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RESEARCH PAPER

Customer behavior of online group buying: an investigation using the transaction cost economics theory perspective

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Abstract

As online group buying (OGB) businesses increasingly face strong competition, understanding the beliefs, attitudes, and behaviors of their customers is critical. Hence, the purpose of this study is to understand why customers choose one OGB vendor over others. By extending the transaction cost economics (TCE) theory, we explain OGB customers' purchase behavior. We conducted a two-stage online survey. The first survey (T_1) captured the perceptions of the respondents before making a purchase (i.e., purchase intention and its antecedents, namely unpredictability, trust, customizability, and frequency of OGB use*)*. In the second stage (T_2), we collected responses from the participants of the first study who committed at least one purchase in the last month. The second survey collected responses about the frequency of OGB use, purchase behavior, and online customer review (OCR). Data were analyzed with partial-least-square-based structural equation modelling technique (PLS-SEM). Results suggest that unpredictability, trust, and customizability influence purchase intention and are influenced by the frequency of OGB use. In addition, customizability decreases unpredictability. Finally, in seeking an answer to how to convert potential customers into actual customers, we found that OCR is a moderator of the relationship between purchase intention and purchase behavior. The findings from the longitudinal study extend TCE theory in electronic markets by capturing the OGB dynamics (i.e., antecedents and effects), the mediating effects (i.e., purchase intention) and the moderating effect (i.e., OCR) in a robust nomological relationship.

Keywords Online group buying · OGB · Transaction cost economics · Intention · Actual behavior · Online customer review

JEL classification L81 · M310

Introduction

Online group buying (OGB) emerged as one of the most successful types of online business models (Erdoğmus & Çiçek, 2011; Ku, 2012; Xiao et al., 2017). OGB refers to the purchase of products and services by the online shopping community at a price that is significantly reduced from the regular retail price (generally representing a more than 50% discount) when a 'sufficient' number of buyers (a predefined number set by the merchant) participate in the purchase (Chen et al., 2015; Hossain et al., 2018; Jeng & Tseng, 2018). Attracted by its success, every year, new OGB vendor websites join the e-marketplace. Given the fierce competition, many OGB ceases to operate (Liu & Sutanto, 2012) and many others encounter declining traffic and purchases (Che et al., 2015). Despite the growth and potential of OGB, there remains a great deal of confusion surrounding customer behavior in relation to OGB. This lack of understanding compels OGB businesses to consider carefully how they attract not only visitors but also actual customers and poses an intriguing question for academic research (Mena & Bourlakis, 2016).

Transaction cost economics (TCE) theory (Williamson, 1979) provides an understanding of why customers choose one vendor over others. In a transaction in the online environment, for example, customers choose an e-commerce vendor with whom the

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transaction costs (i.e., the set of costs incurred by the customer in each transaction) are minimized. It is considered that the "real illuminating power of TCE comes from three variables that are employed to characterize any transaction. They are frequency, uncertainty, and asset specificity. Transactions can be rare or frequent; have low or high uncertainty; or involve specific or non-specific assets" (Teo & Yu, 2005, p. 452). Applying TCE, for example, Che et al. (2015) demonstrated that consumers' OGB revisit intention can be explained by uncertainty (e.g., unpredictability) and *asset specificity* (e.g., trust and personalization). However, their study ignored the influence of frequency, which is one of the three important variables of TCE (along with uncertainty and asset specificity), and an important variable in the information systems (IS) field (e.g., Shih & Venkatesh, 2004). Also, the nomological structure of Che et al.'s model is inconsistent with IS theories/models where user behavior is expressed using the belief–attitude–behavior chain (Wang, 2008), whereas they explained only belief-behavior relationships. Finally, like many other OGB studies, Che et al. postulated that OGB customer behavior can be explained through *intention to revisit*, assuming that customers "make a purchase after repeatedly revisiting an OGB website" (Che et al., 2015, p. 588). This is an optimistic assumption; rather, "purchase behavior [than purchase intention] is undoubtedly the most important concern in online businesses" (Lee & Lee, 2015, p. 57).

The main purpose of the current study is to explain customers' OGB behavior from the perspective of TCE. In doing so, we revise Che et al.'s model and validate it using longitudinal data. We incorporate *frequency* in our TCE model for OGB and examine both customer *intention* and actual *behavior* to fit within the belief–attitude–behavior framework. Further, we investigate the non-linear intention–behavior link, positing that this relationship is contingent on a fundamental variable for e-commerce—online customer review—which is a subject of current ongoing discussion among IS scholars and IS journals (Chen et al., 2019; Huang et al., 2018; Li, Pham, & Chuang, 2019; Li, Wu, & Mai, 2019).

This paper is organized as follows. Section 2 explains the development of our research model for OGB and presents a comprehensive set of hypotheses. Section 3 presents the methods, measures, and data collection process of the study. Section 4 presents the data analysis and results. Section 5 discusses the results in relation to their theoretical and managerial implications. Section 6 concludes the study.

Research model and hypotheses development

The well-known IS theories suggest a belief–attitude–behavior chain (see Appendix Table 4). For example, the technology acceptance model (TAM) has three categories of variables: beliefs (i.e., perceived usefulness, perceived ease of use), attitude, and behavior (i.e., intention to use, system use) where the two behavioral beliefs influence attitude, which in turn determine user behavior. Although most OGB studies have followed the belief–attitude–behavior chain (e.g., Cheng & Huang, 2013; Hsu, Chang, et al., 2014; Hsu, Chuang, & Hsu, 2014; Kim et al., 2010; Lim & Ting, 2014; Lin & Wu, 2015; Shiau & Chau, 2015; Wang & Chou, 2014), Che et al.'s nomological structure is somewhat inconsistent with the IS theories and therefore warrants modification. The conceptual model developed in the present study theorizes that *frequency* (a customer attribute) influences customer *belief*[1] (i.e., unpredictability, trust, and customization), which affect customer *attitude* (i.e., purchase intention), and that *attitude* eventually affects *behavior* (i.e., purchase behavior). In our study, *behavioral intention* refers to an indication of an individual's readiness to perform a given behavior (attitude), whereas *behavior* refers to an individual's observable response in a given situation with respect to a given target (Wee et al., 2014). According to TCE, *frequency* influences both *uncertainty* (i.e., unpredictability) and *asset specificity* (i.e., trust and customization), which eventually affect customer *attitude*.

