Zhong, Yingyu, Zhang, Yingying, Luo, Meng, Wei, Jiayue, Liao, Shiyang, Tan, Kim-Lim, and Yap, Steffi Sze-Nee (2022) ***I give discounts, I share information, I interact with viewers: a predictive analysis on factors enhancing college students' purchase intention in a live-streaming shopping environment.*** **Young Consumers, 23 (3) pp. 449-467.**

I give discounts, I share information, I interact with viewers: A predictive analysis on factors enhancing college students' purchase intention in a live-streaming shopping environment

Abstract

Purpose: Grounding our research in the stimulus-organism-resource (S-O-R) framework, this study addresses the research gap of explaining and predicting the relationship between price discounts, interactivity and professionalism on college students' purchasing intention in live-streaming shopping. It also attempts to understand if trust plays the role of mediator in the effect of these relationships.

Methodology: This study collected data using a questionnaire protocol adapted and refined from the original scales in existing studies. The partial least squares structural equation modeling (PLS-SEM) was used to analyze data collected from 258 college students in China. Other than assessing the path model's explanatory power, we examined the model's predictive power towards predicting new cases using PLSpredict.

Findings: Results indicated that all three predictors have a positive significant relationship with trust, while only price discounts demonstrate a significant relationship with purchase intention. Simultaneously, our mediation results provide support to the S-O-R framework demonstrating that external factors (professionalism, interactivity, and price discounts) can arouse organism (trust), which in return, generate a behavioral outcome (purchase intention),

Originality: This study is the first few studies that focus on college students' behavioral responses in an online shopping environment. At the same time, this is the first study supplement the explanatory perspective with a predictive focus, which is of particular importance in making sound recommendations on managerial decision making

Keywords: Price discounts, Professionalism, Interaction, College students, China, PLS-SEM

Introduction

The rapid development of innovation and new product selling mediums have changed how consumers receive their products and services. The traditional media of television, newspaper, radio, billboards, and leaflets have led to more contemporary internet and social media methods. A primary reason for the shift is the changing consumers, especially young consumers' expectations. As highlighted in a recent report, McKinsey (2021) highlighted that millennials wanted more than just a recipient of information. As consumers, millennials want to participate and co-create the shopping experiences that drive their engagement and purchasing intention (McKinsey, 2021). This trend makes a recent purchasing behavior ever more popular live-streaming shopping.

Being described as the next big thing, live stream shopping is one of the hottest trends to emerge from a pandemic-scarred 2020, as retailers and brands embrace this virtual approach to engaging consumers, especially young consumers (Lee and Chen, 2021, Guo *et al.*, 2021). Live streaming shopping promotes and sells products through live-streamers' own social media channels, most often housed in China's online shopping malls. It is like Home Shopping Network but with charismatic, trendy anchors. Greenwald (2020) described live-streaming shopping as part infomercial, part variety show. Therefore, a key feature of live streaming shopping lies in the social aspect, that is, the real-time interaction with the live-streamers and the peers (Clement Addo *et al.*, 2021). Consumers can post real-time questions and comments visible to the live-streamers and all other consumers (Lee and Chen, 2021). Other than responding to the questions promptly, the live-streamers value-add to the shopping experience by presenting the products, demonstrating their usage, and even suggesting ways on how consumers can mix and match the different products (Greenwald, 2020). Live-streamers incorporate gamification such as lucky draws, flash sales, quizzes with monetary rewards, and even inviting celebrity guests to offer an all-around shopping experience (Luo *et al.*, 2020). For consumers, purchasing the product while interacting with live-streamers and other consumers offers utilitarian and hedonic shopping experience. Given its unique propositions, it is not surprising that the live-streaming boom in China is set to thrive in other parts of the world, including Europe (Greenwald, 2020).

McKinsey (2021) report revealed that approximately 300 million Taobao users watched live streams during the 11.11 sales period from 1 November 2020 through 11 November 2020. The same report also highlighted that 33 live streaming channels achieved over a sales revenue of 100 million RMB (McKinsey, 2021). Greenwald (2020) estimated that live streaming shopping is worth \$60 billion annually, with a compound annual growth rate of 7.7% from 2020 to 2024. Among these, there is a visible shift in internet advertising towards mobile devices. It is estimated that the proportion of mobile internet advertising will increase to

63% by 2024, with live streaming shopping advertising becoming the new driving force (McKinsey, 2021). The potential of live-streaming e-commerce attracted many businesses. Many businesses are beginning to engage consumers using this new medium to gain competitiveness in this constantly changing landscape.

Despite its promising growth, live streaming has not received as much research attention as it should (Sun *et al.*, 2019). Only some studies have investigated how customer purchase intention is influenced by live streaming (Yu *et al.*, 2018, Lee and Chen, 2021). Additionally, the underlying construct linking the predictors to live-streaming shopping environment outcomes is unclear (Sun *et al.*, 2019). As such, this study offers an exciting opportunity to address these gaps. Specifically, its contributions and novelties can be seen from four perspectives.

First, many existing works suggest that the live-streamers' charm is the sole determining factor in influencing purchase intention. For instance, Clement Addo *et al.* (2021) examined how the number of likes and exposure time drives consumers' engagement and purchase intention. In the same vein, Sun *et al.* (2019) studied how the perspective of affordance lens of visibility, meta voicing, and guidance in shopping leads to purchase intention. From these works, it seems that many authors have yet to consider a vital aspect of a live-streamer – the ability to provide price discounts. Top live-streamers have their shows and appear each night for four hours at a stretch (McKinsey, 2021). On average, live-streamers would showcase approximately 12 products per hour, making it a total of 48 products per night (Greenwald, 2020). For top live-streamers, these products can sell out in seconds. For instance, Austin Li, a top live-streamer in China, attracted more than 40 million viewers and raised more than US$145 million in sales on Singles' Day just by selling lipsticks (Huang, 2020). Given the popularity of top live-streamers, it makes business sense for manufacturers pitching their products to the live-streamers. Part of it would be negotiating to get the lowest prices possible (Greenwald, 2020). Therefore, this study extends the body of knowledge by including live-streamers ability to provide price discounts as a predictor of purchasing intention - a construct that earlier studies did not consider.

