Journal of Organizational and End User Computing
Volume 33 • Issue 4 • July-August 2021

Buying Through Social Platforms:
Perceived Risks and Trust

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ABSTRACT

Social platforms are currently encountering a set of burning issues: low ad conversion rates, cross-channel free-riding phenomena, lack of monetary incentives to retain premium content creators, etc. Direct purchase behaviors between social platform users (e.g., making a direct purchase through a seller's promotional post) can largely resolve these problems. Therefore, it is imperative to study the factors that influence users' direct purchase behavior. This paper focuses on risk- and trust-related factors, proposing a theoretical model that was tested on two samples of Chinese users of WeChat. The authors concluded that users tend to evaluate the shopping risk associated with the social platform first, then go through a process of building trust in the platform before making purchases. Further, this trust can generate a halo effect on seller risk. Finally, trust and seller risk directly impact on users' purchase intention to buy from the seller on the platform.

KEYWORDS

Platform Risk, Purchase Behavior, Purchase Intention, Seller Risk, Social Commerce, Social Computing, Social Media, Social Media Monetization, Trust Beliefs

INTRODUCTION

Purchase behaviors are of paramount importance in the monetization of social media platforms. Monetization can be achieved through sales design, promotions and advertising (Kim, 2013), but these approaches must also address the central issue of how purchase decisions are made by social platform users. Conversion rates are the first critical factor in selecting the optimal advertising channel. Social platforms such as Facebook and Twitter may have the highest traffic rates in comparison to other major online platforms, but they also have the lowest ad conversion rates (Priceonomics, 2018). According to a recent survey (Parikh, 2018), the average conversion rates (in brackets) of major social platforms such as Facebook (4.7%), Instagram (3.1%), Twitter (0.9%), Snapchat (0.6%) and YouTube (0.5%) are lower than those of traditional digital advertising channels such as Google (8.2%) and Bing (7.6%). Brands and retailers would be more willing to run their ads on a social platform and pay higher ad fees if the platform was able to convert ads into more direct purchases. Second, content is king. Direct purchase behaviors provide content creators with financial incentives to create and share original content where otherwise they would be reluctant to continually offer premium content for free (Team Laal Patti, 2018), and this could eventually lead to a social platform losing its most prized asset: premium content. This could be why Facebook is testing a paid subscription feature that

DOI: 10.4018/JOEUC.20210701.oa4

requires users to pay for access to exclusive premium content in interest groups. Likewise, Weibo has launched paid question answering services to motivate content creators as well as profit from them. For example, a follower can ask a movie star a question (e.g. "What is your favorite food?") for a fee of around 15 US dollars. Other followers then pay around 15 US cents to access the answer, and all revenue is shared between the questioner (45%), the star respondent (45%) and the platform (10%). Third, sellers who use a social platform to merchandise their product are not willing to tolerate cross-channel free-riding (Chiu et al., 2011), whereby social platform users are interested in items in their messages or posts, but go to other channels (e.g. e-commerce sites, bricks-and-mortar stores) to complete their purchases. It is reported, for example, that over 80% of Instagram users who discovered a brand on Instagram later purchased the item on other channels, such as the brand's own website, Amazon, or bricks-and-mortar stores (Garcia, 2018). In a word, it is imperative for social platforms to find a way to increase direct sales, thereby resolving these three critical issues. This would explain why many social platforms have rolled out, or are experimenting with, buy buttons (e.g. Facebook buy buttons) to allow users to make direct purchases by clicking on a button that directs them to the seller's website to complete their purchase without leaving the platform.

The idea is appealing, but relevant practices are far from satisfactory. Previous research has not found e-commerce to be an appealing monetizing opportunity for social platforms, concluding that people are not willing to purchase items while engaged in their online social gatherings (Clemons, 2009). Regarding Facebook and Twitter's buy buttons, a study revealed that 45% of respondents did not intend to use them (Business Insider Intelligence, 2016). Twitter aborted its e-commerce operations and is sticking with social networking services (Lunden, 2017). Over 30% of social platform users state they have never bought anything directly on a social platform (Statista, 2017). People may believe that social platforms are a good source of information referral for business, but might not trust them for making direct purchases due to risk-related concerns such as security and privacy (Cha, 2009; Sharma, Menard & Mutchler, 2017; Zarouali et al., 2017; Zhu & Chen, 2015). This paper, therefore, will study how social platform users' direct purchase behaviors are affected by risk- and trust-related factors, and thus determine how to increase direct and actual purchases through social platforms. It will show how platform risk and seller risk influence purchase intention, and the role that trust plays in this causal path to purchase. Understanding this influential relationship can help to make social platforms aware of the factors that significantly inhibit their s-commerce practices, as well as how to improve the social shopping environment and achieve better s-commerce performance.

