I could buy the recommended brands with discounts, rebates, gifts, etc. with the help of the streamer	
	PFS3	Compared to in other channels, the same brands recommended by the streamer have lower prices	
	PFS4	I often receive some shopping red envelopes, coupons, vouchers, tokens, etc. from the streamer	
Perceived Affectionate Support	PAS1	A streamer who shows me love and affection is available	[36,61]
	PAS2	A streamer who makes me feel wanted and loved is available	
	PAS3	A streamer who comforts me with love and affection is available	
	PAS4	A streamer whom I can count on to listen to me when I need to talk is available	
Perceived Social Network Support	PSNS1	Connecting with others for a good time via the streamer is available	[10,36]
	PSNS2	Getting together with others via the streamer for relaxation is available	
	PSNS3	Doing something enjoyable with others via the streamer is available	
Consumer–Streamer Identification	CSI1	I am proud to be the streamer's follower	[7,10,12,47]
	CSI2	The streamer represents values that are important to me	
	CSI3	My values are similar to the streamer's values	
	CSI4	The streamer is a model for me to follow	
	CSI5	The streamer is the sort of person I want to be like myself	
	CSI6	Sometimes I wish I could be more like the streamer	
	CSI7	The streamer is someone I would like to emulate	
	CSI8	I would like to do the kinds of things the streamer does	
	CSI9	My personality and the streamer's personality are very similar	
	CSI10	I have a lot in common with the streamer	
	CSI11	I feel an overlap between my self-image and the streamer's image	

Table 2. *Cont.*

Constructs	Codes	Items	Sources
Consumer–Streamer Stickiness	CSS1	I view the steamer's live streaming studio almost every day	[7,12,54]
	CSS2	I am in the habit of viewing new contents on the streamer's live streaming studio while accessing the internet	
	CSS3	I visit the streamer's posts frequently	
	CSS4	I watch the streamer's live steaming sales for a long time	
	CSS5	I usually spend a lot of time watching the streamer's channels	
	CSS6	I intend to prolong my stays on the streamer's live streaming studio	
Consumer–Brand Stickiness	CBS1	I would stay a longer time on the brands in live streaming sales	[7,12,54]
	CBS2	I would view the brand's live streaming sales as often as I can	
	CBS3	I intend to view the brand's live streaming sales once noticed in advance	
	CBS4	I intend to prolong my stays on the brand's live streaming sales	
	CBS5	I browse this brand in live streaming sales almost everyday	
	CBS6	I am in the habit of looking for the brand's live streaming sales while accessing the internet	

4.3. Testing for Common Method Bias

In order to limit the common method bias (CMB) risk, we made an attempt to describe all items clearly and concisely, ensure that all questionnaires would be responded anonymously [62], and that the independent and dependent construct measures in the survey were spatially separated [63,64]. However, since all the constructs were elicited from the same source of self-reporting respondents, we conducted tests for CMB [63,64]. Harman's single-factor test was applied to check for CMB risk by conducting a principal axis factoring (PAF) analysis of the multi-item scales. Eight latent factors whose eigenvalues exceed 1.0 are extracted, and the first factor accounts for 34.7% of the total variance among variables, far below the 50% threshold for CMB [65], indicating the relative absence of CMB in our study. Meanwhile, a common method factor was incorporated into the conceptual model, which was uncorrelated with the other constructs but loaded on each manifest variable [64]. There was no change in the direction and the significance of the path coefficients, also signifying that CMB is not a serious concern for our study. In addition, the score of variance inflation factor (VIF) was adopted to test CMB [66,67]. The multicollinearity is not a serious problem for our study, in that, the highest VIF (1.574) is far below the critical value of 3.

5. Data Analysis and Results

Partial least squares structural equation modeling (PLS-SEM) was adopted to assess both the measurement model and the structural model [66]. PLS-SEM is a composite-based SEM approach that does not assume normally distributed data in terms of the manifest variables, and has minimal computation requirements for the underlying algorithm [67]. The PLS-SEM is advantageous as it can be applied to small sample size, has limited distributional requirements, predicts and explains endogenous variables in a theoretically grounded structural model, evaluates sophisticated models with many variables and relationships, shows strong statistical power for hypotheses examining, and obtains reliability and validity of the measurement models [66–68]. Moreover, PLS-SEM can considerably address measurement error because it creates proxies as weighted composites [69]. In particular, our research model is rather predictive than confirmatory, examining how different factors can explain and predict consumer stickiness in the specific circumstances of live streaming sales; thus, adopting PLS-SEM has a predictable advantage [69]. Therefore, it is appropriate for our study to use PLS-SEM.