Frequency, customer belief, and customer attitude

Frequency, with which transactions occur, is one of the critical dimensions for describing transactions and thus becomes one of the fundamental dimensions of TCE (Williamson, 1981). In IS, *frequency of use* is typically operationalized through consideration of how often a particular technology is used by an individual. In the current context, *frequency* is a customer attribute (Wang & Chou, 2014), which can be defined as the degree to which customers frequently visit OGB websites. Several OGB studies (e.g., Chen et al., 2015; Cheng & Huang, 2013; Shiau & Luo, 2012) have considered the *frequency of OGB use* as a demographic variable, but they did not examine its effect on customer attitude or behavior. Nonetheless, Rudawska et al. (2015) and Yen and Chang (2015) found no influence of frequency on group buying motivation. Thus, the effect of frequency of use on transactional beliefs is inconclusive, particularly in the context of OGB, and require further detailed examination.

Prior studies (e.g., Bucklin & Sismeiro, 2003) have found that the number of times a user visits a website has several consequences, including affecting user beliefs, e.g., perceived ease of use and usefulness (Vekiri & Chronaki, 2008; Yingchen & Kinzie, 2000). It is intuitive that rational users would learn and upgrade their skills from every visit and enhance positive perception of the ease of use of the website. Similarly, frequent visits may expose the usefulness of the website more than in a discrete visit. As frequency affects customer attitude too (Bovée et al., 2007; Meelissen & Drent, 2008), we hypothesize that frequency of OGB use will

[1] For example, *frequency of use* can influence *trust* but not necessarily the *trustworthiness* of a business (which is a business attribute); similarly, *frequency* may affect *customization* but not *personalization*.

affect unpredictability (H1), customizability (H2), and trust (H3) as well as customers' purchase intention (H4).

Frequent use of an IS removes mental obstacles and discomfort that have occurred in the past when using the same IS. Such learning-from-doing reduces transaction costs. In general, for an online environment, customers with high buying frequency perceive lesser transaction costs than the customers with low buying frequency. In an online shopping environment, Teo and Yu (2005) found that the reaction of frequent and less-frequent customers to the same level of uncertainty in the transaction process could be different. For instance, the level of user perception about the unpredictability of a website may decrease with frequent visits. Alternatively, lower transactional investment (i.e., frequency of use) leads to higher uncertainty. Here, transactional uncertainty is minimized through a higher investment of transaction costs (through time and effort expended by visiting a website, i.e., frequency). With the same reasoning, frequency of visits may enhance customer trust by reducing their perceived risk, uncertainty, and anxiety (Sirdeshmukh et al., 2002). This is supported by Kaya et al. (2019), who found that frequency of website visit has direct as well as moderation effects on customer trust.

The perceived customizability of a website can vary depending on the number of visits of a given customer in a specific period. Customers who visit regularly are likely to get familiar with the website, its contents, and styles than those who visit less frequently and thus can customize the website more easily and to more extent. The more a customer visits a particular website, the more he/she would try to lessen the transaction costs and thus likely to customize the website. Finally, the frequency of website visit has a significant positive effect on customers' purchase decision (Kaya et al., 2019). Specifically, Wang and Chou (2014) suggest that prior purchasing frequency from OGB websites not only increases users' positive perceptions of, and but also behavioral intention toward, the OGB website. Therefore, we propose the following hypotheses:

H1. The frequency of OGB use will have a negative effect on the perceived unpredictability of OGB websites.
H2. The frequency of OGB use will have a positive effect on the perceived trust of OGB customers.
H3. The frequency of OGB use will have a positive effect on the perceived customizability of OGB websites.
H4. The frequency of OGB use will have a positive effect on customers' purchase intention.

Uncertainty, asset-specificity and customer attitude

Unpredictability and purchase intention

For TCE, *uncertainty* refers to the costs associated with the unexpected outcomes of a transaction that may affect the contract and its fulfillment (Cheon et al., 1995). Che et al. conceived the unpredictability of OGB websites to represent the variable of 'uncertainty'.

Predictability in overall user confidence reflects that the website will be similar regarding content and presentation on their next visit. In contrast, unpredictability is an undesirable feature of websites that "refers to the extent to which a buyer believes that the current product offering at the target OGB website is unpredictable" (Che et al., 2015, p. 591). Che et al. (2015) reported that OGB websites continuously change their discounted offers (sometimes in every hour) and update product offers every day, having some products available only for a brief period. An additional challenge is that the products and offers are not often repeated. Customers have no or little information when those products and offers return. Such unpredictable offerings may increase perceived information asymmetry and transaction costs. Che et al. (2015) found that unpredictability decreases customers' intention to revisit OGB websites; increases transaction costs, which may lead to a lower likelihood of purchase (Akter et al., 2011). Therefore, we suggest:

H5. The unpredictability of OGB websites will have a negative effect on customers' purchase intention.

Customizability and purchase intention

According to Che et al., *personalization* is an asset-specificity variable. IS studies consider *personalization* as an umbrella term for "preference matching" of users (Salonen & Karjaluoto, 2016) and often use it interchangeably with *customization*. However, personalization and customization are not identical and have "completely different meanings and implications" (Davis, 2018). While "both personalization and customization achieve the same goal—an experience tailored to a user's interests—the paths used to reach this objective are different" (Babich, 2017). "Most researchers distinguish personalization as a company-initiated, automatic process, whereas customization is user-initiated" (Salonen & Karjaluoto, 2016, p. 1089). When personalization is executed from the user end, it is referred to as "active personalization" or "customization". The differences between personalization and customization are summarized in Appendix Table 5.

Perceived customizability is a customer belief and refers to the extent to which customers are given the opportunity to customize an IS (e.g., OGB website, apps) according to their needs and preferences (based on Rangel, 1968). Given that customer preference is in the epicentre of any business, businesses, as well as IS practitioners, consider customization to be an effective tool for achieving business success (e.g., Salonen & Karjaluoto, 2016). TCE suggests that retailers can increase customer value by lowering transaction costs. As customization involves transaction costs invested from the customer end, *customization* is relevant and important to TCE (Budiu, 2013).

Customization is marginally discussed in the context of online businesses, including OGB (Xiao et al., 2017). As mentioned early, OGB websites offer hundreds of products, sometimes too many to follow. In addition, the sales offer often last only for several hours. Customers worry that they would miss a good offer because of not browsing on the right day and right time. Therefore, OGB websites enable users to customize. For instance, after login, a customer can view his/her dashboard that consists of a list of his/her preferred products (or would receive notifications) if they are on sale. Prior studies suggest that the perceived customizability of a retail website may increase customers' adherence to and purchase intention from the same website (Schubert & Ginsburg, 2000). In addition, customization – an asset-specific investment – may diminish transaction-related uncertainties for customers, i.e., the website's unpredictability. Therefore, this study proposes the following hypotheses.