The paper opens with a discussion of the conceptual aspects of s-commerce and its key inhibitors. The authors then go on to discuss the study's hypotheses, describe the main methodological aspects and present their findings. Theoretical conclusions are then drawn and the managerial implications are discussed. Finally, the authors describe certain limitations and outline future research opportunities.

BACKGROUND

Given the multidisciplinary nature of s-commerce, there is no clear definition of the content and boundaries of the field (Turban et al., 2017). By adopting a structural approach to the concept, s-commerce can be regarded as a combination of two intertwined components – e-commerce and the social web (Constantinides, Romero & Boria, 2008) – and hence understood as e-commerce activities delivered by social web applications (Liang & Turban, 2011; Liang et al., 2011). Having conducted a multifaceted analysis of s-commerce based on marketing, online shopping, computer science, sociology and psychology, Huang and Benyoucef (2013) defined s-commerce as "an Internet-based commercial application, leveraging social media and Web 2.0 technologies which support social interaction and user generated content in order to assist consumers in their decision making and acquisition of products and services within online marketplaces and communities" (p. 247). S-commerce sites can be divided into two classes: (1) social networking sites that add commercial elements to support advertising and commerce; and (2) traditional e-commerce sites that add social networking capabilities to utilize the power of social networking (Liang & Turban, 2011). This paper is interested in the former, studying the factors that influence social platform users' direct purchase behavior through a seller's buyable content.

A historic overview can contribute to an improved, dynamic and evolutionary understanding of s-commerce. The term "s-commerce" was first coined in 2005, emerging from several different fields. S-commerce first appeared with the origin of the social web. Social web technologies led to the development of a great deal of efficient, effective social software (e.g. blogs, wikis, social media) which prompted collaboration between employees, partners and customers (Turban et al., 2017). Subsequently, the dramatic increase in mobile commerce has facilitated the wide dissemination of s-commerce, since mobile devices, like smartphones, are generally cheaper, more accessible and convenient than desktop computers and laptops; this explains how s-commerce can flourish in developing and populous countries like China. Finally, awareness of the tremendous business opportunities in social media marketing has boosted s-commerce. As social media have become more and more popular, many social media-based marketing strategies have shifted in support of s-commerce (Turban et al., 2017). S-commerce is able to generate business unicorns even in countries where e-commerce is relatively well developed. Pinduoduo Inc., an s-commerce-focused startup that became a business unicorn worth 1.5 billion US dollars in 21 months, is now China's fourth biggest e-commerce player (Elstrom & Ramli, 2017). The company's business model is a kind of hybridization of Facebook and Groupon, using Chinese social platforms to launch online group buying. Since its beginnings, s-commerce has continued to evolve as new technologies (e.g. mobile devices), new marketing approaches and business models have become globally prevalent. In the future, it is possible that these forces will render more innovative business models (e.g. advertising models, brokerage models, subscription models) and more monetizing opportunities for social platforms.

Despite the promise of the future of s-commerce, a number of significant inhibitors currently demotivate firms and users from using social platforms for commercial activities. Existing studies have tended to focus on s-commerce facilitators, paying little attention to inhibitors (Farivar, Turel & Yuan, 2017; Zhang & Benyoucef, 2016), particularly in relation to s-commerce activities executed directly through social platforms. Companies are affected by a number of inhibitors: doubts about the efficacy of s-commerce in supporting brand development (Michaelidou, Siamagka & Christodoulides, 2011), waste of time and money on s-commerce campaigns (e.g. Wal-Mart) (Liang & Turban, 2011), integration of existing information systems with new s-commerce platforms, loss of control over companies' brand images and reputations on UGC-dominated sites, and difficulty in measuring the ROI of s-commerce business (Turban et al., 2017), among others. On the user side, factors inhibiting users from involvement in s-commerce include risk, price, cost, responsiveness, social recommendation, interface-friendliness, delivery time, ease of purchase, content credibility, and merchandising approaches. Among these inhibitor factors, risk may be a leading inhibitor of s-commerce as well as of traditional e-commerce (Farivar, Turel & Yuan, 2017; Featherman & Hajli, 2016; Wang & Chang, 2013; Wang, Min & Han, 2016), yet few studies have investigated in depth the influence of the risk mechanism on direct purchase behaviors in s-commerce. Social shopping involves a potential array of risks. For instance, s-commerce transactions can lead to losses of private data, time and money (Featherman & Hajli, 2016). Sellers can access a buyer's transactional information as well as private information and shared content. Risk may be produced by the wide variety of sellers, in that traditional e-commerce platforms primarily allow verified sellers to sell, while social platforms admit verified and unverified sellers, from self-employed households to famous brands. In essence, it may be difficult for a loose, decentralized, virtual social structure to create a reliable and trustworthy shopping environment.