Second, many studies, such as Wongkitrungrueng and Assarut (2020), often assume similar data characteristics across their population group. Often, these assumptions are unrealistic (Hair *et al.*, 2018). Individuals are different because of their genes, the way they are brought up, and how they are affected by their environment. Naturally, such differences mean their expectations on products and services are different as well. Therefore, conducting a study without specifying a context would threaten the validity of the results, producing an incomplete picture of the model relationships and generating misleading conclusions (Hair *et al.*, 2017). For instance, Hu and Chaudhry (2020) studied 327 respondents of Taobao

Live from different age groups and educational qualifications. Similarly, Wongkitrungrueng and Assarut (2020) developed their outcomes and recommendations based on 261 respondents without further distinction. These studies highlighted a standard limitation on the necessity for future researchers to be more focused to understand on how specific population groups' purchasing behaviours. As such, by being the first few empirical studies focusing on China college students in live streaming shopping, we provide insights that complement existing studies of Clement Addo *et al.* (2021), Luo *et al.* (2020), Lim *et al.* (2020) by elucidating the evolving behaviors and habits of this younger consumer group.

Third, trust has been widely studied in the online business environment. However, existing studies such as Leong *et al.* (2020), Wong *et al.* (2019) focus primarily on how functional specifications of online transactions such as privacy, perceived usefulness, perceived ease of use, and perceived mobility influence consumers' trust in technology. However, live-streaming shopping is more than these. As shared earlier, live-streaming shopping offers a utilitarian and hedonic shopping experience to the consumers. Zhao *et al.* (2018) further explained that live streaming shopping is a form of human-computer interaction that has seen a meteoric rise over the last few years. Building on this, it is essential to incorporate consumers' perceptions and the feature of live-streaming shopping together to examine how these translate to trust and eventually purchase intention – the most critical performance measure of a live-streamer's social media presence.

Finally, we differentiate from earlier works by performing predictive analysis. According to Shmueli (2011), many researchers have generally emphasized explanatory more than prediction modelling. In other words, the focus is mainly on assessing whether model coefficients are significant and in the hypothesized direction rather than on testing whether a model can predict new cases. After all, the purpose of managerial implications is to provide certainty into the future and make it relevant for practitioners. Therefore, without an additional assessment, implications made in different papers related to live-streaming shopping (see Lee and Chen, 2021, Clement Addo *et al.*, 2021, Sun *et al.*, 2020, Luo *et al.*, 2020, Wongkitrungrueng and Assarut, 2020, Hu and Chaudhry, 2020, Ham and Lee, 2020, Xu and Ye, 2020) are questionable, as we are unsure if the model estimates will produce similar results in terms of the outcome variables across time, samples and context. In sum, we argue that assessing a statistical model's predictive power is equally important to identify the likelihood of future outcomes based on historical data. The goal is to go beyond knowing what has happened to provide the best assessment of what will happen in the future.

Literature Review

Theoretical Framework

The stimuli-organism-response (S-O-R) framework has been the dominant theory to explain how environmental psychology influences one's behavioural response. The central theme of the S-O-R framework stipulates how different stimuli (S) influence individual internal organisms (O) to derive behavioural responses (R) (Mehrabian and Russell, 1974). This framework was widely used in studies relating to online shopping behaviour. For instance, Eroglu *et al.* (2001) examined how atmospheric cues of online stores served as stimuli to consumers' mind states that influenced their outcomes. Likewise, McKinney (2004) explained that the motivations for online shopping result from atmospheric variables that act as stimuli that influence consumers' level of satisfaction. At the same time, Peng and Kim (2014) use the S-O-R framework to examine how consumers' reasons for shopping and website stimuli affect their attitudes toward online shopping. Similarly, Wong *et al.* (2019) leveraged the S-O-R framework to evaluate the relationship of how technology trust, as the stimuli influences trustworthiness and consumer e-loyalty. Following the above, it is natural that the current study develops a conceptual model based on the S-O-R framework (see Figure 1). Consistent with the extant studies, we operationalize professionalism and interactivity as the environmental stimuli (S). Both professionalism and interactivity have been consistently highlighted as critical factors that determine the success of a live-streamer. Wongkitrungrueng and Assarut (2020) highlighted that live-streaming adds value to social networking sites through the existence of live-streamers. It allows sellers to reveal their faces, offices/homes, and personalities (i.e., social presence) and brings the buyer-seller interpersonal interaction and related selling techniques used offline back to the online world. Such live streaming enabled interaction that can enhance the shopping experience, reduce shoppers' uncertainty, and increase the level of trust they have toward the s-commerce seller (Clement Addo *et al.*, 2021). Other than interactivity, professionalism has been found to be another key characteristics of live-streamers. Through live-streaming, shoppers rely on information created and shared by live-streamers to make purchase decisions (Lee and Chen, 2021). At the same time, through the interaction live-streamers have with others via text-based dialogues in exchanging their thoughts about products and services, it can help shoppers to infer the popularity of products and whether they will purchase them (Xu and Ye, 2020, Sun *et al.*, 2019, Wang and Wu, 2019). The importance of these factors is also seen in recent studies such as Xu et al. (2020). They leverage aspects of interaction and aspects of professionalism as the stimuli that drive consumer behavior in live-streaming. To differentiate this study from the rest, we further consider one additional factor, price discounts, as another stimulus. Together, we posit that these three factors would influence trust, which is the organism (O) in the model, before affecting the behavioural response (R) of purchase intention.