H6. The customizability of OGB websites will have a positive effect on customers' purchase intention.

H7. The customizability of OGB website use will have a negative influence on its unpredictability.

Trust and purchase intention

In consumer studies, *trust* is defined as a general willingness of a customer to depend on a vendor in situations of risk (Akter et al., 2011; Xiao et al., 2017). This definition of trust reflects the customer's expectation that the vendor will perform an action as promised. The direct relationship between *trust* and *behavioral intention* is clear in the IS literature (Akter et al., 2011). More specifically, OGB literature supports the notion that trust in an OGB website is a strong predictor of customer attitude (Che et al., 2015; Hsu, Chang, et al., 2014; Hsu, Chuang, & Hsu, 2014; Lin & Wu, 2015; Shiau & Chau, 2015; Wang et al., 2016) e.g., intention to purchase (e.g., Che et al., 2015; Shiau & Chau, 2015). Hence:

H8. Customer trust will have a positive effect on customers' purchase intention.

Intention, behavior and online customer review

The TRA, TPB, TAM, IS success model, UTAUT, and UTAUT2 suggest that intention has "the most proximal influence on behavior and mediates the effect of other determinants on behavior" (Venkatesh & Brown, 2001, p. 76). At the same time, they recommend *use behavior* as the dependent variable because it is considered as "a surrogate measure for IS success" (Taylor & Todd, 1995, p. 144). But there is a tendency among many IS researchers to test part of a model/theory (Venkatesh et al., 2012) – the most common is to assume an intention–behavior alignment (Polites et al., 2018). Those studies assess the *intention,* ignoring *actual behavior,* whereas Lee and Lee (2015) warn that examining 'intention' without 'behavior' would lose its importance. OGB literature is alike (e.g., Chen & Lu, 2015; Erdoğmus & Çiçek, 2011; Ku, 2012; Shiau & Chau, 2015; Wang et al., 2016). Those researchers' argument "is grounded on the assumption that higher purchase intention results in more purchases … In reality … discordance is often observed between purchase intention and purchase behavior" (Lee & Lee, 2015, p.57). Recently, Polites et al. (2018) demonstrated that although e-commerce websites experience a reasonable amount of traffic, the percentage of visitors that actually make a purchase is relatively low. Therefore, what transforms potential OGB customers (who intends to purchase) into actual customers remains a mystery and requires investigation.

In an online environment, customers need to evaluate products and eventually make purchase decisions based on incomplete or asymmetric information (Chen et al., 2019; Hossain et al., 2018) and thus accept higher risks (than in offline transactions). On top of that, there are many more 'lemons' on the web than there are 'oranges'. To avoid the 'lemons' (and thus the risk of buying poor quality products) and to evaluate a vendor or products, customers often look at signals, e.g., testimonies from other customers (e.g., product reviews, ratings, referrals, and recommendations), which is known as online customer review (OCR). It is a customer-generated communication channel provided by the vendor website to allow customers to share their knowledge (Shi & Liao, 2017), especially those who had a positive or noteworthy service experience (Abubakar et al., 2016). An OCR mechanism can provide valuable information to potential customers and minimize their transactional risks (Kauffman et al., 2009) and transaction costs (Shi & Liao, 2017). It thus provides an initial evaluation shaping customers' purchase decisions (Chen et al., 2019; S.-T. Li et al., 2019). The recent studies found that the availability and quality of OCRs on a website increase customers' purchase decisions (Abubakar et al., 2016) and sales performance for businesses (Chen et al., 2019; Li, Wu, & Mai, 2019), which is useable for OGB too (Chen & Lu, 2015). Based on IS theories and OCR literature, we hypothesize that OCR may have a moderating effect on the relationship between purchase intention and purchase behavior. For example, a potential customer who intends to purchase may not commit the purchase if there are unfavorable reviews from previous customers, i.e., positive OCRs may positively influence the intention to complete a transaction and *vice-e-versa* (Fig. 1).

H9. The relationship between customers' purchase intention and purchase behavior will be moderated by online customer review.

Method

Scales

The research model consists of seven variables. The variables were measured using multiple items, and all items were taken from previously-validated scales of prior studies and then adapted to the OGB context. For example, *unpredictability* was measured with four items adapted from (Che et al., 2015) and *trust* from (Hossain et al., 2018). Four items were employed to measure *customizability*. The first three items were adapted from Che et al. (2015)'s *personalization* scale because their items reflect customization rather than personalization, and the fourth item was adopted from Srinivasan et al. (2002) to include a context-specific measure. The measures of *frequency of OGB use* (Chen et al., 2015; Teo & Yu, 2005), *purchase intention* (Ku, 2012), and *purchase behavior* (Bhattacherjee et al., 2008) were also adopted from prior studies. Finally, *online customer review* was measured using the scale developed by (Chen & Lu, 2015) and (Shi & Liao, 2017). All the items are reflective and used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items are presented in Appendix Table 6.

Pre-test of the instrument

To collect data, a questionnaire was developed with demographic questions, and the items presented in Appendix Table 6. The primary version of the questionnaire was in English, which then was translated into Mandarin by native Chinese. Three rounds of pretests were conducted. The first pretest involved five doctoral students and two online entrepreneurs. Based on their comments, changes were made to the wording, sequence, format, layout, and question-difficulty of the questionnaire. The second pretest was conducted with seven graduate students and three academics. Slight modifications were made based on their comments. The questionnaire was then tested with 22 people who are familiar with OGB business, including customers and academic researchers. Given that there were no major concerns reported and basic statistical analysis seemed sound, the questionnaire was deemed ready to administer to the participants.