THEORETICAL MODEL AND HYPOTHESES

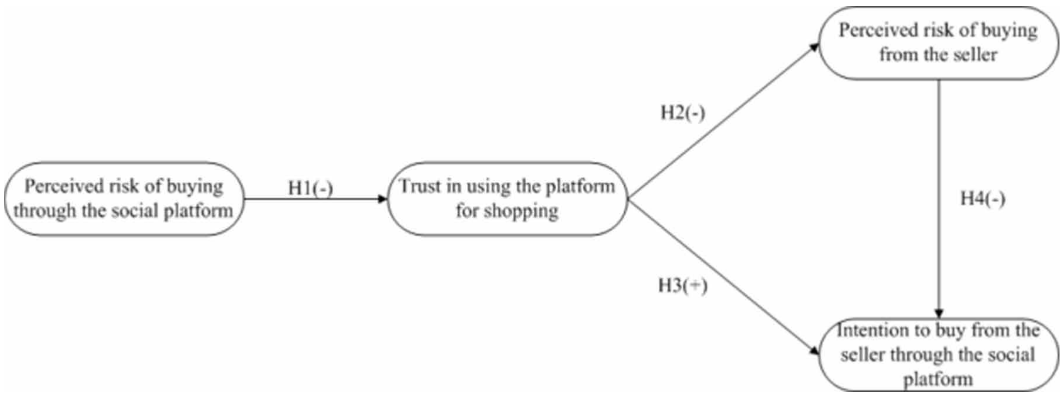
This paper shows how social platform users' direct purchase behavior is affected by trust- and risk-related factors. Although many published studies have addressed similar issues in traditional e-commerce settings, further investigation is needed in an s-commerce context, given the significant differences between the two types of commerce (Huang & Benyoucef, 2013); moreover, relevant research in direct purchase behavior remains scarce.

Because perceived risk is a fundamental inhibitor when an online user is considering an online purchase, it is necessary to include this critical antecedent variable in the overall research model. Perceived risk is defined as a user's belief in "the potential uncertain negative outcomes from the online transaction" (Kim, Ferrin & Rao, 2008, p. 546). As shown in the authors' research model (Figure 1), two types of risks are defined and considered here. Risk refers to potential negative outcomes in s-commerce, and occurs on two levels: at platform level, users may perceive risks associated with using the platform for shopping, such as financial loss or privacy disclosure (Farivar, Turel & Yuan, 2017); at transaction level, users may perceive the sellers as a risk. Both types of risks can influence purchase behavior, but the influence mechanism should be different. Platform-level risk is the consumer's overall perceived risk when using the platform to purchase, not including the specific transaction context in which a buyer transacts with a seller. By contrast, seller risk is believed to directly affect purchase behavior because it is a contextual risk that entails the buyer's involvement and evaluation of a specific transaction context (Hong, 2015). Along these lines, Meents and Verhagen (2018) designed a model to study the direct effect of both platform risk and seller risk on users' attitudes to buying a particular product at a C2C website; their results showed a non-significant direct effect of platform risk, but a significant direct effect of seller risk. The authors of this study therefore propose an indirect influential path for platform risk and a direct path for seller risk.

Moreover, considering the physical separation and low accessibility of products that is a feature of the internet, trust is a crucial predictor of users' internet purchase behavior (Kim, Ferrin & Rao, 2008), and becomes more important when risk is perceived as high (Mutz, 2005). This is congruent with a risky situation in which most current social platforms take inadequate *ex ante* measures to reduce the risks associated with direct purchases. On the one hand, as trust declines, users are more likely to be unwilling to take risks, and will need shopping safeguards to ensure against being cheated. On the other hand, trust explains why a consumer is willing to enter into a risky situation whose outcome they cannot *ex ante* control (Ratnasingham, 1998). An increase in trust can effectively reduce transaction costs and render one party less sensitive to another's opportunistic behavior (Tyler, 1996). In s-commerce, trust may be affected by unique s-commerce characteristics, such as information and experience sharing, as well as by conventional characteristics such as company size and reputation (Kim & Park, 2013). In this paper, our interest is in an environmental form of trust, i.e. trust in using the platform for shopping. Previous research has studied similar trust constructs such as trust in a social networking site (Hajli et al., 2017), trust in social media (Lin et al., 2016), and trust in online communities (Chen & Shen, 2015). Few studies have re-labelled this trust in a commercialized social platform context, however. Social platform users may trust a social platform to conduct social interactions, but this trust may not extend to making purchases. Users may not view social platforms as a suitable marketplace for online transactions, and may require their online social circle to be free of commercialization (Clemons, 2009). Although research has shed light on WeChat users' trust in products and services-related comments posted on WeChat (Lien & Cao, 2014), this trust is different from trust in using a social platform for shopping: users may trust purchase comments made by their social contacts, but be sceptical about the commercial features of the same platform. On the basis of this discussion, the present study includes trust as a crucial prerequisite to making purchases from sellers.