*** Insert Figure 1 ***

Effect of Professionalism on Trust and Purchase Intention

As an important node connecting the brand and consumers, we can judge the live-streamers professionalism from words and actions. Like the structural bonds, professionalism is about sellers' ability to provide correct information about the product (Chang *et al.*, 2019). Wang *et al.* (2020) further explained that professionalism is about live-streamers knowing the product well, whether they can provide relevant and accurate information about the product. At other times, live-streamers demonstrate their professionalism by suggesting how consumers can mix and match the different accessories and inform consumers if they meet problems in the payment process. Unlike the brick-and-mortar shop where a consumer can make their purchase decision based on the sense of touch and smell, providing accurate information is crucial in a live-streaming shopping environment that supports consumers in framing their choices. Hence, it is not surprising when Wang *et al.* (2016) elucidated that providing professional knowledge reflects the seller's competence in the product and has been found that it increases consumers' trust. Besides, Chang *et al.* (2019) also discovered that providing accurate information enhances commitment to the e-retailer. In the same vein, Chou *et al.* (2015) mentioned that excellent delivery by professional live-streamers is characterized by professional reviews of products, professional selection, and accurate recommendations.

On this note, purchase intention is a behavioral possibility of consumers to purchase products or services in marketing activity (Zhang *et al.*, 2019). For marketers, purchase intention is a viral metric because they tend to predict buying behaviors. According to Ajzen (2020), consumers are more likely to take action in the future, such as purchasing a product, if they have a robust motivational intention towards it. Additionally, intention to purchase also reflects the levels of knowledge present in consumers' minds, which is helpful for organizations to iterate the kind of content they should display in an advertisement (Gefen *et al.*, 2003). Given its growing importance, it is not a surprise when scholars such as Sun *et al.* (2019) paying increasing attention to what factors drive purchase intention in an online environment. Based on the above argument, we believe that live-streamers professionalism is likely to become an essential factor influencing consumers' purchase intention as well as the building of trust, leading us to the first set of hypotheses:

H1a. Live-streamers' professionalism has a positive influence on purchase intention.
H1b. Live-streamers' professionalism has a positive influence on consumers' trust

Effect of Interactivity on Trust and Purchase Intention

Interaction is a process of information exchange and mutual communication between two parties (Ham and Lee, 2020). In a live streaming shopping environment, interaction is a direct form of communication between the live-streamer and the consumers. Live-streamers' high degree of interaction with consumers through real-time visibility and other characteristics of live-streaming, enabling consumers to have a more targeted understanding of product information (Sun *et al.*, 2020). According to Sun *et al.* (2019), live-streamer interactivity can be shown in three ways. First, high-density information exchange involves responding to real-time comments from consumers and notices that appear on the pages that inform viewers with important information. Second, performative interaction, where the live-streamer is "present and interactive" with the audience through "live images". This requires the live-streamer to demonstrate to the viewers the look of the product (Sun *et al.*, 2019). Third, inciting merchandising where the live-streamer constantly uses repetitive marketing language during the live-streaming session, emphasizing the various selling points and offers of the products in the live streaming to encourage the viewing user to place an order. On this note, Wang *et al.* (2020) and Zhang *et al.* (2020) believe that the more live-streamers interaction on live live-streaming platforms, the more conducive it will be to enhance the audience's trust in live-streamer. Based on this arguments, we have reasonable grounds to believe that if consumers feel the excitement and happiness brought by the interaction during live-streaming shopping, it promotes the purchasing behavior of consumers. Therefore, real-time interaction improves the authenticity of live-streamers opinions, wins the audience's trust, reduces the audience's perceived risk, and enhances consumers' purchase intention. As such, the hypotheses that will be tested are:

H2a. Live-streamers' interaction has a positive influence on purchase intention.

H2b. Live-streamers' interaction has a positive influence on consumers' trust.

Effect of Price Discounts on Trust and Purchase Intention

A unique advantage of any live-streamer is the ability to negotiate for lower prices while not compromising on the quality of the products or services sold during the live-streaming sale (Wang *et al.*, 2020). Greenwald (2020) emphasized that live-streamers with many online viewers and a strong overall purchasing power of fans can consume a large amount of inventory in a short period, hence having a more considerable bargaining power. Therefore, suppliers are willing to provide discounts to live-streamers to get them to carry the products (Greenwald, 2020). Often, such deals are lower than what consumers can obtain outside of these sessions. Besides, consumers can compare the prices of the same product offer by different live-streamers (Hu and Chaudhry, 2020). According to Alagarsamy *et al.* (2021), trust can also emerge through a capability process, which means assessing another party's ability to meet its obligations. Peterson (1995) has suggested that saving money is one of the customers' motivations to be involved in relational exchanges. Besides, Lee and Chen (2021) further espoused that price would positively affect consumer behavior, which includes an increase in trust and perceived usefulness. Given these arguments, and based on the S-O-R framework, it is logical to believe that the ability to offer a lower price would positively influence trust and purchase intention. However, studies have also reported that while price discounts may not be as effective in building consumers' trust (Alagarsamy *et al.*, 2021). This proposition is especially so when trust is as important, if not more important than price for today's consumers (McKinsey, 2021). It was revealed that trust exerted a more substantial effect than perceived price on purchase intentions for both potentials and repeated customers of an online store (Kim *et al.*, 2012). Given the inconsistent findings, examining the impact of price discounts on consumers' trusting beliefs and purchasing intention, through the following hypotheses, will significantly augment our existing understanding of consumers' psychological.

H3a. Price discounts have a positive influence on purchase intention.
H3b. Price discounts have a positive influence on consumers' trust.