Data collection

An online survey was employed to collect data from Mainland China. China was chosen because it has the most users of OGB in the world. The survey was conducted in two stages. During the first stage, the survey was advertised on one of the most popular OGB websites in China for one month. The users of the OGB website were invited to participate in an

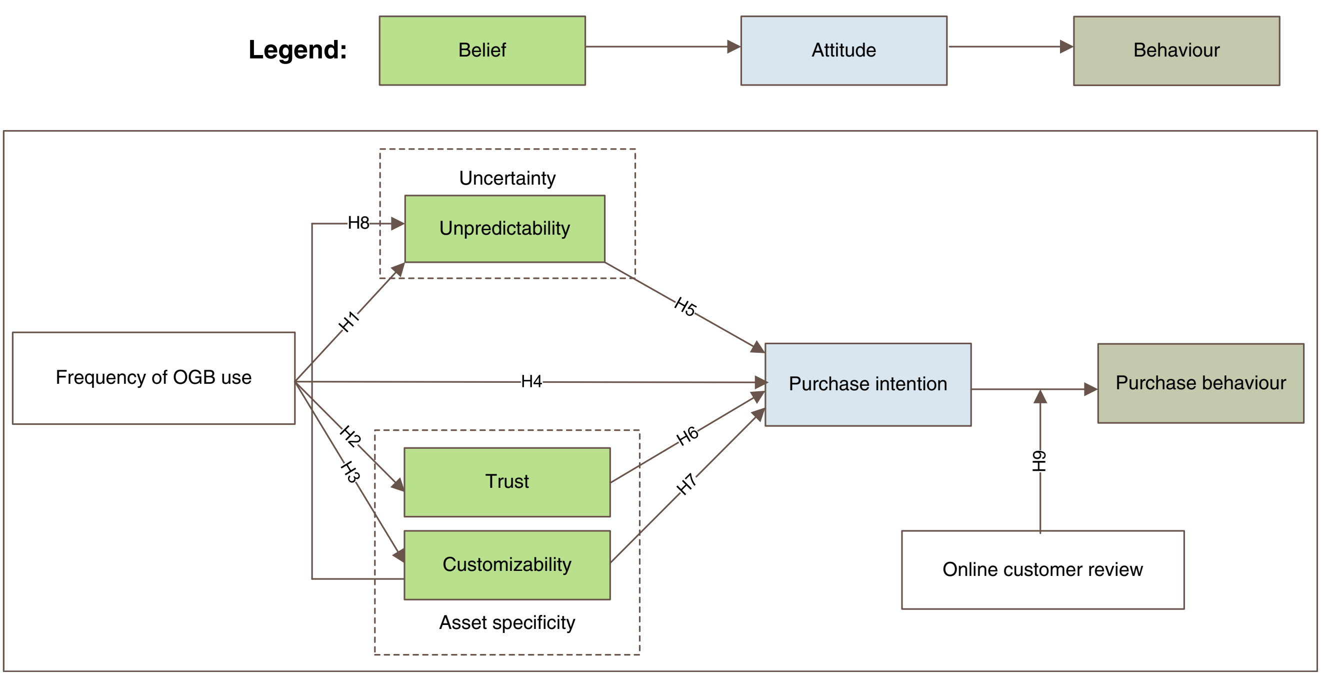

Fig. 1 Research model

online survey, which would allow them to enter into a prize to win a Huawei smartphone. The first survey (T_1) began with a screening question to screen out the participants who had made a purchase from an OGB website in the past. The survey captured the perceptions of the respondents before making a purchase. We measured *purchase intention* and its antecedents (i.e., unpredictability, trust, and customizability) and *frequency of OGB use*.

One month later, we sent an email invitation to the first-stage participants to participate in the second stage of the survey (T_2). The second stage of the survey screened out the respondents who had *not* made at least one OGB purchase in the past month. The second questionnaire measured the *frequency of OGB use*, *actual purchase behavior,* and *online customer review*. Given that frequency of use can change over time, the *frequency of OGB use* was measured in both periods (T_1 and T_2) and was averaged. There were 458 respondents to the first-stage survey and 353 respondents to the second-stage survey. After deleting responses with higher missing values, data analysis was based on the 339 respondents who participated in both stages of the survey. Of these respondents, 58% were women, and the average age of respondents was approximately 28 years. On average, respondents had approximately ten years of experience using the Internet. The demographic distribution of the participants was consistent with prior studies (e.g., Cheng & Huang, 2013; Hossain et al., 2018; Hossain & Rahman, 2019): mostly younger and educate females with nine years of internet experience are more likely to participate in OGB. The demographic details of the participants are presented in Appendix Table 7.

Data analysis and results

To test the research model, this study used partial least squares (PLS), a variance-based structural equation modeling (SEM) method, specifically Smart-PLS 3.2.9 software (Ringle et al., 2015). We used PLS-SEM due to its algorithmic advantages in distributional assumptions (i.e., non-normal distributions), factor determinacy, and the ability to handle complex relationships (Chin et al., 2008; Dijkstra, 2010). In contrast to covariance-based SEM (CBSEM), it establishes predictive validity in a complex model by being flexible on data and relationship assumptions (Akter et al., 2017). Overall, we used PLS-SEM as it is suitable for estimating overall model fit parameters using bootstrapping (Sarstedt et al., 2016), calculating interaction effects and yielding robust latent variable scores with due model specification (Chin et al., 2003; Fassott et al., 2016).

Assessment of data validity

Because of the self-reported nature of the data collected from one single source, i.e., survey, common method bias (CMB) is a potential threat to the validity of the observed relationships. To evaluate the severity of this bias and validate our results, we conducted common method variance tests. First, we used Harman's one-factor test. The result of this analysis did not show evidence of a dominant common factor (which accounted for 31% of the variance). Second, we used the marker variable (MV) technique (Lindell & Whitney, 2001). The theoretically unrelated MV deliberately added to the research variables possesses the highest correlation with Purchase Behaviour (2.82%), indicating that CMB was not high. Additionally, all variance inflation factor (VIF) values of the constructs (1.146–2.660) were well below the threshold of 5 (Hair Jr et al., 2017); hence collinearity was not an issue in our model.

To check non-response bias, we performed a two-independent-sample Mann-Whitney U test. As mentioned earlier, the responses for the *frequency of OGB use* were captured in both waves, we compared the responses in two waves (i.e., T_1 and T_2) and found that the p values for the four items are insignificant (0.630, 0.412, 0.895, and 0.607, respectively), confirming that non-response bias is not a concern for this sample.