Social platform users' purchasing behavior is crucial for s-commerce performance. Purchase behavior is a processual concept. It reflects a process in which individuals discover, search for,

Figure 1. Research model



compare and buy products or services to satisfy individual wants and needs (Chen et al., 2015). Purchase behaviors can emerge via a social platform. For example, a WeChat user finds a product featured in commercial content on WeChat, but searches for it on other channels such as Amazon to complete the purchase. In this case, WeChat gains no monetary value, but this aspect falls outside the scope of this paper. The authors' research interest is the study of purchase behaviors that lead buyers to purchase products directly on social platforms, thereby generating profits for the social platform in question. Many social platforms have rolled out buy buttons that enable sellers to sell directly to buyers; the platforms monetize this activity by using these buttons to take a cut from each sale (i.e. charge per click). As most purchase actions through social platforms are eventually concluded on the seller's website instead of on the platform, it is difficult to observe and measure these purchase behaviors (Curty & Zhang, 2011). It is reasonable, therefore, to use purchase intention to represent actual, direct purchase behaviors (Hu, et al., 2016).

The Effect of Platform Risk on Trust

Social platforms are good at generating interest through digital social interactions, but there are many obstacles in the path from interest to purchase. The first is the user's perceived risk in relation to the social platform in question, such as theft of users' private photos and shared content. Platform risk refers to a user's belief that they will suffer negative consequences due to transaction operation failure on the part of the platform, poor e-commerce regulations and ineffective safeguards against seller fraud, or opportunistic behavior (Meents & Verhagen, 2018).

Risk is often associated with the measures established by a social platform to safeguard online transactions. Facebook, for example, has launched an ad review feature allowing users to make comments on ads. Based on this new feature, if a seller receives a lot of negative comments, Facebook will send them a warning to improve. If the seller does not react accordingly, Facebook will take down their ads. But this only amounts to an *ex post* measure to reduce shopping risk; Facebook offers no pre-purchase safeguards or guarantees now. Thus, the purchase risk related to a particular social platform is often associated with the security and privacy measures the social platform already has in place.

Furthermore, should users fail to detect any measures to safeguard their transactions with sellers on a particular social platform, they will perceive greater risk in using that platform to make purchases. From a cognitive perspective, trust relies on a cognitive assessment of a situation (Kim, Prabhakar & Park, 2009; Harrison & McKnight, 2001). If a platform appears too risky, its users' assessment of the platform may deteriorate and, as a consequence, their trust levels in using the platform for shopping could drop considerably. Research has also identified the negative effect of risk on trust in different contexts (e.g. Kim, Prabhakar & Park, 2009; Yang et al., 2015). From this discussion, the following hypothesis is proposed:

H1: The higher the user's perceived risk of buying on the social platform, the lower their trust in using the social platform for shopping.

The Effect of Trust on Seller Risk

Trust in using a social platform for shopping may attenuate users' perceived risk of purchasing from sellers. The phenomenon by which trust in the platform has a halo effect on the perceived risk associated with in-platform sellers can be understood by Heider's (1958) Cognitive Balance Theory. According to this theory, the user's cognitive dissonance on a social platform depends on the configuration structure of three entities: user, seller, and platform. For example, when Pentina, Zhang & Basmanova (2013) studied the issue of trust in relation to social media brands, they adjusted these entities to brand, follower, and Twitter. The theory implies that users are inclined to maintain a cognitively balanced relationship between the entities. This means that users who trust a social platform will transfer this positive belief to the sellers they follow on such a platform. If a user trusts their favorite social platform, say Facebook, and then comes across an interesting product image and commercial information posted by a "legitimate" seller, this user will tend to maintain the cognitive balance derived from their trust in the platform and will feel less at risk when purchasing this seller's product on the platform. The halo effect should be strengthened when one object is aligned with another. In our case, trust in the platform and seller risk should center on transactional activities. A user's trust in a platform for social activities may not affect their transactional activities with sellers because social activities and purchase transactions are distinct from each other. On the contrary, if a user does not trust a social platform (e.g. certain gossip-based social networks), they will not trust a seller on that platform, even if the seller arouses no security or privacy concerns; nor will they wish to provide the seller with any sensitive information (e.g. credit card number, product preference). Hence, the authors propose the following hypothesis:

H2: The greater the user's degree of trust in using the social platform for shopping, the lower their perceived risk of buying from a seller on that platform.

The Effect of Trust on Purchase Intention

Trust is a crucial precursor of cooperative behavior (Shneiderman, 2000). Its working mechanism is this: while individuals are aware of their potential vulnerability in financial, security and privacy issues, they do not believe another party would take advantage of them, even if they could (Friedman, Kahn & Howe, 2000). Within the context of this study, when a user trusts in a social platform for shopping, this trust belief will dictate their shopping-related behaviors, even though they know that sellers are able to access and use their private information.

When trust is scarce or absent, individuals will not engage in financial transactions, nor are they likely to disclose personal information (Cassell & Bickmore, 2000; Jarvenpaa & Tractinsky, 1999). On the contrary, when trust is present and its working mechanism kicks in, one party becomes more satisfied with their relationship with another party, and this renders outstanding performance in transactional activities (Whipple, Lynch & Nyaga, 2010). In other s-commerce contexts, researchers have found that trust has a significant influence on purchase intention (Chen & Shen, 2015; Hajli, 2015; Kim & Park, 2013; Lu, Fan & Zhou, 2016). Chen and Shen (2015) found that trust in Douban – a crowdsourcing review forum – had a positive effect on intentions to purchase products recommended by Douban users; Hajli (2015) showed that trust in social networking sites positively affects purchase intentions on social networking sites (SNS); Kim and Park (2013) found that trust in an s-commerce company (which uses SNS to promote its deals) had a significant positive influence on purchase intentions on the respective s-commerce site; and finally, Lu, Fan and Zhou (2016) studied traditional e-commerce sites with added social commerce features and pointed out that trust in an s-commerce marketplace positively influences purchase intentions towards a seller. This leads to the following hypothesis:

H3: The higher the user's trust in using social platforms for shopping, the greater their intention to buy from a seller through such a platform.

The Effect of Seller Risk on Purchase Intention

Wang, Min and Han (2016) conducted a meta-analysis on social commerce- and risk-related papers and found that a direct risk-purchase relationship was not discussed in 43 relevant IS studies between 2006 and 2014. Seller risk is the buyer's belief that they will suffer negative consequences as a result of a seller's misconduct (Meents & Verhagen, 2018). Misdemeanors include misrepresenting products, overcharging for shipping fees or not sending items on time (Pavlou & Gefen, 2005). In s-commerce, this situation can be aggravated by sellers having access, not only to transaction-related information, but also to social-related information such as private photos and shared content. On a social networking site, the likelihood of buyer identity exposure is much higher than with traditional e-commerce sites. Technical affordances of social platforms such as connectivity, visibility and accessibility can easily expose private purchases and render a user's identity recognizable (Fox & Moreland, 2015). Shopping is a private activity, and buyers may not want others to know or disseminate information on what they have bought or commented on; not all buyers are flamboyant show-off shoppers in their online social circles. Unauthorized sharing of their shopping-related and personal information by sellers or third-parties could be perceived by the buyer as damaging to their social image and cause them distress.

Sitkin and Weingart (1995) argue that people will be less likely to undertake risky actions when the risk is perceived as high, as people tend to "associate risk with negative outcomes". When an individual's perceived risk is higher, with a feeling that there is a strong probability of experiencing a loss, thus lowering value expectations of the seller's product (Sitkin & Weingart, 1995), naturally the user is less willing to buy from the seller. The fact that major social platforms provide no protection mechanism or specific regulations for safeguarding purchases made directly through their platform, often disclaiming all responsibility to do so, could explain why direct purchasing is perceived as risky and is, therefore, infrequent on social platforms. Between 2015 and 2019, several s-commerce researchers used different constructs to shed light on how risk directly influences purchase behavior (Farivar, Turel & Yuan, 2017, 2018; Li, Liang & Li, 2018). Farivar, Turel and Yuan (2017, 2018) found that risk associated with using an s-commerce website for commerce has a negative influence on a general intention to purchase from an s-commerce platform. Li, Liang and Li (2018) found that product risk affects intention to purchase the product. The following hypothesis is therefore proposed:

H4: The greater the user's perceived risk of buying from sellers on social platforms, the lesser their intention to buy from a seller through such a platform.