Effect of Trust on Purchase Intention

Gefen *et al.* (2003) defined trustworthiness as a belief that both parties involved in the transaction will act in good faith, without worrying that the other parties would have any nefarious thoughts of acting opportunistically. In live-streaming shopping, the absence of face-to-face interaction, coupled with temporal and spatial separation between the influencer and consumers, makes trust an even more critical construct (Gefen *et al.*, 2003). Consumers are not able to physically touch, test, or try on items before purchase, which increases the perceived risk of online shopping, vendor's legitimacy, and product authenticity (Wongkitrungrueng and Assarut, 2020). This explains why Hsu *et al.* (2014) describe that consumers' trust can be described in different aspects – (1) Belief that cross-platform collaboration can lead to accurate, relevant, and timely information; (2) Belief that all parties involve acts in goodwill and following the industry norms and accepted practice; (3) Belief that cross-platform collaboration would result in transaction agreements that meet the needs of the actors involved. On this note, there have been several studies indicating that trust is the main component that drives purchase intention. This proposition is evident from Hidayat *et al.* (2021) where they found that when consumers want to shop or do other online transactions, consumers need assurance that the funds transferred will not just disappear, and the products they receive must be following what was promised and explained by the live-streamer. In the same vein, Sun *et al.* (2019) also found that the higher the consumers' trust in the live-streamer, the more likely consumers will develop the purchase intention。 Based on the above arguments, the following hypothesis is proposed:

H4. Consumers' trust has a positive influence on purchase intention.

Mediating Effect of Trust

The mediating role of trust is developed based on the S-O-R framework. Accordingly, if a consumer is exposed to several external factors (professionalism, interactivity, and price discounts), he/she will likely develop organism (trust), which in return, generate a behavioral outcome (purchase intention). This postulation is in line with several studies demonstrating the possible presence of such a relationship. For instance, Alagarsamy *et al.* (2021) showed that professionalism and interactivity build customers' trust levels. Other studies have also found similar results, including Singh and Sinha (2020), Wongkitrungrueng and Assarut (2020), Liu and Tang (2018). At the same time, trust is also found to be influencing purchase intention. Available literature from Sun *et al.* (2019) concluded that if a customer has a higher trust developed on the online seller, he/she is also more likely to develop the purchase intention. Overall speaking, these evidence demonstrated that the intention of purchase requires establishing trust in the buyer-seller relationships. And the building of trust will require the presence of antecedents. Despite these postulations, there is a lack of studies examining trust as a mediator in a live-streaming environment. Earlier studies in other fields such as in online shopping shows that trust mediates the relationship between security and customer e-loyalty in online shopping (Wong *et al.*, 2019). Another study by Singh and Sinha (2020) on mobile wallets explained that trust mediates the relationship between perceived usefulness and intention to use. Based on the aforementioned, we have reasonable grounds to believe that trust plays a key role in mediating the following relationships:

H5a. Trust mediates the relationship between live-streamers professionalism and purchase intention.
H5b. Trust mediates the relationship between live-streamers interaction and purchase intention.
H5c. Trust mediates the relationship between price discounts and purchase intention.

Methodology

Sample

Data collection was through an online questionnaire from college students in China who have visited a live-streaming room. College students were selected as the research participants for three main reasons. First, college students are savvier and more open to this new way of shopping (Xu and Ye, 2020). Second, the China Internet Network Information Center, whose 2019 report shows that the most significant internet users are students (CNNIC, 2019). Finally, McKinsey (2021) show that the number of followers of influencers on *Taobao*, *Tik Tok,* and *Weibo* increased by 25 percent compared with last year, with the age composition of influencers' followers is significantly younger, more than 80 percent of them are born in the 1980s and 1990s. Snowball sampling was adopted where we begin with a small population of known individuals and expands the sample by asking those initial participants to identify others that should participate in the study. This sampling method is especially helpful during the pandemic when face to face interaction is discouraged (Memon *et al.*, 2017). We have also noted that studies such as Le et al. (2021) involving respondents of specific activity use a similar sampling method.

Instrument

The questionnaire was first developed in English, translated to Chinese. We have invited five college students who have previous live-streaming shopping experiences to check if the translated measurement items are easy to understand. Any ambiguities in terminology and any non-clarity in instructions were amended to improve the readability of the questionnaire. Thereafter, we performed a back-translation to English by asking two researchers with relevant research experience to ensure the accuracy of the translation.

The measurement items were adopted from earlier studies. Unless otherwise mentioned, all items are measured on a five-point Likert scale, with “1” being strongly disagree to “5” being strongly agree. The five items of interactivity, five items of professionalism, and three items of price discounts were adopted from Wang (2020). Measurement items for trust were adopted from Gefen *et al.* (2003), while the purchase intention was measured using four items adapted from Suh and Chang (2006). Finally, both trust and purchasing intention constructs are measured on a five-point Likert scale of “1” being absolutely untrue to “5 being absolutely true.

Data Collection

The online questionnaire was disseminated using an application call *Wenjuan Xing*. *Wenjuan Xing* is a Chinese commercial online survey service provider, with one of its key advantages of pushing the survey directly through a local messaging platform such as WeChat, which provides accessibility and convenience to respondents (Mei and Brown, 2017). Besides, the recent cybersecurity laws that control web content in China mean that some traditional data collection software would be unstable or inaccessible in China (Mei and Brown, 2017). Hence, *Wenjuan Xing* is a more reliable and user-friendly online survey tool that researchers in China, such as Xu and Ye (2020) and Sun *et al.* (2019), have been using.

Through *Wenjuan Xing,* a web link was generated and disseminated to all respondents. From the cover page, respondents were informed that participation is voluntary, all collected data are confidential and anonymous, and they need to provide their honest opinions. Respondents must give their consent before they can proceed with answering the questions. To ensure that only bonafide respondents participated in our study, we provided a screening question asking if they have visited live-streaming shopping at least one day per week, without specifying a specific timeframe or platform. Similar studies such as Xu and Ye (2020) and Clement Addo *et al.* (2021) have used a similar approach. A total of 258 valid responses were collected, exceeding Kock and Hadaya (2018) recommended minimum sample size of 146 for any PLS-SEM analysis.

