Everyone Can Be a Star: Quantifying Grassroots Online Sellers' Live Streaming Effects on Product Sales

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Abstract

Live streaming is becoming prevalent and its rapid rise also makes it an attractive scientific research subject. Despite recent research focuses on understanding the motivations and behavior of people engaging live streaming, we know little about how the adoption of live streaming strategy for e-commerce on product sales. In this paper, we establish a causal relationship between adopting live streaming strategy for e-commerce and online product sales. Our results indicate that there is a 21.8% increase in online sales volume after adopting live streaming strategy. Furthermore, we find live streaming strategy is more efficient for the sellers who mainly sell experience goods--they have 27.9% more than those whose products are mainly search goods. This work is the first quantitative study, to our knowledge, on how the adoption of live streaming strategy on online product sales.

1. Introduction

Recent years have witnessed an increasing popularity of living streaming services. Living streaming websites such as Twitch are among the most visited websites. Compared to traditional online communication forms such as text (e.g. tweets, Facebook posts) and images (e.g. Instagram photos) which are mostly static, live streaming allows individual to broadcast video and audio of an event to audience over the internet in real time. On the one hand, live streaming offers real-time information, which is much richer than that from text and images. On the other hand, live streaming platforms provide channels that allow rich interactions between the streamers and their audience, and interactions amongst audience members. Streamers can decide topic, duration, and content for streaming, such as dancing, video gaming, or product promotion and education. At the same time, the audience can submit messages anytime to interact with streamers in chat rooms.

These unique features make live streaming a new medium to consumers and a powerful marketing tool for e-commerce. For example, individual sellers and small businesses can create their own product demonstration via live streaming (Figure 1b). Live product demonstration provides richer information and a more interactive experience than product text descriptions and photos on web pages in that streamers not just present how the product looks like and its features, but also demonstrate how to use it or style it, or even offer customized demonstrations based on audience questions that are generated in real-time during the streaming. These features of live streaming considerably reduce viewers' product uncertainty as viewers can easily visualize the products (e.g., clothes) and infer whether the products will fit their preferences [7, 17]. In addition, selling with live streaming can deliver an immense amount of product information in a short period of time, which shortens customers' decision-making path and invokes impulse purchase.

The vigorous development of live streaming as an emerging form of social media has also attracted significant attention from the research community. Existing research studies focus on improving the efficiency and the quality of live streaming service [9, 14, 27], understanding user behaviors [11, 12, 16, 26], and developing applications on gaming [18, 21] and education [8, 15]. However, while anecdotally live streaming has been used by many sellers as a pertinent tool for marketing and consumer product education, no research has examined live streaming in the context of social commerce. Thus, as a first step, we formally investigate the following research questions:

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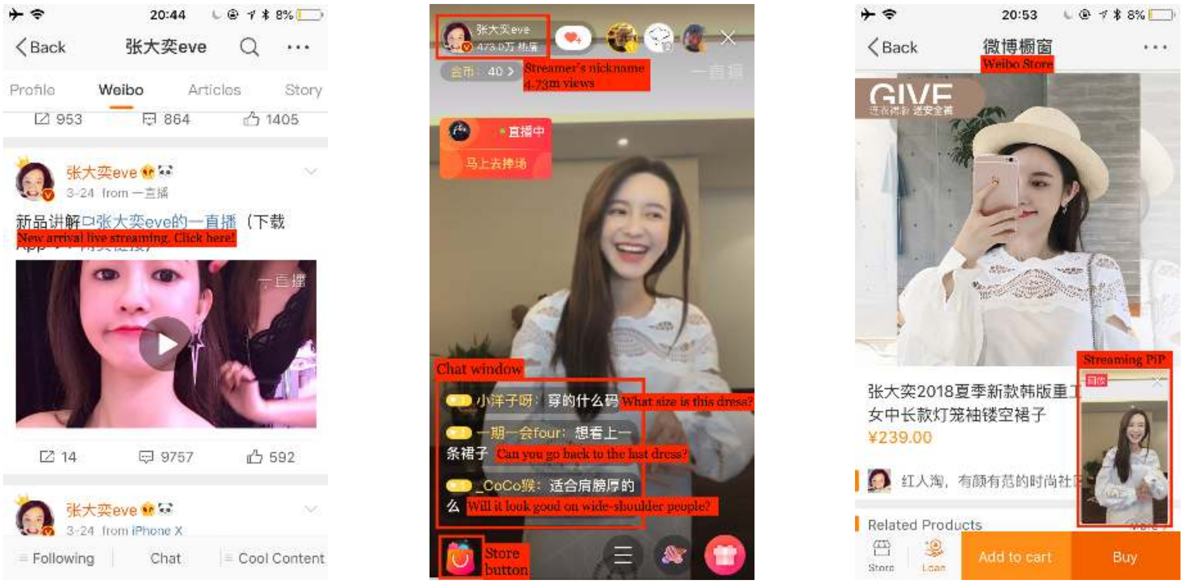