METHOD

The Social Platform and The Purchase Context

The authors surveyed WeChat users via a Chinese online platform, Wjx.cn, and conducted an online survey to collect data. WeChat was selected as the social platform surveyed. It is China's most popular social platform with 980 million active monthly users (Angrymoo, 2018). WeChat includes many s-commerce features such as WeChat Pay and Mini Programs that allow users to transfer money and share commercial content by messaging their friends; it also integrates many third-party e-businesses such as ride-hailing, rail and flights, food delivery, movie tickets, hotels, flash sales and used items.

It is the perfect place for businesses to merchandise and sell their products and, most importantly, it is highly suitable for the purposes of this research. From the range of purchasing activities and methods available, the focus was on a regular purchase context in which a user considers directly purchasing from content generated by a seller. All respondents were told to enter this context by reading a text that began: “Imagine you are browsing your Moment on WeChat, and you are presented with a situation like the one illustrated below. You see that a retailer, MegaSmartphone, has posted a short text and a picture related to a product”. To make the purchase context more credible, two screenshots of WeChat were also included to let respondents know they were shopping and making purchases directly on WeChat.

For these screenshots, a real promotional post was adapted for the purposes of this research. Wei and Lu (2013) suggest that it is better to employ real promotion narratives than to invent them, in order to activate the respondents’ true emotions. The seller and the brand were renamed in case any respondents were familiar with the real case. A cheap, waterproof loudspeaker that can be attached to a shower room wall was chosen as the product in this context. This low-involvement item was deemed acceptable to respondents from diverse backgrounds (in terms of gender, age and prior experiences). In addition, the original purchase link was replaced with a “Buy” icon, vividly conveying the idea that the item could be purchased directly through the social platform. The following text was inserted to illustrate how respondents could complete this direct purchase: “When you press this button, you will be taken to a more detailed product page, where you can examine the product specifications, make the purchase and view your delivery date.” Here, the aim of adding the “Buy” icon and the text was to make it very clear that this was a direct purchase context.

Participants and Procedure

The survey link was sent to WeChat users on the Chinese platform Wjx.cn, which is similar to MTurk in the US. Wjx.cn has a huge respondent database across diverse demographics. Potential respondents were invited to take part by means of a survey link sent to them. Once they clicked on the survey link, they would find the text and the pictures (see Figure 4 in Appendix A) that set up the purchasing context. Participants were then asked to fill in a questionnaire.

Wessling, Huber and Netzer (2017) stated that this online crowdsourcing approach has two disadvantages: one, the anonymity of the online survey platform allows participants to misrepresent their behaviors; and two, many online crowdsourcing workers are experienced in completing surveys because they have received similar surveys before. The authors were aware that these disadvantages could affect their research results, so all participants were asked to answer the questions intuitively, and asked whether they had participated in similar surveys previously; where the answer to the latter was affirmative, those participants’ questionnaires were discarded. Measures suggested by Wessling, Huber & Netzer (2017) were also applied: a reasonable answering time (10 minutes) was allowed; workers’ questionnaires were approved quickly and all workers received a $2 fee; a statement to the effect that their data would only be used for academic purposes was issued; and an email address was provided to allow participants to inform the authors of any factors or inappropriate objects that caught their attention in the questionnaire.

After collecting all data, the original data set was randomly split into two small samples: one for model estimation (n=420), the other for model validation (n=420). In the estimation sample, 37.4% of participants were aged 26 to 35; 34.3% were aged 18 to 25; 14.3% were aged 36 to 45; and 42.1% were male. In the validation sample, 36.2% of participants were aged 26 to 35; 36.9% were aged 18 to 25; 13.1% were aged 36 to 45; and 36.4% were male. Gender and age in the two samples were coded as two dummy variables (e.g. in the dummy gender variable, 0 represents male and 1 represents female). An independent samples t-test was conducted to check for differences in demographics between the estimation sample and the validation sample. No statistical differences were found between the two samples (p_{gender}=0.09; p_{age}=0.40), leading the authors to conclude that the two samples were similar regarding the two demographic variables considered in the study.