Controlling Common Method Bias

Being a cross-sectional study, provisioning socially desirable responses has always been a threat that could potentially bias the results. Hence, controlling common such biases is critical in these studies. Using recommendations from Podsakoff *et al.* (2003), we implemented several procedural measures. First, the questionnaire is pre-tested to ensure that respondents understand the questions as intended. Second, we create temporal measures by placing demographic questions in-between predictor and criterion questions. Third, researchers had constantly highlighted anonymity and confidentiality during the data collection process to respondents. Besides, we reiterated to the respondents that there were no right nor wrong answers. Statistically, Harman's single factor test shows that no single factor accounted for the majority of the covariance in the independent and criterion variables, indicating that common method biases are not a serious issue in this study (Podsakoff *et al.*, 2003). Additionally, we deployed the full collinearity test where the results showed that none of the variance inflation factors (VIF) exceeds 3.3, indicating that the model is free of common method bias (Kock, 2015)

Control Variables

Following Atinc *et al.* (2011), the inclusion of control variables would be needed to minimize the possibility of confounded results that limit the model's explanatory power. For this model, we include gender and the number of purchase times as the control variables. Table 4 shows that none of them have any significant effect on the key endogenous variables.

Analytical Method

The descriptive statistics of the respondents were developed using the Statistic Package for the Social Sciences (SPSS) version 25.0., while the PLS-SEM was used for testing the hypotheses. PLS-SEM is the second-generation technique that allows for the simultaneous evaluation of the measurement and structural models (Hair *et al.*, 2017). Unlike the covariance-based SEM, PLS-SEM's strength lies in its ability to perform predictive analysis of the model, which is one of the research objectives. Being a non-parametric method with no distributional assumptions, PLS-SEM is widely deployed in different study contexts, including tourism (Ali *et al.*, 2018, Tan *et al.*, 2020c, Fam *et al.*, 2020), human resources (Tan *et al.*, 2020a, Sarstedt and Danks, 2021, Tan *et al.*, 2020d), education (Ghasemy *et al.*, 2020, Sim *et al.*, 2020, Tan *et al.*, 2020b), technology adoption (Leong *et al.*, 2020, Wong *et al.*, 2019), consumer behavior (Tan *et al.*, 2021) and knowledge management (Cepeda-Carrion *et al.*, 2019). Following the recommendations by Hair *et al.* (2017), we adopted a two-stage approach of assessing the measurement model followed by the structural model.

Results

Respondents' Profile

From the 258 respondents, it is evident that most of the respondents (60%) are 20 years and younger. This is followed by 21-22 years old (20.6%), with the rest above 23 years old (9.3%). Out of the 258 respondents, almost 70% of the respondents are female, with the rest being male. This is not surprising given that different studies and reports such as Ma (2020) highlighted that females are the dominant consumer group in live streaming shopping. On the number of order times per month, the majority of the respondents (80%) have ordered at least one time per month. The majority ordered 1-5 times per month followed by 6-10 times per month.

*** Insert Table 1 ***

Measurement Model

From Table 2, it is evident that the thresholds of average variance extracted (AVE) and composite reliability (CR) meets the requirement of 0.50 and 0.70, respectively (Hair *et al.*, 2017). At the same time, both Cronbach's Alpha and rho_A fell within the acceptable range of 0.70 and 0.95 (Dijkstra *et al.*, 2015) In Table 3, the heterotrait-monotrait ratio of correlations (HTMT) results also showed that discriminant validity has achieved at $HTMT_{0.85}$ (Hair *et al.*, 2017). Hence, we can conclude that this model is reliable and valid.

*** Insert Table 2***

*** Insert Table 3***

Structural Model

From Table 4, the VIF score showed that they are lesser than 3.3 indicating no multicollinearity issues with the model. The structural results showed that professionalism (H1b. $\beta = 0.324$, $p<0.001$), interaction (H2b. $\beta = 0.195$, $p<0.01$) and price discount (H3b. $\beta = 0.362$, $p<0.001$) are all predictors of trust. However, out of the three predictors, only price discount has a significant positive relationship with purchase intention

(H3a. β = 0.446, $p<0.001$). The remaining two predictors of professionalism (H1a. β = 0.059 $p=0.222$) and interaction (H2a. β = 0.039, $p=0.260$) did not establish any significant relationship with purchase intention. It is found that trust has a significant positive relationship with purchase intention (H4. β = 0.318, $p<0.001$). On mediation analysis, trust is an effective mediator across the three relationships between professionalism and purchase intention (H5a. β = 0.103, $p<0.01$), between interaction and purchase intention (H5b. β = 0.062, $p<0.01$) and between price discount and purchase intention (H5c. β = 0.115, $p<0.01$). Following Zhao *et al.* (2010), H5a and H5b are classified as full mediation, while H5c is classified as a complementary partial mediation. Thus, other than H1a and H2a, the rest of the hypotheses are supported.

The coefficient of determination (R^2) represents the amount of variance in the endogenous constructs explained by all the exogenous constructs linked to it. Table 4 shows that the predictors of professionalism, interaction, and price discount account for 54.1% of the variance in trust. The same set of predictors, together with trust, accounts for 56.3% of the variance in purchase intention. As these values exceed 0.26 suggested by Cohen (1988), it could be considered a substantial model.

As highlighted by Sullivan and Feinn (2012), "while a *p*-value can inform the reader whether an effect exists, it does not reveal the size. Hence, both substantive significance (effect size) and statistical significance (*p*-value) are essential results to be reported." In this regard, Cohen (1988) classification reveals that professionalism (f^2 = 0.004) and interaction (f^2 = 0.002) display negligible effect size in producing R^2 for purchase intention, which explains for its insignificant relationship. Interaction (f^2 = 0.045) has a small effect in producing R^2 for Trust. For professionalism and trust, both exhibited medium effect in producing R^2 for trust and purchasing intention, respectively. Finally, at f^2 = 0.272 and f^2 = 0.205, price discount displayed substantial effect to purchase intention and trust respectively.