Figure 1. Yizhibo user interface and functions

(a) Weibo post of live streaming, (b) Yizhibo chat room, (c) Weibo Store

RQ1: What is the effect of sellers' adoption of live streaming on their online product sales?

RQ2: How does the impact of sellers' adoption of live streaming vary across types of merchants?

To address this research question, we obtained data from multiple archival sources. First, our streaming data is collected from Yizhibo, a leading live streaming platform in China. We collected the matching product sales data from Taobao, a leading online marketplace. We matched sellers who started to live stream during our observational window with those who have not joined the streaming site, and then employ difference-in-difference (DID) models on online product sales. Further, we also use a look-ahead (LA) propensity score matching (PSM) approach to further establish a causal relationship. Our results indicate that the adoption of live streaming strategy significantly increases online product sales. To the best of our knowledge, this is the first empirical study that quantifies the effect of the adoption of live streaming strategy on sellers' online sales. we believe these findings may also shed lights on marketing strategies.

The rest of this paper is organized as follows: we begin with the background of live streaming platform we used in this study, followed by a review of related research on live streaming and social commerce. Next, we describe the data collection process and the statistical models we used for investigating the effects of live streaming strategy on online sales. Finally, we interpret our finding within the frame of existing work.

2. Background

Yizhibo has been rapidly growing and become one of the largest live streaming platforms since it was launched on the leading Chinese Twitter-like social media platform, Weibo. With the exposure to Weibo's massive user base, Yizhibo achieved an average of 7.73 million daily active users during the month after its launch.

As an integration of Weibo, Yizhibo allows users to directly watch streaming within Weibo without installing any new applications. This feature makes Yizhibo a great place for online sellers—they can reduce the advertisement cost caused by platform changes. For example, streamers are able to post on Weibo and release the preview of their live streaming to attract their followers joining the chat room (Figure 1a). In addition, the features in chat room also benefit the streamers. In a chat room, streamers can not only demonstrate the product in various aspects, but also communicate with the audience and learn the concerns about the product real-time through the popped-up messages (Figure 1b) so that they can respond in time and make a customized demonstration. Also, the chat room integrated Weibo Store, which can display the products sold on Taobao (an eBay-like Chinese online marketplace). Audience can click the shop (Figure 1b) and go shopping directly on Weibo during the streaming. Figure 1(c) shows an example that a product is listed in Weibo Store of a streamer while customers can watch the streamer demonstrating the product in picture-in-picture (PiP) window. Audience view product details and add the product to cart without interrupting watching the live streaming and missing any information.

3. Literature review

3.1. Live streaming

Prior research focuses on understanding the motivations and behavior of people engaging live streaming and effect of live streaming on consumer behavior. Haimson and Tang have identified immersion, immediacy, interaction, and sociality as the four driving forces that affect the engagement of remote event streaming on Facebook Live, Periscope, and Snapchat Live Stories [12]. Meanwhile, studies show that information, entertainment and socialization are highly related to time spent of a user on Twitch [11, 16, 26]. Besides, user's continuous intention on live streaming platforms have been studied. While the intention to continue contributing content is primarily affected by a streamer's social capital [4], it was found that audiences' continuous watching behavior intention is positively affected by streamer identification and group identification, where streamer identification is driven by parasocial interaction and group identification is enhanced by co-experience among audiences [18]. The effect of live streaming has also been studied. Live streaming acts as virtual third places for users to socially interact with other people [13], creates a very intimate experience with a remote partner [24], improve learning performance for novice instructors [22], and influences pro and anti-social behaviors [25].