Assessment of the measurement properties

Tables 1 and 2 present the measurement model results that show internal consistency reliability, convergent validity, and discriminant validity. First, the individual items are reliable because most items received standardized loading of more than 0.7 where two items (OCR4, PB3) with high 0.6 range; both values are acceptable (Hair Jr et al., 2017; Igbaria et al., 1995).[2] The item loadings are shown in Table 1 (bold values of the corresponding item). Second, all constructs meet the requirement of construct reliability since their composite reliabilities (ρ_c) and Cronbach's alpha are greater than 0.7 (Hair Jr et al., 2017), presented in Table 2. Third, the latent variables achieve convergent validity because their average variance extracted (AVE), shown in Table 2, surpass 0.5 level (Hair Jr et al., 2017). Finally, confirmation of discriminant validity comes with three tests. First, Fornell and Larcker discriminant criteria, presented in Table 2, confirm that the square root of AVE of the corresponding latent variables (diagonal elements in Table 2) are greater than off-diagonal elements in the corresponding rows and columns. Second, the Heterotrait-Monotrait (HTMT) ratio, presented in parentheses, is below 0.9 thresholds (Henseler et al., 2015). Third, we checked the cross-loading matrix and found that each item loads highest on the construct it is linked to (see Table 1).

[2] The fifth item of *frequency* has been deleted because of having low loading. The reason could be redundancy with the fourth item where respondents were asked about OGB use each day.

Table 1 PLS loadings and cross-loadings

Construct		FQN	UNP	CUS	TST	OCR	PI	PB
Frequency	FQN1	**0.783**	−0.473	0.421	0.469	0.068	0.482	0.512
	FQN2	**0.816**	−0.502	0.472	0.392	0.055	0.516	0.546
	FQN3	**0.851**	−0.483	0.550	0.543	0.060	0.654	0.605
	FQN4	**0.817**	−0.461	0.513	0.509	0.129	0.654	0.568
Unpredictability	UNP1	−0.482	**0.806**	−0.607	−0.475	−0.091	−0.504	−0.556
	UNP2	−0.493	**0.850**	−0.558	−0.433	−0.093	−0.519	−0.525
	UNP3	−0.412	**0.733**	−0.334	−0.395	−0.082	−0.362	−0.339
	UNP4	−0.469	**0.786**	−0.449	−0.394	0.032	−0.495	−0.533
Customization	CUS1	0.524	−0.354	**0.776**	0.464	0.021	0.511	0.478
	CUS2	0.334	−0.525	**0.728**	0.629	0.008	0.389	0.434
	CUS3	0.503	−0.497	**0.825**	0.719	0.003	0.484	0.575
	CUS4	0.523	−0.594	**0.826**	0.582	0.039	0.579	0.579
Trust	TST1	0.512	−0.405	0.499	**0.822**	0.019	0.521	0.429
	TST2	0.465	−0.360	0.538	**0.790**	−0.042	0.479	0.388
	TST3	0.341	−0.486	0.630	**0.716**	0.030	0.396	0.374
	TST4	0.515	−0.457	0.732	**0.819**	−0.007	0.500	0.508
Online Customer Review	OCR1	0.095	−0.065	0.062	0.045	**0.830**	0.057	0.126
	OCR2	0.066	−0.054	0.052	0.002	**0.808**	0.071	0.075
	OCR3	0.089	−0.077	0.001	0.012	**0.842**	0.077	0.122
	OCR4	0.052	−0.037	−0.021	−0.052	**0.677**	0.065	0.151
Purchase Intention	PI1	0.602	−0.549	0.544	0.55	0.135	**0.839**	0.548
	PI2	0.536	−0.413	0.469	0.442	0.035	**0.799**	0.458
	PI3	0.593	−0.485	0.511	0.475	0.029	**0.795**	0.461
Purchase Behaviour	PB1	0.660	−0.563	0.602	0.505	0.146	0.523	**0.897**
	PB2	0.619	−0.559	0.591	0.495	0.202	0.595	**0.906**
	PB3	0.405	−0.440	0.448	0.337	0.008	0.366	**0.686**

Assessment of the structural properties

Given that the explanatory power of a structural model can be evaluated by assessing the R^2 value (variance accounted for) of the exogenous variables, PI and PB have an R^2 value of 0.595 and 0.387, respectively. In this regard, our model explains OGB customer-intention better than Che et al.'s model (their R^2 value for *revisit intention* was 0.381). Moreover, the difference of R^2 of PI with and without *frequency* was 0.104 (i.e., ΔR^2 = 0.595–0.491), resulting in f^2 effect size as 0.257, which is between medium (0.15) and large (0.35) (Henseler et al., 2009). The results justify the inclusion of *frequency* in the model.

Table 2 Discriminant validity of the combined model

	Alpha	CR	AVE	FQN	UNP	CUS	TST	OCR	PI	PB
FQN	0.834	0.889	0.667	**0.817**						
UNP	0.807	0.873	0.632	−0.586(0.713)	**0.795**					
CUS	0.799	0.869	0.624	0.602(0.726)	−0.627(0.758)	**0.790**				
TST	0.797	0.867	0.621	0.590(0.708)	−0.535(0.673)	0.755(0.895)	**0.788**			
OCR	0.804	0.870	0.627	0.097(0.115)	−0.074(0.126)	0.023(0.076)	−0.001(0.069)	**0.792**		
PI	0.741	0.852	0.658	0.713(0.896)	−0.599(0.758)	0.628(0.805)	0.606(0.779)	0.085(0.119)	**0.811**	
PB	0.783	0.873	0.699	0.685(0.829)	−0.626(0.770)	0.659(0.821)	0.542(0.673)	0.160(0.195)	0.605(0.773)	**0.836**

Alpha is Cronbach's alpha, CR: composite reliability; the bold diagonal elements are the square root of variance shared between the constructs and their measures (AVE). Off-diagonal elements are the correlations among constructs. The values in parentheses represent the HTMT ratio

To assess the hypotheses, the direction of the path coefficients, the magnitude of the *t*-statistics, and the significance of *p* values were checked. We also checked the 95% bias-corrected bootstrap confidence interval values of the relationships. As the confidence interval values do not include zero, we conclude that the effects are significant (null hypotheses are rejected). The results (presented in Table 3 and Fig. 2) reveal that all our hypotheses are supported. In addition, we checked the mediation effects in Table 3, which show that PI partially mediates the relationship between PB and frequency ($\beta = 0.423$), unpredictability ($\beta = -0.103$), customizability ($\beta = 0.131$), and trust ($\beta = 0.086$).