Measurement

The variables in this study were adapted from previously validated scales: Appendix B shows all scales and their sources. In particular, the trust variable refers to trust in using the social platform for shopping. It is different from existing scales such as trust in a social networking site (Hajli et al., 2017), trust in social media (Lin et al., 2016), trust in products/services-related comments posted on WeChat (Lien & Cao 2014), and trust in community (Chen & Shen, 2015). The authors needed to measure trust belief in a particular s-commerce context, and required respondents to view the social platform as an online marketplace when scoring these items; Lu, Fan & Zhou (2016)'s trust in marketplace was therefore adapted to the purpose of the study. Purchase intention was measured by four items adapted from Vendemia (2017). In terms of the authors' interest in studying direct purchase behaviors through a social platform, this adaptation emphasized that purchase actions were made "through this social platform". All the study variables were measured with 7-point Likert scales.

RESULTS

Validity and Reliability

Covariance-based Structural Equation Modeling (CB-SEM) and Partial Least Square Structural Equation Modeling (PLS-SEM) are both widely applied methods in SEM. In this study, CB-SEM is preferred to PLS-SEM for two reasons. CB-SEM produces better parameter consistency and accuracy than PLS-SEM when the sample size exceeds a threshold of 250 observations (Reinartz, Haenlein & Henseler, 2009). The sample size in this case is 420 (840 in total), way over this threshold, making CB-SEM a more suitable option. Two samples are also used, requiring the additional action of testing the invariance of our structural model between the two samples. This action requires an SEM technique that generates goodness-of-fit indices for model comparison. Conventional model fit indices (e.g. CFI, GFI, RMSEA) are applicable in CB-SEM, but there are no established goodness-of-fit indices applicable in PLS-SEM (Hair et al., 2017).

First, the reliability of all measurements was assessed by calculating their internal consistency. In both samples, Cronbach's alpha coefficients on four scales exceeded the 0.7 cut-off. Second, we used AMOS 22.0 to conduct a CFA to confirm each scale's construct validity. Several conventional fit indices are reported, including χ^2/df, GFI, RMSEA, CFI, NFI, IFI, and TLI. Ratios of χ^2/df below 5 indicate an acceptable fit (see Bados, Gómez-Benito & Balaguer, 2010). Values for GFI, CFI, NFI, IFI, and TLI greater than 0.9 indicate a good model fit (see Nunkoo & Smith, 2013). Values of RMSEA below 0.1 indicate an adequate fit (see Curran et al., 2011). The fit indices shown in Table 1 satisfied all cut-offs. The measurement models for the estimation sample and the validation sample demonstrated an acceptable fit. Third, the convergent validity of the constructs was good, with values of Cronbach's alpha, average variance extracted (AVE), and composite reliability (CR) greater than conventional cut-offs (see Table 2). Finally, discriminant validity can be assessed by determining whether the square root of a construct's AVE is greater than the construct's correlations with the other constructs (see Martínez-López, Gázquez-Abad & Sousa, 2013). As shown in Table 3, the square root of all the AVE values was greater than all the other cross-correlations. Hence the authors were able to conclude that the discriminant validity of all the scales was adequate.

Hypotheses Testing (Structural Model)

Some conventional fit indices are reported in Table 1. Based on the multiple model fit criteria discussed previously, the structural models for the estimation sample and the validation sample also demonstrated an acceptable fit.

The path coefficients of our research model can be seen in Figure 2 and Figure 3. The R^2 of trust is: 0.40 (estimation); 0.42 (validation). The results show that the effect of platform risk on trust was significant in both samples ($\beta_{estimation}$=-0.63, p-value<0.001; $\beta_{validation}$=-0.64, p-value<0.001). So, as

Table 1. Model fit indices

		χ^2/d.f.	GFI	RMSEA	CFI	NFI	IFI	TLI
Measurement model	Estimation	2.38	0.94	0.06	0.98	0.96	0.98	0.97
	Validation	2.37	0.94	0.06	0.97	0.95	0.97	0.97
Structural model	Estimation	3.85	0.91	0.08	0.95	0.93	0.95	0.94
	Validation	3.95	0.90	0.08	0.94	0.92	0.94	0.93
Unconstrained model		3.90	0.91	0.06	0.94	0.93	0.94	0.93
Constrained model		3.84	0.91	0.06	0.94	0.93	0.94	0.93

Table 2. Lambda loadings and reliability for both the estimation and the validation sample