3.2. Social commerce

As social commerce has evolved quickly in practice, social interactions have been viewed as keys to online transactions and activities [28]. In social commerce context, social interactions are mainly referred as online word of mouth. Prior research offers insights on how social interactions shape buyer behaviors, such as reducing consumers' psychological distance [30] and affect consumers' purchase decision making [5, 10]. While the impact of social interactions on product sales have been studied [1, 5], no research has identified how real-time social interactions contribute to product sales.

4. Data

To determine the effect of live streaming strategy on online sales, we conduct our analysis with data from Taobao and Yizhibo. We randomly collect 319,337,021 users from Yizhibo. Among these users, we identify 2,223,542 streamers who have replays in their replay list. We further select 63,366 streamers who started streaming after October 1st, 2017. As aforementioned in Section 2, the chat rooms on Yizhibo provide the information of Taobao shops managed and owned by streamers. Thus, we are able to identify e-commencers who engage in live streaming on Yizhibo. Finally, we were ultimately able to collect 1,717 Taobao shops, 62,959 products, and 10,667,227 product reviews.

Table 1. Summary statistics

Variable	Std.	Min	Med.	Mean	Max
#Reviews	161.78	0	5	42.94	6348
After Adoption	0.45	0	1	0.73	1

To inspect the effect of live streaming on product sales, we construct data as product-time panel data. Specifically, we aggregate reviews of each product by month. With this data structure, we are able to identify if a seller adopted live streaming strategy in a certain period of time and thus construct treatment group and control group to uncover the causal relationship between live streaming adoption and online product sales. The descriptive statistics for the constructed panel data are displayed in Table 1. The AfterAdoption variable is a dummy variable, indicating if the seller has adopted live streaming strategy in current period. This variable will be further discussed later in Section 5.

4.1. Measuring product sales

Without proprietary data, accurately measuring product sales data on an e-commerce platform is challenging because it involves long continuous observations. Instead, we choose the number of reviews of a certain product as the proxy for product sales volume. This approach is also used in the previous literature [29]. Taobao users can leave feedback for products they purchased—the format of feedback includes rating, leaving a comment, and uploading photos. Taobao will only post a review if it is from a verified purchase, which means, unlike Amazon, users cannot write reviews for a product they didn't purchase even if the product is identical to what they purchased from another seller. Furthermore, if a purchase has not received a review 15 days after delivery, Taobao will assign a default positive review to each of the products within that purchase. Therefore, the number of times a product can reliably measure product sales on Taobao.

4.2. Measuring adoption time

On Yizhibo, a video record (replay) is automatically saved and publicly available to audience, by default, once streamers finish streaming. This function enables others to watch historical videos on a streamer's replay list. To investigate how live streaming affect online sales volume, we are interested in knowing when streamers started live streaming. Thus, we take the date of the first replay of a user as the time that a user started live streaming.

5. Empirical models

Running randomized trials is the gold standard method to understand causal relationships [2]. Applying to our study, the ideal experiment is pictured to go as follows: (1) we take the population of shop owners who are willing to adopt live streaming strategy to boost online sales, (2) randomly split these sellers into two groups: one group will be allowed to adopt live streaming strategy (treatment group) while the other group will be prevented from adopting it until at a certain time (control group), (3) and watch the differences between the treatment group and control group after the treatment. Since both the treatment and the control groups expressed the desire to adopt live streaming strategy but only the treatment group could randomly succeed with the adoption, the differences in future outcomes cannot be explained by pre-existing differences and must be attributed to the effect of the actual early adoption of live streaming strategy. However, randomly blocking the adoption of live streaming strategy is practically infeasible in our field context.

In lieu of a randomized experiment, a traditional approach is to employ the difference-in-difference (DID) technique with. Specifically, the approach is three-step if applied in our case: (1) collect treatment group (streamers) and control group (general online sellers), (2) employ PSM to match each treated individual to the most similar control individual, and (3) estimate the changes between the groups. However, a key limitation of PSM is that it can only account for observed and observable characteristics [6, 23], which leads to a potential estimation bias.