Before we ran the moderation analysis, we first checked the measurement properties of the moderator; all values (item loadings, composite reliability, and AVE) associated with online customer review (OCR) are above the threshold limit. Further, Table 2 indicates that the inter-correlations between the moderator and the other variables are satisfactory. To examine the moderating effects, we used the two-stage approach because it "is versatile and should generally be given preference for creating the interaction term" (Hair Jr et al., 2017, p.263). We used the 'moderating effect' function in SmartPLS and chose the 'standardized' product term generation method and 'automatic' weighting mode. The results ($\beta = 0.091$, $t = 2.481$, $p = 0.013$) confirm the significance of the moderator because the path-coefficient of the interaction variable (OCR*PI–PB) is significant, independently of PI–PB ($\beta = 0.593$, $t = 16.886$, $p = 0.000$) and OCR-PB ($\beta = 0.109$, $t = 2.827$, $p = 0.005$) relationships in the interaction model. The inclusion of the moderator in the main model increased R^2 value of PB ($\Delta R^2 = R^2_{\text{interaction}} - R^2_{\text{main}} = 0.387–0.365 = 0.022$). Moreover, Hair Jr et al. (2017, p.263) suggested that "in the context of moderation, particular attention should be paid to the f^2 effect size" (p. 255); the effect size is weak ($f^2 = 0.036$).

Next, we checked the Q^2 values. Running the blindfolding technique, SmartPLS generated the construct cross-validated redundancy scores. The Q^2 values of all endogenous constructs are considerably above zero: unpredictability (0.283), customizability (0.221), trust (0.211), PI (0.381), and PB (0.260). Finally, the q^2 effect size was estimated. When OCR is deleted from the path model, and the model is re-estimated, the Q^2 of PB drops to 0.247; thus, the q^2 *effect size* for this relationship (i.e., $q^2_{OCR\text{-}PB}$) is 0.018. We thus can conclude that the inclusion of OCR in our model is justified. Furthermore, we developed the moderation graph. In Fig. 2, Appendix Fig. 3, the two lines represent the relationship between PI and PB for low and high levels of OCR. The relationship between PI and PB becomes stronger with high levels of OCR; alternatively, with low levels of OCR, the relationship between PI and PB becomes weaker.

Discussion

This study investigated customers' purchase behavior in the OGB context. Drawing on TCE theory, we found evidence of the persistent influence of TCE dimensions namely frequency, uncertainty, and asset specificity on customers' purchase intention. Applying the belief–attitude–behavior chain of IS theories, our results suggest that customer beliefs about OGB websites (namely unpredictability, trust, and customizability) are

Table 3 Structural model results

	β Values	*t* Values	*p* Values	*95% CIs*	*Result*
Hypothesized direct effects					
Frequency to Unpredictability	−0.327**	5.182	0.000	[−0.445, −0.200]	Supported
Frequency to Trust	0.590**	13.821	0.000	[0.505, 0.670]	Supported
Frequency to Customization	0.602**	14.305	0.000	[0.528, 0.680]	Supported
Frequency to PI	0.437**	8.209	0.000	[0.327, 0.543]	Supported
Unpredictability to PI	−0.173**	3.474	0.001	[−0.274, −0.076]	Supported
Trust to PI	0.145*	2.556	0.008	[0.033, 0.253]	Supported
Customizability to PI	0.146*	2.305	0.015	[0.018, 0.266]	Supported
Customizability on Unpredictability	−0.430**	7.855	0.000	[−0.540, −0.327]	Supported
PI to PB	0.593**	15.098	0.000	[0.511, 0.666]	Supported
Indirect effects					
Frequency to PB	0.423**	10.255	0.000	[0.345, 0.498]	Partial mediation of PI
Unpredictability to PB	−0.103**	3.417	0.001	[−0.164, −0.044]	Partial mediation of PI
Trust to PB	0.086*	2.638	0.009	[0.024, 0.151]	Partial mediation of PI
Customizability to PB	0.131**	3.668	0.000	[0.030, 0.117]	Partial mediation of PI

*$p < 0.05$, **$p < 0.001$; PI: Purchase Intention; PB: Purchase Behavior; CI: Confidence Interval

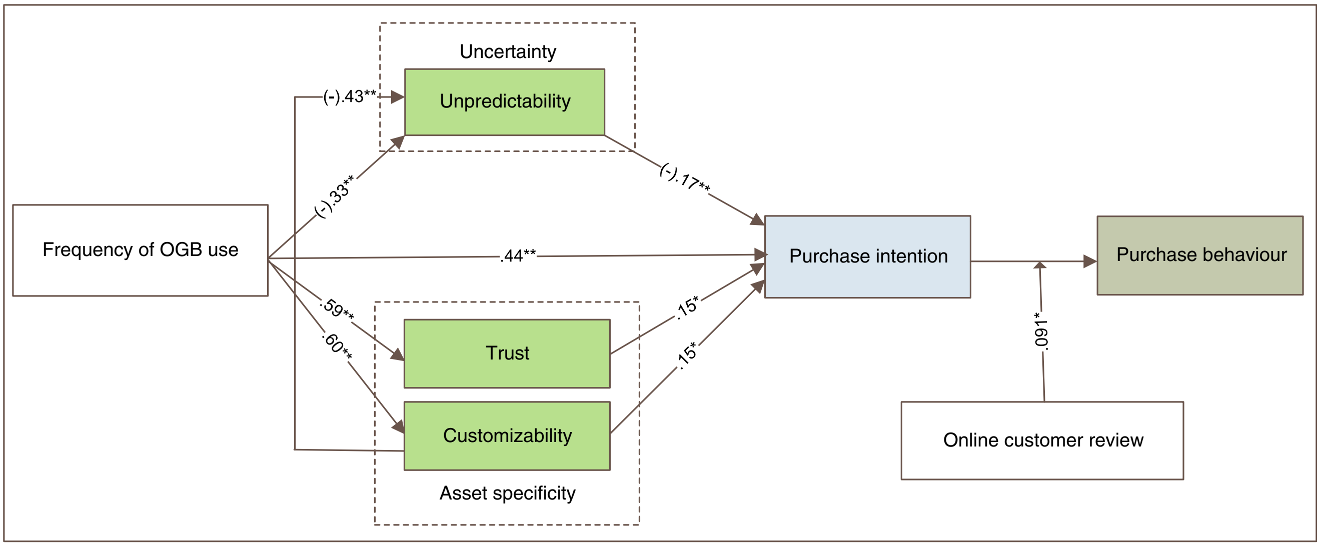

Fig. 2 The model with results

influenced by the frequency of customers' OGB use. These beliefs, in turn, affect customers' purchase intention, which ultimately affects their purchase behavior. Furthermore, customizability decreases unpredictability, and the relationship between customers' purchase intention and purchase behavior is moderated by OCR.