5.1. Measurement Model Evaluation

We used the statistical software Smart PLS 3.0 for PLS-SEM, employing 5000 bootstrap resamples to examine the reliability and validity of all the constructs in the model [66]. The values of α (Cronbach's alpha) and CR (composite reliability), shown in Table 3, signify a high-internal reliability of the measurement model [66]. Furthermore, all the values of SFL (standardized factor loading), CR and AVE (average variance extracted), in Table 3, imply a high-convergent validity of the measurement model based on the judgment criteria [66] that (1) the SFL values of all items in each construct exceed 0.7 and are significant, (2) the CR value of each construct exceeds 0.7, and (3) the AVE values of all constructs exceed 0.5. Regarding the discriminant validity of the measurement model, we adopted Fornell–Larcker criterion, comparing the values of the square root of AVE of all the constructs with the values of the corresponding inter-construct correlation coefficients [70], and the HTMT (heterotrait-monotrait) ratio of correlations, calculating the ratios of within-trait to between-trait correlations, in order to discern the true correlations among constructs [66]. As shown in Tables 4 and 5, the values of the square root of AVE (values along the diagonal in boldface) exceed the values of the corresponding inter-construct correlation coefficients [70], and the values of HTMT range from 0.305 to 0.698, which are all less than the conservative threshold of 0.850 [66]. Therefore, both findings of the Fornell–Larcker criterion analysis and HTMT examination corroborate the evidence that the measurement model has adequate discriminant validity.

Table 3. Construct Reliability and Validity Assessment.

Constructs	Items	SFL	CR	AVE	α
Perceived Emotional Support	PES1	0.885	0.942	0.802	0.939
	PES2	0.902			
	PES3	0.904			
	PES4	0.892			
Perceived Informational Support	PIS1	0.870	0.927	0.760	0.919
	PIS2	0.845			
	PIS3	0.904			
	PIS4	0.868			
Perceived Financial Support	PFS1	0.787	0.899	0.690	0.884
	PFS2	0.876			
	PFS3	0.862			
	PFS4	0.794			
Perceived Affectionate Support	PAS1	0.878	0.941	0.800	0.932
	PAS2	0.892			
	PAS3	0.907			
	PAS4	0.901			
Perceived Social Network Support	PSNS1	0.859	0.886	0.722	0.865
	PSNS2	0.812			
	PSNS3	0.877			

Table 3. *Cont.*

Constructs	Items	SFL	CR	AVE	α
Consumer–Streamer Identification	CSI1	0.921	0.981	0.822	0.974
	CSI2	0.894			
	CSI3	0.918			
	CSI4	0.906			
	LSI5	0.883			
	CSI6	0.901			
	CSI7	0.927			
	CSI8	0.914			
	CSI9	0.897			
	CSI10	0.913			
	CSI11	0.898			
Consumer–Streamer Stickiness	CSS1	0.915	0.963	0.814	0.941
	CSS2	0.924			
	CSS3	0.877			
	CSS4	0.892			
	CSS5	0.917			
	CSS6	0.887			
Consumer–Brand Stickiness	CBS1	0.902	0.960	0.800	0.946
	CBS2	0.905			
	CBS3	0.874			
	CBS4	0.882			
	CBS5	0.895			
	CBS6	0.908			

Notes: SFL = Standardized Factor Loading; CR = composite reliability; AVE = average variance extracted; α = Cronbach's alpha. SFL is significant at the 0.001 level.

Table 4. Correlation and Square Root of the AVE.