To account for both observable and unobservable covariates, we adopt Look-Ahead PSM (LA-PSM)[3]. The LA-PSM approach has seen emerging popularity in the IS literature [19, 20]. The idea behind this identification strategy is that if we assume there is randomness in the adoption time, early adopters should be very similar to late adopters, especially when they are matched on all observables. Specifically, we focus on the sellers who adopt live streaming strategy between October 2017 and December 2017 (e.g. 1710, 1711, and 1712) as our treatment group. Then we match each of these users in the treatment group to a user who has not adopted live streaming strategy but will do it between January 2018 and May 2018. We employ one-to-one static propensity score matching (PSM) method without replacement as our matching procedure. We rely on the demographic variables of Taobao shops to calculate the propensity scores, including industry where shops belong to, overall seller rating, sales volume, and average product price. The propensity score equation is as follow:

$$\log\left(\frac{\mathrm{Pr}(\mathrm{Treatment_i} = 1)}{\mathrm{Pr}(\mathrm{Treatment_i} = 0)}\right) = \alpha + \beta \mathrm{D_i} + \epsilon$$

where for each shop i , the $\mathrm{Pr}(\mathrm{Treatment_i} = 1)$ represents the propensity to adopt live streaming strategy and $\mathrm{D_i}$ are demographic attributes of the shop.

With the matched sample, we use product-month-level panel data and employ DID with the fixed effects of time and product to identify the effect of adopting live streaming strategy on online sales. Since the number of reviews is scale-free distributed, we use a logarithmic transformation on the number of reviews, $\log(\#\mathrm{Reviews} + 1)$, as our dependent variable, which also applies when the number of reviews is zero. Then for each product j in month t,

$$\begin{aligned}\log\big(\#\mathrm{Reviews_{jt}} + 1\big) &= \beta_1 \times \mathrm{AfterAdoption_{jt}} \\ &+ \beta_2 \times \big(\mathrm{AfterAdoption_{jt}} \times \mathrm{Treatment_j}\big) \\ &+ \gamma_1 \times \mathrm{Month_t} + \gamma_2 \times \mathrm{Product_j} + \epsilon_{jt}\end{aligned}$$

where $\mathrm{Month_t}$ and $\mathrm{Product_j}$ denote month-level and product-level fixed effects respectively, the $\mathrm{Treatment_j}$ variable is a dummy variable indicating if the seller of product j is in the treatment group (i.e. adopt live streaming strategy), and the $\mathrm{AfterAdoption_{jt}}$ variable is another dummy variable showing if the time t is after the matched date of adopting live streaming strategy.

6. Results

Table 2 displays the results derived from DID with LA-PSM discussed above. The result shows the $\mathrm{Treatment} \times \mathrm{AfterAdoption}$ is positively and significantly affect the number of reviews, meaning that the adoption of live streaming strategy brings ($e^{0.197}$ −

$1 =$) 21.8% increase in sales volume after adopting the strategy. Besides, we observe that 1711 and 1712 are positively associated with online sales volume. Compared with other months, the coefficients of 1711 and 1712 are the two highest ones. Online sales volume in November and December 2017, for example, are 57.8% and 204% higher than that in October 2017, respectively, which reflect the fact that the Double 11 (November 11) and Double 12 (December 12) promotion on Taobao significantly boost sales volume.

Table 2. DID with LA-PSM

VARIABLES	log(#reviews+1)
AfterAdoption	-0.156***
	(0.019)
Treatment × AfterAdoption	0.197***
	(0.023)
1711	0.456***
	(0.017)
1712	1.112***
	(0.018)
Observations	41,805
Number of products	23,370
R-squared	0.929

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7. Impact of live streaming on different types of merchants

To further identify effect of live streaming strategy adoption on online sellers, we categorize Taobao shops with their demographic attributes. Specifically, Taobao provides category of a shop, including electronics, furniture, home improvement, cloth, baby food & health, antique & collection, jewelry, service, beauty, car, outdoor sports, and nutrition. To simplify our model, we group these categories into two groups: search goods and experience goods. Search goods are referred to the products that can be evaluated before purchase. For example, laptop is a search good as the purchase can be decided when all the specifications available online. One the other hand, experience goods are the products that hard to observe and evaluate in advance before purchase. For instance, cloth is an experience good as fit or not is only known after the cloth is put on.