*** Insert Table 4 ***

Predictive Analysis

Lastly, we perform predictive analysis using the PLS predict technique. Before this, researchers used Stone Geisser's Q^2 value as the sole criterion to assess predictive relevance. According to Hair *et al.* (2017), Table 4 showed that the value of Q2 is larger than 0, indicating that the model has predictive relevance. However, we value-add to the predictive analysis by leveraging the PLS predict. As elucidated by Shmueli *et al.* (2019), the Q^2 value, while is useful, is still a combination of in-sample and out-of-sample prediction, and does not clearly indicate whether the model has a good explanatory fit or exhibits predictive power. As such, PLS predict is a more reliable way of assessing the predictive relevance of a model as it separates testing and training data (Shmueli *et al.*, 2019). Referring to Table 5, analysis showed that majority of the values of the root mean squared error (RMSE) values for the PLS model were smaller than that of the linear model (LM), indicating that the model has medium predictive power.

*** Insert Table 5 ***

Discussions

Grounded on the S-O-R. framework, this study examines the predictors of trust and purchasing intention. At the same time, it also aims to investigate if trust is a mediator in these relationships. On this note, our results show that all the three predictors of professionalism, interaction, and price discount are instrumental in enhancing one's trust in live-streaming shopping. These results are similar to other studies such as Shanka and Buvik (2019), where they found the three relational bonds are shaping trust. Likewise, Lin *et al.* (2003) found that relational bonds that foster customer trust can be categorized empirically into three types: economic, social, and structural bonds. Taken together, these findings signpost the significant role of these three elements. A probable reason could be the nature of live-streaming shopping. As highlighted earlier, live-streaming shopping faces an inherent disadvantage of having the void of physical touch and human-to-human interaction. As Wertz (2019) has put it, a brick-and-mortar store can easily curate a unique branded experience for its consumers, which is what many consumers desire and are willing to pay. To replicate this experience in a live-streaming shopping environment, it would take more effort and rely on the live-streames ability to provide both hedonic and utilitarian experience to the consumers, through its professionalism in presenting the products, interacting with consumers, and ability to obtain products with significant price reductions.

Interestingly, when the same set of constructs are applied to examine their influence on purchasing intention, only price discount demonstrates a direct relationship with it. Our results are different from existing studies. For instance, Sun *et al.* (2019) study on 504 chinese consumers shows that interactivity and providing guidance to consumers influence shopping intention. Similarly, other studies such as Lee and Chen (2021), Clement Addo *et al.* (2021) displayed similar results. However, a common feature among these studies is the homogenous assumptions of their respondents. As highlighted by Hair *et al.* (2018), these assumptions are unrealistic. Evident from our results, we have found that the antecedents of professionalism and interactivity do not matter to college students. A possible reason is that this group of consumers are well-informed and highly resourceful where they can perform research about the product before participating in the live-streaming. This is also known as the zero moments of truth. Han and Kim (2020) further explained that college students are the first generation to be surrounded by the internet from a very early age. And given the wide availability of information, a unique decision-making process has been developed where they would search for information online to decide whether or not they want to buy it.

From this perspective, it is apparent from our results that college students' motivation to participate in live-streaming is to obtain price discounts. Price discount has been analogous to lower prices (Greenwald, 2020). The more price discount a live-streamer can provide, the prices of the products would be brought down further. As college students, it is natural that they would have limited spending power. When it comes to spending, most college students' money goes toward essentials such as tuition fees, textbooks, and bills (Shim *et al.*, 2010). Other than creating brand awareness, another powerful way to encourage purchases, especially first-time purchases among college students, is discounts. This reasoning is supported by Kuo and Nakhata (2016) where they conducted experiments and conclude that discount positively shapes college students' responses toward products, even those with low consumer ratings.

At the same time, our study shows that trust is a strong predictor to purchase intention. This result is not surprising as evidence can be found in other studies such as Lin and Lu (2010), Hidayat *et al.* (2021), Singh and Sinha (2020), Wong *et al.* (2019). The importance of trust is evidenced in the mediation hypotheses, where it is the key construct bridging the predictor and the criterion variables together. A probable explanation could be attributed to the environment that live-streaming shopping operates. The expansion of the internet and different communication channels has expanded retailers' markets and provides alternatives for consumers (Hidayat *et al.*, 2021). With a rapid expansion of the Internet, enormous opportunities have been created for businesses to be part of a global market with global consumers. This expansion means cross-border transactions are possible, which naturally increases uncertainty due to the possibility of fraud, malware, and system errors. Additionally, there is uncertainty on whether live streamers will deliver the product after payment, as per their promise to consumers. In this sense, when consumers recognize that their interests and welfare are taken care of, trusts develop, and they are likely to remain in this relationship.

Theoretical Implications

This study makes several theoretical contributions. First and foremost, it is the first few empirical studies focusing on college students' behavioral responses in a live-streaming shopping environment. As highlighted earlier, many existing works, such as Lee and Chen (2021), assumed homogeneous data characteristics across the population, which according to Hair *et al.* (2017), is not realistic. Hence, our results complemented existing work by understanding the emotional effects deriving from the different forms of stimuli. In this respect, this study answers Wongkitrungrueng and Assarut (2020) call to include a range of factors and examine other consumer groups' live-streaming shopping behavior. Second, our study addresses a research gap by demonstrating that price discount builds trust and purchase intention. This study shows a significant positive correlation between price discount on trusts and purchase intention, which is commonly treated as separate predictors in earlier studies (Kuo and Nakhata, 2016). This study reveals that price discount are the only predictor that directly affects purchase intention among three predictors, which is a unique proposition among college students that earlier studies did not espouse. Finally, our study demonstrates that the research model is robust and display good predictive power. According to Sarstedt and Danks (2021), the need to supplement the explanatory perspective with a predictive focus is particularly important to social sciences researchers, given the efficient nature of the research and the direct impact on managerial decision-making. In sum, our results help live-streamers to determine customer responses or purchases and promote cross-sell opportunities (Liengaard *et al.*, 2020). End of the day, predictive models help businesses attract, retain and grow their most profitable customers.