Constructs	1	2	3	4	5	6	7	8
1. Perceived Emotional Support	**0.896**							
2. Perceived Informational Support	0.620	**0.872**						
3. Perceived Financial Support	0.581	0.679	**0.831**					
4. Perceived Affectionate Support	0.447	0.523	0.651	**0.894**				
5. Perceived Social Network Support	0.488	0.498	0.581	0.429	**0.850**			
6. Consumer–Streamer Identification	0.390	0.567	0.723	0.586	0.639	**0.907**		
7. Consumer–Streamer Stickiness	0.418	0.537	0.711	0.602	0.647	0.683	**0.902**	
8. Consumer–Brand Stickiness	0.395	0.575	0.613	0.549	0.581	0.498	0.514	**0.894**

Notes: Values along the diagonal in boldface represent the square roots of the AVE.

Table 5. Heterotrait–Monotrait (HTMT) Ratio of Correlations.

Constructs	1	2	3	4	5	6	7	8
1. Perceived Emotional Support	-							
2. Perceived Informational Support	0.497	-						
3. Perceived Financial Support	0.469	0.536	-					
4. Perceived Affectionate Support	0.387	0.373	0.574	-				
5. Perceived Social Network Support	0.462	0.395	0.493	0.516	-			
6. Consumer–Streamer Identification	0.312	0.491	0.698	0.482	0.585	-		
7. Consumer–Streamer Stickiness	0.305	0.412	0.664	0.504	0.521	0.554	-	
8. Consumer–Brand Stickiness	0.328	0.429	0.527	0.418	0.436	0.351	0.379	-

5.2. Structural Model Evaluation and Hypothesis Test

Smart PLS 3.0 software was used to assess the structural model and test the hypotheses. We used the standard interpretation that the R^2 (coefficient of determination) values of 0.75, 0.50, or 0.25 for an endogenous construct can indicate that the structural model has a substantial, moderate, or weak predictive power, respectively [66]. Table 6 and Figure 2 demonstrate that the endogenous constructs are moderately explained by their corresponding exogenous constructs, and that the structural model has a moderate predictive power because the values of R^2 exceed 0.50. Furthermore, in keeping with Hair et al. [66], the f^2 effect size is used to evaluate the explanatory power of a specified exogenous construct over its endogenous constructs, and the f^2 values of 0.02, 0.15, and 0.35 signify that an exogenous construct has a small, medium, or large effect size on an endogenous construct, respectively. Table 6 and Figure 2 also show that all the exogenous constructs have a medium or large effect size on their corresponding endogenous constructs, respectively, except that perceived social network support has no explanatory power over consumer–streamer identification ($f^2 = 0.011$, $\rho = 0.832$). According to Hair et al. [66], we selected Stone–Geisser's Q^2 value to examine the prediction validity of the structural model by using the resampling blindfolding technique, and the results demonstrate that the Q^2 values of all the endogenous constructs exceed 0.00, thus signifying that the structural model has a high-predictive validity (Table 6 and Figure 2).

Table 6. Results of PLS Path Analysis.

Hypotheses	β	f^2	R^2	Q^2	ρ	Results
CSI			0.558	0.442		
H1a: PES→CSI	0.528	0.252			***	Support
H1b: PIS→CSI	0.317	0.151			**	Support
H1c: PFS→CSI	0.471	0.214			***	Support
H1d: PAS→CSI	0.619	0.303			***	Support
H1e: PSNS→CSI	0.003	0.011			0.832	Reject
CSS			0.514	0.386		
H2a: CSI→CSS	0.717	0.352			***	Support
CBS			0.544	0.395		
H2b: CSI→CBS	0.598	0.277			***	Support
H3: CSS→CBS	0.311	0.154			**	Support

Notes: CSI = Consumer–Streamer Identification; PES = Perceived Emotional Support; PIS = Perceived Informational Support; PFS = Perceived Financial Support; PAS = Perceived Affectionate Support; PSNS = Perceived Social Network Support; CSS = Consumer–Streamer Stickiness; CBS = Consumer–Brand Stickiness; β = Standardized Path Coefficients; f^2 = Effect Size of Path; R^2 = Coefficients of Determination; Q^2 = Stone–Geisser's Q^2; ** $\rho < 0.01$, *** $\rho < 0.001$.