Theoretical implications

There are several theoretical implications arising from our application of the dimensions of conventional TCE to OGB, and findings of the influence of frequency on the transactional variables. Studies suggest that low transaction costs have a positive influence on customer attitude but how transaction costs can be decreased remains a question for research. Our study adds knowledge to the literature, arguing that uncertainty, related to the predictability of the website, is a factor of recurrence, which can be reduced if customers can be influenced to revisit the website often. Also, trust and customizability can be positively influenced by the frequency of use.

In the past, users of an IS had to be happy with what they were offered. However, now the users consider it their right to use a system according to their preferences – customizability becomes a basic feature of any application or website. Our study confirms that customizability plays an important role in predicting purchase intention for OGB. Building on our model, future studies could integrate and examine other key constructs that are important to customization, including personalization, self-efficacy related to OGB operations, and prior experience.

Another significant aspect of our research is highlighting the importance of customization in eliminating customer belief in the unpredictability of an OGB website. Our study found that customization reduces unpredictability. The theoretical implication of this finding is profound because it suggests that uncertainty can be managed by allowing customers to customize the website to their needs. Based on this finding, future studies could aim to identify different forms of uncertainties (Santoro & McGill, 2005) from the customers' perspective and examine the influence of customization and frequency of use on these relationships, given that people may behave differently for different types and levels of uncertainty.

We integrated both intention and actual behavior into the TCE model, given that "purchase intention can be considered meaningful, as in most previous studies, only when the strong association between intention and action is supported" (Lee & Lee, 2015, p. 57). Our study found evidence of a strong effect of purchase intention on purchase behavior, which suggests that many IS theories are useful in explaining OGB behaviors. Furthermore, in the OGB context, finding the moderation effect of OCR between intention and behavior is a major theoretical contribution in explaining the mythical relationship between PI and PB. Our study suggests that OCR can influence converting potential customers to actual customers. Future research could incorporate other factors, e.g., affordability in this relationship.

Managerial implications

This study offers several managerial implications. First, this study indicates that the unpredictability of OGB websites is the most important factor affecting customers' PI. OGB customers are concerned about the uncertainty related to the offers and promotions published on OGB websites. Thus, OGB websites should provide clear indications when an offer is likely to be repeated or which products may be included in future offers (e.g., provide a weekly forecast). Further, to minimize unpredictability, OGB vendors should ensure clarity of the length of an offer (e.g., daily). Such provisions require strong coordination between OGB websites and merchants (who provide the OGB products) (Hossain et al., 2018). Another way to reduce customer's perception of the unpredictability of OGB is by designing the website in such a way that the customers can customize their OGB website. Additionally, OGB website may send notifications and recommendations to the customers about customers' preferred products and services if those are on sale. This would reduce transaction costs and uncertainties for customers.

Second, trust in the OGB website is a critical determinant of customers' purchase intention, especially in online purchasing (PushOn, 2018). In China, online customers experience frequent cybercrimes, particularly related to transactions and non-delivery (Clemons et al., 2016). OGB vendors should clearly communicate to customers about their terms and conditions in relation to cancellations, payments, deliveries, returns, and dispute resolutions. Online stores that provide better after-sales-services and handle consumers' inquiries and complaints promptly will build credibility and thereby increase customer trust. Building a trusting relationship with consumers is also very important because it can encourage customer loyalty.

Third, the customizability of an OGB website is positively associated with customers' purchase intention. Customization has an additional effect: the unpredictability of an OGB website can be reduced by empowering the customers to customize their OGB website. Customizability is important because customers are busy and have a great deal of choice in the e-marketplace. Updating customers with offers of their preferred products is a good way to keep them engaged with the OGB website. In addition, OGB website designers must ensure that customers are aware of the availability of the customization feature and that it is easy for the user to perform the customization.

Fourth, the moderation test confirms that the relationship between PI and PB is not linear but contingent on OCR. That is, an OGB customer who intends to make a purchase from an OGB website is more likely to proceed (i.e., make the purchase) if there are favorable OCRs. This finding provides one step toward solving the mystery of why websites experience declining sales even when there is an increase in visitors ("hits") on their website and why people sometimes do not make a purchase even after placing an item in the shopping cart (Polites et al., 2018). In general, customers engage in a significant amount of research before making an online purchase (particularly for expensive items) (PushOn, 2018). Here, customers have limited cognitive resources available and thus seek to reduce uncertainty by applying mental shortcuts, such as through examining previous customers' feedback and service ratings. In OGB context, recently, Hossain et al. (2018) found that, in the presence of information asymmetry, OGB customers rely on OCRs about the OGB website and the products. In addition, online customers tend to reduce risks by examining the reviews from previous customers (Clemons et al., 2016). Therefore, OCR is an important factor that OGB website managers need to consider with great care. In line with the recommendations of the current study, Shi and Liao (2017) prescribe that customers should be given the opportunity to share their reviews about their shopping experience.

Fifth, this study finds the influence of frequency of OGB use, which has significant managerial implications. The frequency of OGB use affects unpredictability, trust, and customizability. That is, frequency of use reduces customers' negative perception that an OGB website is not predictable because customers can see the offers every time they visit the website, thus reducing the possibility that they will miss a sale of a product they want to purchase. In addition, when a customer visits a website more often, a sense of trust is built because of the customer's familiarity with the website itself and the products it offers (Blanco et al., 2010). Thus, OGB businesses need to devise strategies for how to make customers use the website more often; if they can ensure this, many obstacles related to OGB acceptance will be removed.

Limitations and future research

Although our study has important implications for theory and practice, we acknowledge its limitations. First, to assess customers' actual PB, we relied on a survey-based self-report approach and did not collect objective purchase data. This means our measures of PB are subjective and susceptible to potential recall bias (Junco, 2013; Park et al., 2016). To minimize the risk of recall bias, we asked participants to recall their purchase behavior on an OGB website in the past month. One benefit of our approach is that we were able to gather data in an unobtrusive manner that did not risk interfering with the decision making of the participants as they engaged in the purchase process. Second, given that we collected data about OCR in the second stage of the study (i.e., T_2), we were unable to verify whether OCR moderated the relationship between trust and PI (or between trust and PB). That is, we did not test whether trust and OCR together have a more significant effect than their individual effects; this would be interesting to examine in future studies. Third, given that it is beyond the scope of TCE, we did not consider customer attributes (e.g., self-efficacy) in our study. Fourth, we assumed *price discount* as a constant, i.e., every OGB business offers the same discounts, whereas prior studies (e.g., Erdoğmus & Çiçek, 2011; Zhang et al., 2013) found that high discounts increase customer numbers and satisfaction.