Then we take beauty, cloth, jewel, and service as experience goods and rest as search goods. Thus, we have shops which mainly sell experience goods and shops that mainly sell search goods.

We employ a similar DID model with same LA-PSM procedure as the previous experiment as follow:

$$\log(\#\mathrm{Reviews}_{jt}+1)=\beta_1\times \mathrm{AfterAdoption}_{jt} + \beta_2\times \left(\mathrm{AfterAdoption}_{jt}\times \mathrm{Treatment}_j\right) + \beta_3\times\left(\mathrm{AfterAdoption}_{jt}\times \mathrm{Treatment}_j \times\mathrm{Experience}_j\right) + \gamma_1\times \mathrm{Month}_t+\gamma_2\times \mathrm{Product}_j+\epsilon_{jt}$$

where for each product j in month t, $\mathrm{Experience}_j$ denotes a dummy variable indicating if the shop selling product j mainly sells experience goods. The rest of denotations remain the same as the previous equation.

Table 3 displays the results discussed above. The result shows the Treatment × AfterAdoption× Experience is positively and significantly affect the number of reviews, meaning that the adoption of live streaming strategy for the shops mainly sell experience goods have ($e^{0.246} - 1 =$) 27.9% more in sales volume than those whose products are mainly search goods.

Table 3. Effect on different types of shops

VARIABLES	log(#reviews+1)
AfterAdoption	-0.275***
	(0.047)
Treatment × AfterAdoption	0.298***
	(0.065)
AfterAdoption × Experience	-0.161**
	0.057
Treatment × AfterAdoption × Experience	0.246**
	0.076
1711	0.589***
	(0.021)
1712	1.163***
	(0.023)
Observations	20,831
Number of products	11,275
R-squared	0.925

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

8. Conclusion

Live streaming is a new era of social media services, which offers real-time information and interactions. A key challenge in research community is to understand the role of adopting live streaming in e-commerce area. In this paper, we took a first step toward uncovering the effect of adopting live streaming strategy on online product sales. We find the adoption of live streaming strategy significantly increases in sales volume by 21.8% after adopting the strategy. The result of our model also reflects the significant impact of the two Taobao annual promotion events on sales volume. Moreover, we further study how the impact of sellers' adoption of live streaming varies across types of merchants. We find live streaming plays a more efficient role on convincing online users purchase experience goods--the adoption of live streaming strategy for the shops mainly sell experience goods sells 27.9% more than those whose products are mainly search goods.

9. References

[1] Amblee, N., and T. Bui, “Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts”, International Journal of Electronic Commerce 16(2), 2011, pp. 91–114.

[2] Aral, S., and D. Walker, “Creating social contagion through viral product design: A randomized trial of peer influence in networks”, Management science 57(9), 2011, pp. 1623–1639.

[3] Bapna, R., J. Ramaprasad, and A. Umyarov, “Monetizing freemium communities: Does paying for premium increase social engagement?”, 2016.

[4] Bründl, S., and T. Hess, “Why do Users Broadcast? Examining Individual Motives and Social Capital on Social Live Streaming Platforms.”, PACIS, (2016), 332.

[5] Chen, Y., Q. Wang, and J. Xie, “Online social interactions: A natural experiment on word of mouth versus observational learning”, Journal of marketing research 48(2), 2011, pp. 238–254.

[6] Cook, T.D., D.T. Campbell, and W. Shadish, Experimental and quasi-experimental designs for generalized causal inference, Houghton Mifflin Boston, 2002.

[7] Dimoka, A., Y. Hong, and P.A. Pavlou, “On product uncertainty in online markets: Theory and evidence”, MIS quarterly, 2012, pp. 395–426.

[8] Fuller, M.Y., S. Mukhopadhyay, and J.M. Gardner, “Using the Periscope live video-streaming application for global pathology education: a brief introduction”, Archives of pathology & laboratory medicine 140(11), 2016, pp. 1273–1280.

[9] Garcia-Pineda, M., J. Segura-Garcia, and S. Felici-Castell, “Estimation techniques to measure subjective quality on live video streaming in Cloud Mobile Media services”, Computer Communications, 2017.