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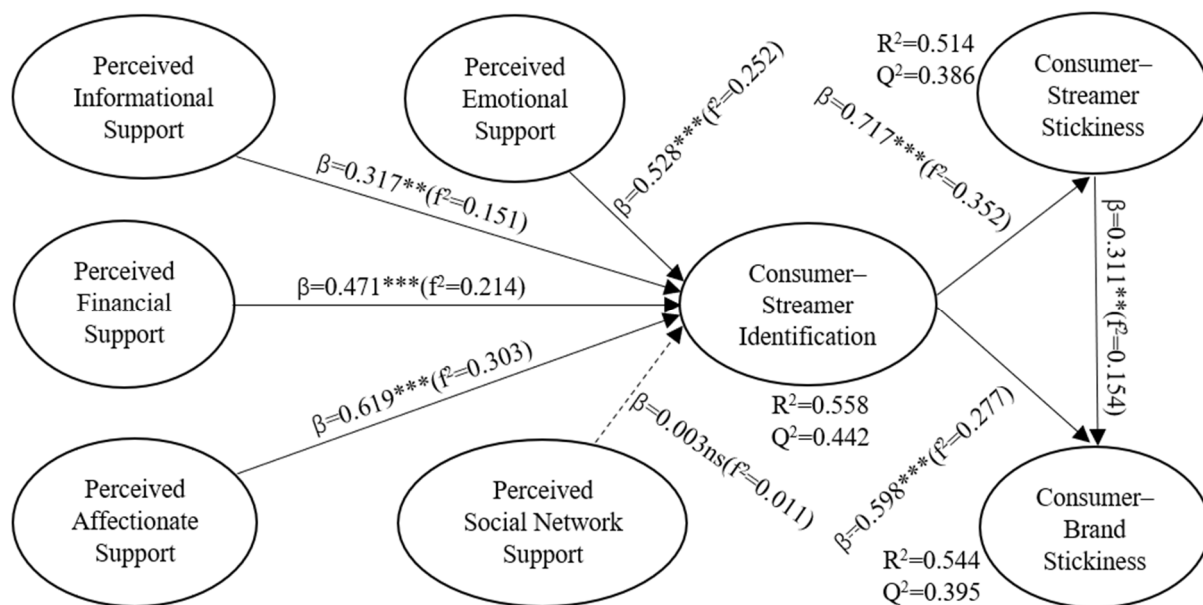
Figure 2. Results of PLS Path Analysis. Notes: ** ρ < 0.01, *** ρ < 0.001; ns: nonsignificant.

Regarding the hypothesis test, the results of the data analysis reveal that all hypotheses are supported, except for the rejection of hypothesis 1e. Table 6 and Figure 2 provide a summary of the hypothesis test results.

The data analysis results indicate that perceived emotional support, perceived informational support, perceived financial support and perceived affectionate support have a medium-strong positive impact on consumer–streamer identification, respectively. Specifically, the effect of perceived emotional support on consumer–streamer identification is medium-strong positive (β = 0.528, ρ < 0.001, f^2 = 0.252), thus H1a is supported. The impact of perceived informational support on consumer–streamer identification is also medium-strong positive (β = 0.317, ρ < 0.01, f^2 = 0.151), thus H1b is also supported. The effect of perceived financial support on consumers streamer identification is also medium-strong positive (β = 0.471, ρ < 0.001, f^2 = 0.214), thus H1c is also supported. The impact of perceived affectionate support on consumer–streamer identification is medium-strong positive, too (β = 0.619, ρ < 0.001, f^2 = 0.303), thus H1d is also supported. However, the impact of perceived social network on consumer–streamer identification is not significant (β = 0.003, ρ = 0.832, f^2 = 0.011), thus H1e is rejected. Taken together, H1 is partially supported.

The analysis results also show that consumer–streamer identification has a large or medium–strong positive impact on consumer–streamer stickiness or consumer–brand stickiness, respectively. Specifically, the impact of consumer–streamer identification on consumer–streamer stickiness is large–strong positive (β = 0.717, ρ < 0.001, f^2 = 0.352), thus H2a is accepted. The impact of consumer–streamer identification on consumer–brand stickiness is medium–strong positive (β = 0.598, ρ < 0.001, f^2 = 0.277), thus H2b is also accepted. To sum up, H2 is fully accepted.

The results also authenticate the positive impact of consumer–streamer stickiness on consumer–brand stickiness (β = 0.311, ρ < 0.01, f^2 = 0.154), thus H3 is accepted.