Managerial Implications

From a managerial perspective, this research has several significant implications for live-streamers. The real-time nature of live-streaming shopping facilitates the live-streamer to reveal his or her identity. In other words, consumers can see how this person is, his or her facial expression, and the background. These atmospheric elements would cast an expectation on the consumers that influence their perception and eventually responses. In relation to this, the live-streamer should position the product so that consumers can have a clear view of how it looks and how it can be used. Hence, using better quality equipment that supports such visualizations is essential in improving professionalism. At the same time, live-streamer can demonstrate professionalism in providing a timely and accurate response to consumers' questions. Examples of demonstration of professionalism include collecting and acting on consumers' feedback.

Watching live-streaming takes more time than browsing a webpage. It also takes more effort to pay attention to the descriptions than visiting a brick-and-mortar store. It takes more patience to wait for the desired product to be featured instead of going to the specific product shelf in a brick-and-mortar store. Hence, live-streamers should keep the consumers engage and reduce boredom by increasing their interactivity. Live-streamers can consider including enjoyable and entertaining activities relating to products (e.g., product demonstration shows with a sense of adventure and fantasizing) or incentives (e.g., games, flash sales). These activities can create positive emotions that will induce affective trust regarding the products and sellers. The challenge lies in creating content to excite customers continuously. Efforts must be made to present the amicable traits of the live-streamer. Verbal expression, appearance, postures, and choice of words send signals to the consumers that eventually influence consumers' perception of professionalism, interactivity, and ultimately trust and purchase intention. Hence, the live-streamer must demonstrate characteristics of likability and identify themselves with the values of the consumers.

At the same time, live-streamers must secure goods at a lower price yet not compromising on the quality. And for that to happen, live-streamers must continue to maintain their popularity. With a strong fans-base, they can easily convert them to consumers, which provides them a strong bargaining power to ask brands for an exclusive discount. Once live-streamers establish the above alignment, a sense of belonging among the consumers would be created. Coupled with rich experiences and interactions, it will establish trust, loyalty that drives purchase intention.

Limitations and Future Research Directions

This study endeavored to recruit as many respondents as possible. However, as the responses to the survey were voluntary and snowball sampling also contributed to the collection of responses, it poses difficulty in getting more respondents. Besides, this is a cross-sectional study. Hence, it does not capture the change in respondents' perceptions over time. As the pandemic progresses into a recovery stage where more brick-and-mortar stores reopen, it would be interesting to see if the attitude towards live-streaming shopping changes. Even though efforts were made to minimize CMB, we cannot deny the possibility that respondents would still provide a socially desired response. They may tend to assume the "middle ground" for questions that they could not connect. Hence, future studies could adopt the longitudinal approach or multiple data collection waves that involve different generations of consumers. With trust being is a critical construct in this study, it could be further examined by operationalizing trust as a multidimensional construct. According to Hsu *et al.* (2014), trust can be classified into trust in the website, trust in the vendor, trust in group members, and trust in the auction initiator. Finally, future researchers could extend the model by incorporating additional antecedents or moderators such as the personality traits of customers or sellers.

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Figure 1. Conceptual Model

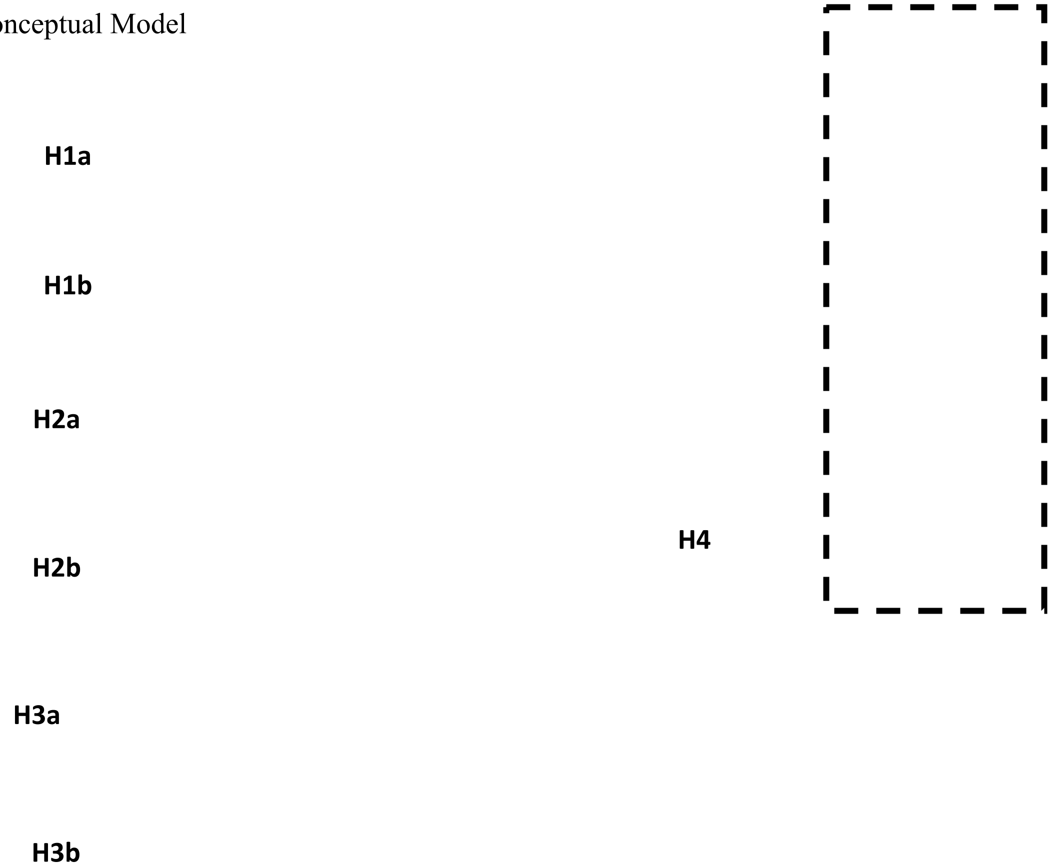

Table 1. Respondents' Profile (n=258)