[10] Godes, D., D. Mayzlin, Y. Chen, et al., “The firm’s management of social interactions”, Marketing letters 16(3–4), 2005, pp. 415–428.

[11] Gros, D., B. Wanner, A. Hackenholt, P. Zawadzki, and K. Knautz, “World of streaming. Motivation and gratification on Twitch”, International Conference on Social Computing and Social Media, (2017), 44–57.

[12] Haimson, O.L., and J.C. Tang, “What makes live events engaging on Facebook Live, Periscope, and Snapchat”, Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, (2017), 48–60.

[13] Hamilton, W.A., O. Garretson, and A. Kerne, “Streaming on twitch: fostering participatory communities of play within live mixed media”, Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, (2014), 1315–1324.

[14] He, J., A. Chaintreau, and C. Diot, “A performance evaluation of scalable live video streaming with nano data centers”, Computer networks 53(2), 2009, pp. 153–167.

[15] He, W., “Examining students’ online interaction in a live video streaming environment using data mining and text mining”, Computers in Human Behavior 29(1), 2013, pp. 90–102.

[16] Hilvert-Bruce, Z., J.T. Neill, M. Sjöblom, and J. Hamari, “Social motivations of live-streaming viewer engagement on Twitch”, Computers in Human Behavior 84, 2018, pp. 58–67.

[17] Hong, Y., and P.A. Pavlou, “Product fit uncertainty in online markets: Nature, effects, and antecedents”, Information Systems Research 25(2), 2014, pp. 328–344.

[18] Hu, M., M. Zhang, and Y. Wang, “Why do audiences choose to keep watching on live video streaming platforms? An explanation of dual identification framework”, Computers in Human Behavior 75, 2017, pp. 594–606.

[19] Jung, J., R. Bapna, J. Ramaprasad, and A. Umyarov, “Love Unshackled: Identifying the Effect of Mobile App Adoption in Online Dating”, 2018.

[20] Kumar, N., L. Qiu, and S. Kumar, “Exit, Voice, and Response in Digital Platforms: An Empirical Investigation of Online Management Response Strategies”, 2016.

[21] Lim, S., S.Y. Cha, C. Park, I. Lee, and J. Kim, “Getting closer and experiencing together: Antecedents and consequences of psychological distance in social media-enhanced real-time streaming video”, Computers in Human Behavior 28(4), 2012, pp. 1365–1378.

[22] Payne, K., M.J. Keith, R.M. Schuetzler, and J.S. Giboney, “Examining the learning effects of live streaming video game instruction over Twitch”, Computers in Human Behavior 77, 2017, pp. 95–109.

[23] Pearl, J., Causality, Cambridge university press, 2009.

[24] Procyk, J., C. Neustaedter, C. Pang, A. Tang, and T.K. Judge, “Exploring video streaming in public settings: shared geocaching over distance using mobile video chat”, Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, (2014), 2163–2172.

[25] Seering, J., R. Kraut, and L. Dabbish, “Shaping pro and anti-social behavior on twitch through moderation and example-setting”, Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, (2017), 111–125.

[26] Sjöblom, M., and J. Hamari, “Why do people watch others play video games? An empirical study on the motivations of Twitch users”, Computers in Human Behavior 75, 2017, pp. 985–996.

[27] Wamser, F., F. Loh, M. Seufert, P. Tran-Gia, R. Bruschi, and P. Lago, “Dynamic cloud service placement for live video streaming with a remote-controlled drone”, Integrated Network and Service Management (IM), 2017 IFIP/IEEE Symposium on, (2017), 893–894.

[28] Yadav, M.S., K. De Valck, T. Hennig-Thurau, D.L. Hoffman, and M. Spann, “Social commerce: a contingency framework for assessing marketing potential”, Journal of Interactive Marketing 27(4), 2013, pp. 311–323.

[29] Ye, Q., R. Law, and B. Gu, “The impact of online user reviews on hotel room sales”, International Journal of Hospitality Management 28(1), 2009, pp. 180–182.

[30] Zhou, F., and W. Jia, “How a Retailer’s Website Quality Fosters Relationship Quality: The Mediating Effects of Parasocial Interaction and Psychological Distance”, International Journal of Human--Computer Interaction 34(1), 2018, pp. 73–83.