6. Discussion and Implications

This study investigated the impact of the consumer's perception of streamer support on consumer–streamer identification and, in turn, the impact of consumer–streamer identification on consumer stickiness in live streaming sales. Building on the theories of social support, social identity and consumer stickiness, a conceptual model was developed, arguing that perceived emotional support, perceived informational support, perceived financial support, perceived affectionate support and perceived social network support have a positive impact on consumer–streamer identification, respectively, consumer–streamer identifica-

tion has a positive impact on consumer–streamer stickiness and consumer–brand stickiness, respectively, and consumer–streamer stickiness has a positive impact on consumer–brand stickiness. Data analysis supported most of our hypotheses in the conceptual model. To summarize, perceived emotional support, perceived informational support, perceived financial support and perceived affectionate support enhance consumer–streamer identification, respectively, which in turn, increases consumer–streamer stickiness and consumer–brand stickiness. Additionally, consumer–streamer stickiness strengthens consumer–brand stickiness.

Contrary to our expectation, H1e, i.e., perceived social network support, which has a positive impact on consumer–streamer identification, is not supported. This might be due to two reasons. First, despite the streamer being situated in the key hub position of relationship structure in live streaming sales, consumers can directly interact well and thus identify with them. Therefore, consumers do not need to identify with the steamer through a network of relationships around them. Second, the direct interaction abridges the psychological distance between consumers and a steamer, such that consumers feel intimately connected to the streamer, and in contrast, consumers consider their relationships with their peers not so important as their relationships with the streamer. Obviously, the consumer's perception of unimportant peer relationships does not enhance their identification with the streamer.

6.1. Theoretical Contributions

This study contributes to the literatures on e-commerce, especially on live streaming sales, social support, social identification and consumer stickiness in several ways. First, to the best of our knowledge, almost no studies have applied social support theory to the context of live streaming sales to explore consumer interactions with streamers. Our study emphasizes that streamer-related factors are critical to improve the marketing performance of live streaming sales, since streamers are situated in the core hub position in live streaming sales [9,15]. Due to this role of streamers, our study applies social support theory into the domain of live streaming sales and proposes the concept of perceived streamer support comprising of perceived emotional support, perceived informational support, perceived financial support, perceived affectionate support and perceived social network support. Thus, we lay a foundation for subsequent applications of social support theory in the domain of live streaming sales.

Second, to the best of our knowledge, few studies have applied social identification theory to individual streamers in live streaming sales. Considering that streamers play a pivotal role in interacting with consumers in the context of live streaming sales [4,10,26,27], our study develops the concept of consumer–streamer identification based on social identification theory, whose positive impact on consumer–streamer stickiness and consumer–brand stickiness is well supported. Thus, the development of consumer–streamer identification in our study enriches social identification theory by expanding its application into the research domain of live streaming sales.

Finally, consumer stickiness is conducive to offering companies competitive advantages in the fiercely competitive digital economy era, thereby improving marketing performance [11]. Although business practice considers consumer stickiness as a key success indicator for live streaming sales, to the best of our knowledge, academic research on the topic is deficient [10]. Considering the core role of streamers in live streaming sales [9,15], our study conceptualizes, develops and operationalizes the constructs of both consumer–streamer stickiness and consumer–brand stickiness in dealing with the concept of consumer stickiness. In this regard, not only is the key pivotal role of streamers underscored, but also the important marketing performance indicator of consumer–brand stickiness is considered. Therefore, our study advances the development and application of consumer stickiness theory in the live streaming sales context.

6.2. Managerial Implications

Streamers play a key role in live streaming sales and consequently acquire and increase consumer identification, which is a driver of attracting fans, increasing network traffic and enhancing fan stickiness. Therefore, our study suggests twofold managerial implications for firms that engage their consumers in e-commerce, especially in live streaming sales campaigns.

Establishing streamer evaluation systems according to the consumer's perception of streamer support. In view of the positive impact of the four constructs of perceived streamer support, i.e., perceived emotional support, perceived informational support, perceived financial support and perceived emotional support on consumer–streamer identification, firms need to establish streamer evaluation systems depending on these constructs to strengthen the streamer's professionalism and, consequently, achieve a perfect match between their individual brand images and the firm's brand images. Firms can take the following measures to evaluate the consumer's perception of streamer support.