	Frequency	Percent	Cumulative Percent
Age			
18 years and younger	14	5.4	5.4
19-20 years old	141	54.7	60.1
21-22 years old	79	30.6	90.7
23-24 years old	20	7.8	98.4
25 years and older	4	1.6	100.0
Gender			
Male	83	32.2	32.2
Female	175	67.8	100.0
Order Times per month			
0 times	53	20.5	20.5
1-5 times	179	69.4	89.9
6-10 times	10	3.9	93.8
11-15 times	7	2.7	96.5
16-20 times	4	1.6	98.1
21-25 times	4	1.6	99.6
More than 25 times	1	.4	100.0

Table 2. Measurement Model

	Items	Outer loadings	Cronbach's Alpha	rho_A	CR	AVE
PD1	The prices of products sold by live-streamer are the lowest among live streaming rooms in all platforms.	0.766	0.846	0.853	0.896	0.684
PD2	The products' prices in live-streamer's room is favorable enough.	0.842				
PD3	The discount won over from supplier by live-streamer is always the best.	0.863				
PD4	The live-streamer can get the products that fans want at a favorable price.	0.835				
INT1	The live-streamer shows his enthusiasm to me.	0.803	0.730	0.745	0.831	0.556
INT2	The live-streamer shows his care to me.	0.869				
INT3	If I ask questions, the live-streamer can always answer them positively.	0.659				
INT5	My attention is always attracted to products when the live-streamer abruptly change the volume.	0.625				
PI1	I would recommend others to buy products in the live-streamer's room.	0.814	0.832	0.845	0.888	0.664
PI2	I think the product recommended by the live-streamer is worth purchasing.	0.858				
PI3	I want to buy the product the live-streamer recommends.	0.795				
PI4	When I need any products, I will consider buying them from the live-streamer.	0.792				
PRO1	The live-streamer knows his recommended products well.	0.814	0.827	0.845	0.885	0.659
PRO2	The live-streamer has enough experience (e.g. working experience, trial experience) to judge the products he recommends.	0.851				
PRO3	The live-streamer's introduction of the product can give me a complete understanding of it.	0.764				
PRO4	The live-streamer recommends the products only after his research.	0.816				
TR1	The information provided by the live-streamer is authentic with the actual condition of the products.	0.862	0.871	0.874	0.912	0.721
TR2	The live-streamer is responsible for his products.	0.842				
TR3	The live-streamer is worth my trust due to the information known about his from different online platforms.	0.852				
TR4	The platform where the live-streamer does his job, makes me feel that he is a trustworthy anchor.	0.840				

Note: (1) PD – Price discount, INT – Interaction, PI – Purchase Intention, PRO – Professionalism, TR-Trust

Table 3. Discriminant Validity

	PD	INT	PRO	PI	TR
PD					
INT	0.567				
PRO	0.595	0.829			
PI	0.807	0.559	0.604		
TR	0.703	0.691	0.742	0.756	

Note: (1) PD – Price discount, INT – Interaction, PI – Purchase Intention, PRO – Professionalism, TR-Trust;

(2) HTMT achieved at $HTMT_{0.85}$

Table 4. Structural Model

	Hypotheses	Standard Beta	Standard Error	t-value	CI (5.00%)	CI (95.00%)	VIF	f^2	R^2	Q^2
H1a	Professionalism -> Purchase Intention	0.059	0.077	0.764$^{(NS)}$	-0.069	0.187	2.164	0.004	0.563	0.363
H1b	Professionalism -> Trust	0.324	0.088	3.695***	0.160	0.449	1.935	0.118	0.541	0.380
H2a	Interaction -> Purchase Intention	0.039	0.061	0.645$^{(NS)}$	-0.066	0.136	1.922	0.002		
H2b	Interaction -> Trust	0.195	0.071	2.738**	0.077	0.312	1.839	0.045		
H3a	Price discount -> Purchase Intention	0.446	0.060	7.501***	0.342	0.538	1.678	0.272		
H3b	Price discount -> Trust	0.362	0.089	4.071***	0.221	0.511	1.392	0.205		
H4	Trust -> Purchase Intention	0.318	0.072	4.387***	0.193	0.433	2.177	0.106		
H5a	Professionalism -> Trust -> Purchase Intention	0.103	0.035	2.950**	0.055	0.171				
H5b	Interaction -> Trust -> Purchase Intention	0.062	0.028	2.222**	0.023	0.116				
H5c	Price discount -> Trust -> Purchase Intention	0.115	0.038	3.000**	0.063	0.194				
	Control Variables									
	Gender -> Purchase Intention	0.062	0.044	1.428$^{(NS)}$	-0.023	0.146				
	Order -> Purchase Intention	0.025	0.033	0.760$^{(NS)}$	-0.042	0.090				

Note: NS- not significant, * $p < 0.05$ ** $p < 0.01$, *** $p < 0.001$

Table 5. PLS predict

	PLS		LM		PLS-LM	
	RMSE	Q²_predict	RMSE	Q²_predict	RMSE	Q²_predict
PI1	0.679	0.242	0.701	0.194	-0.022	0.048
PI2	0.493	0.458	0.498	0.447	-0.005	0.011
PI3	0.647	0.189	0.643	0.197	0.004	-0.008
PI4	0.626	0.387	0.645	0.350	-0.019	0.037

Note: PI – Purchase Intention