Conclusions

The objective of this study was to develop and test a model of OGB acceptance. We collected longitudinal data from a two-stage survey to validate our research model, which was developed from the TCE theory. We incorporated two factors—frequency of OGB and online customer review—that were expected to be particularly relevant for the context of the study. The results particularly demonstrated the importance of frequency of use on transaction costs, which has been overtly ignored in previous studies on OGB. Moreover, the moderating influence of online customer review suggests a way to convert potential customers into actual customers. Overall, the findings of this work significantly enhance understanding of OGB acceptance and serve to further highlight the important role of context in our theorizing.

Appendix 1

Table 4 Belief–attitude–behavior variables in leading IS theories

Theory/model	Belief	Attitude	Behavior
Definition	The subjective probability that the behavior will produce a certain outcome	Refer to the way people feel towards a particular behavior	An individual's observable response in a given situation with respect to a given target
Theory of reasoned action (TRA) (Fishbein & Ajzen, 2011)	Behavioral beliefs, normative beliefs	Attitude towards behavior	Behavioral intention; actual behavior
Theory of planned behavior (TPB) (Ajzen, 1991)	Behavioral beliefs, normative beliefs, control beliefs	Attitude	Intention; actual behavior
Technology acceptance model (TAM) (Davis, 1989; Davis et al., 1989)	Perceived usefulness, perceived ease of use	Attitude towards usage	Intention to use; system use
IS success model (Delone & McLean, 2003)	Information quality, system quality, service quality	User satisfaction	Intention to use; use
E-commerce success model (Wang, 2008)	Information quality, system quality, service quality, perceived value	User satisfaction	Intention to reuse
Expectation-confirmation model (ECM) (Bhattacherjee, 2001)	Perceived usefulness, confirmation	User satisfaction	Continuance intention
Unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003)	Performance expectancy, effort expectancy, social influence, facilitating conditions	Behavioral intention	Use behavior

While there is general agreement among IS scholars on what constitutes behavioral beliefs, IS theories have not reached a consensus on what constitutes attitude and behavior. Specifically, TRA, TPB, and the IS success model consider that both *intention* and *actual behavior* constitute *behavior*; however, UTAUT argues that *intention* represents *attitude* while *use behavior* represents *behavior*. The ECM and the e-commerce success model argue that *satisfaction* represents *attitude* and *continuance intention* represents *behavior;* in both models, *actual use* is an implicit variable of *user behavior*, which somewhat supports UTAUT's argument that user *behavior* confirms that the *intention* has been converted into actual action

Appendix 2

Table 5 Differences between personalization and customization

	Personalization	Customization
Definition	a means of meeting customer needs more effectively and efficiently, making interactions faster and easier.	is the action of configuring the content or structure of an information system – done manually from the customer end – to suit an individual customer.
Who does?	Company driven - done by the system being used.	User driven - done by the user.
What it uses?	Uses artificial and business intelligence.	Relies on users' natural intelligence.
How is done?	Performed using user data (behaviour in Internet), user profiling; predictive technology/ recommender systems, artificial intelligence and business intelligence systems.	Based on natural intelligence of the users.

Appendix 3

Table 6 The measures

Construct	Item
Unpredictability	1. I cannot predict what products will be on sale
	2. It is unknown to me what products will be on sale
	3. I do not know what products will be on sale next time
	4. It is difficult for me to know beforehand what products will be on sale
Customizability	1. This OGB website is customizable to meet my needs
	2. In this OGB website, I can customize features to suit my needs
	3. The promotion-notifications of this OGB website can be customized to meet my need
	4. This OGB website makes purchase recommendations that match my needs
Trust	1. This OGB vendor will deliver me a product that matches the posted description
	2. This OGB vendor will deliver me a product within assured timeframe
	3. This OGB vendor is respectful to its terms and conditions
	4. This OGB vendor fulfills the commitments it assumes
Frequency on OGB	1. On an average, visit OGB website once in last one month
	2. On an average, visit OGB website at least once per fortnight
	3. On an average, visit OGB website at least once per week
	4. On an average, visit OGB website at least once per day
	5. On an average, visit OGB website a couple of times in a day
Purchase intention	1. I am willing to select this OGB website as a shopping source
	2. I am willing to visit this OGB website to purchase products
	3. I am willing to select this OGB website as a channel for buying products
Purchase behavior	1. In the past one month, I made purchase(s) from this OGB site
	2. A percentage of my shopping was made from this OGB site in last one month
	3. Purchasing from this OGB site is worthy
Online customer review	1. The OCRs on OGB are helpful
	2. I find OCRs informative
	3. The OGB experience by other customers is interesting
	4. OCRs on OGB are well intended

Appendix 4

Table 7 The demographics of the respondents

Category	Distribution (%)
Gender	
Male	42
Female	58
Age	
18–22	32.1
23–32	26.5
33–42	13.3
43–52	12.1
53–62	9.2
>62	6.8
Education	
Primary School	3.8
High School	8.6
Diploma	21.5
Bachelor	42.1
Postgraduate	14.1
Other	9.9
Income (CNY/month)	
<=2000	39.4
201–3000	23.6
3001–5000	19.1
5001–8000	13.2
>=8000	4.7
Internet experience (year)	
<3	8.8
3–5	13.6
6–8	21.4
9–10	42.1
>10	14.1

Appendix 5

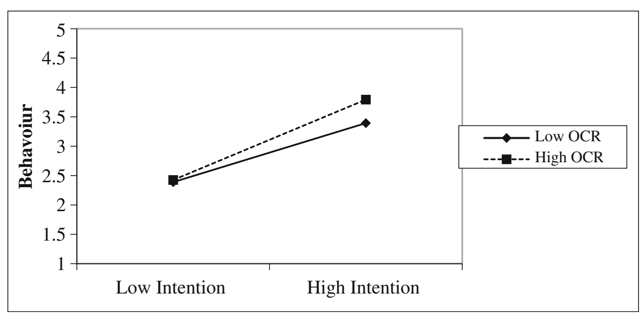

Fig. 3 The slop plot of the moderation test

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