Firstly, streamers should be required to be sympathetic and empathetic to their fans. Sympathy and empathy is the basis on which people communicate and share emotions, meaning emotional resonance and attitudinal alignment between sympathizers/empathizers and those who are sympathized/empathized with. Therefore, the streamer's sympathy and empathy can enhance the consumer's perception of emotional support.

Secondly, firms should regard streamers not only as partners but also as employees. Firms should require streamers to be vastly familiar with the recommended brands and to skillfully demonstrate expert knowledge of the brands to their fans, thus thrusting streamers into the role of "key opinion leaders", thereby strengthening the consumer's perception of informational support.

Thirdly, firms should improve their capacity to cooperate closely and communicate effectively with streamers, and invite streamers to participate in the firm's live streaming sales planning, and authorize streamers to flexibly use preferential prices so that consumers can perceive that streamers are recommending the brands with the best value for money, therefore contributing to the enhancement of the consumer's perception of financial support.

Fourthly, streamers should show their love and affection to consumers, which can help consumers to maintain positive, long-lasting relationships with streamers, thus strengthening the consumer's trust in and identification with streamers, and thereby enhancing the consumer's perception of affectionate support.

Giving full play to the core role of streamers when launching influencer marketing campaigns. In view of the positive impact of consumer–streamer identification on consumer–streamer stickiness or consumer–brand stickiness, and the positive impact of consumer–streamer stickiness on consumer–brand stickiness, it is imperative that firms provide full play to the core role of streamers when launching influencer marketing campaigns. Influencer marketing is a strategic approach for firms seeking to gain a competitive advantage in the digital economy era, and internet influencers are usually invited to cooperate with brands for the role of streamers. Internet influencers promote and endorse brands in live streaming studios, thus increasing the consumer's identification with streamers, improving brand awareness and brand stickiness. Brands can launch influencer marketing campaigns through strategic alliances, content sponsorship, affiliate links, discounts, free samples, contests, brand ambassadors and other marketing approaches, which can consequently support the roles of streamers in attracting and retaining fans. Such influencer marketing campaigns can enhance consumer identification with streamers, strengthen the key opinion leadership of streamers, and thereby improve brand influence, increase brand usage, and ultimately realize the conversion from consumer–streamer identification to consumer–streamer stickiness and consumer–brand stickiness.

6.3. Limitations and Further Research Avenues

Our study explores how perceived streamer support enhances consumer–streamer identification and, in turn, how consumer–streamer identification enhances consumer–streamer stickiness and consumer–brand stickiness in live streaming sales settings, which enriches the existing literature on live streaming sales, social support, consumer identification and consumer stickiness. However, we do acknowledge the limitations of our study and correspondingly put forward new avenues for future research.

Firstly, our study focuses exclusively on the consumer's perception of social support from streamers. However, other actors such as brands, live streaming platforms, firm employees, other consumers, etc. can also elicit this perception of social support. As such, it may be worthwhile for future research to investigate the consumer's social support from other actors in live streaming sales.

Secondly, our study only regards streamers as the objects that consumers identify with, in other words, only consumer–streamer identification is investigated. However, other objects should be considered, such as brands, live streaming platforms, employees, other consumers, etc. that consumers can identify with and, accordingly, consumer–brand identification, consumer–platform identification, consumer–employee identification, and consumer–consumer identification can also be investigated in live streaming sales research.

Thirdly, we present only streamer-related factors, especially the positive aspects affecting streamer marketing and sales; however, viewer-related factors, especially the negative aspects, such as loneliness [29] and the fear of missing out [32,33], may also affect parasocial interactions and parasocial relationships between viewers and streamers [10,29], thus affecting streamer marketing and sales. Therefore, it may be worthwhile for further studies to empirically inquire about how these negative factors affect consumer–streamer identification, consumer–streamer stickiness and consumer–brand stickiness.

Fourthly, anyone can act as a streamer in live streaming sales practice, thus different types of streamers such as corporate employees, showbiz stars, professional Internet celebrities, government officials and even virtual robots can step into live streaming studios to promote brands [4,26]. And so, the roles of different types of streamers in live streaming sales may be quite a bit different, which should be investigated in future research.

Finally, considering the population size of Mainland China, a sample size of 280 is considered substantially small. Thus, future research should consider extending the sample size, in order to guarantee its representativeness.

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