	Platform risk		Trust		Seller risk		Purchase intent	
	Estim. sample	**Valid. sample**	**Estim. sample**	**Valid. sample**	**Estim. sample**	**Valid. sample**	**Estim. sample**	**Valid. sample**
Platform risk1	0.79	0.79						
Platform risk2	0.82	0.78						
Platform risk3	0.86	0.84						
Platform risk4	0.85	0.85						
Trust1			0.85	0.78				
Trust2			0.85	0.87				
Trust3			0.87	0.87				
Trust4			0.82	0.80				
Seller risk1					0.87	0.80		
Seller risk2					0.90	0.87		
Seller risk3					0.85	0.80		
Seller risk4					0.85	0.84		
Purchase intent1							0.81	0.77
Purchase intent2							0.84	0.83
Purchase intent3							0.87	0.85
Purchase intent4							0.89	0.89
Cronbach's alpha	0.90	0.89	0.91	0.90	0.92	0.90	0.92	0.90
CR	0.90	0.89	0.91	0.89	0.92	0.90	0.91	0.90
AVE	0.69	0.67	0.72	0.69	0.75	0.69	0.73	0.70

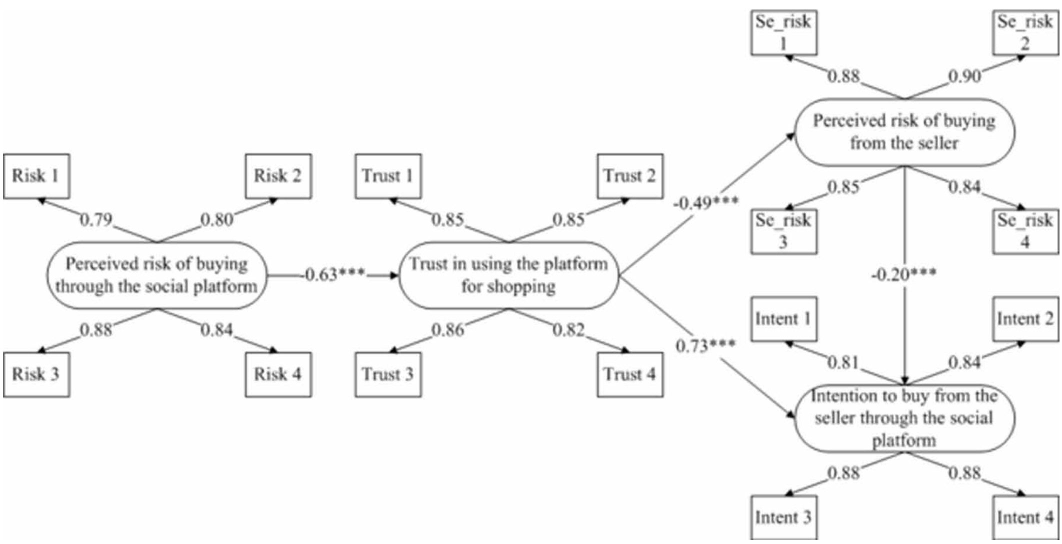
hypothesized, platform risk will reduce user trust. Therefore, H1 was supported. The R^2 of seller risk is: 0.24 (estimation); 0.33 (validation). The effect of trust on seller risk was significant ($\beta_{estimation}$=-0.49, p-value<0.001; $\beta_{validation}$=-0.57, p-value<0.001): trust beliefs can effectively reduce perceived seller risk. Therefore, H2 was supported. The R^2 of purchase intention is: 0.72 (estimation); 0.63 (validation). The effect of trust on purchase intent was also significant ($\beta_{estimation}$=0.73, p-value<0.001; $\beta_{validation}$=0.71, p-value<0.001): trust beliefs can increase users' purchase intentions. Therefore, H3 was supported. The effect of seller risk on purchase intent was also significant ($\beta_{estimation}$=-0.20, p-value<0.001; $\beta_{validation}$=-0.13, p-value<0.01): perceived seller risk negatively affects users' purchase intentions towards the seller. Therefore, H4 was supported. In sum, all the hypotheses in this study were supported by both the estimation and the validation sample.

Table 3. Discriminant validity

	Mean	SD	Platform risk	Trust	Seller risk	Purchase intent
Platform risk$_E$	4.14	1.60	**0.83**			
Trust$_E$	4.26	1.43	-0.61	**0.85**		
Seller risk$_E$	4.54	1.53	0.73	-0.46	**0.87**	
Purchase intent$_E$	3.90	1.54	-0.62	0.82	-0.56	**0.85**
Platform risk$_V$	4.02	1.58	**0.82**			
Trust$_V$	4.27	1.44	-0.60	**0.83**		
Seller risk$_V$	4.57	1.53	0.78	-0.53	**0.83**	
Purchase intent$_V$	4.03	1.49	-0.59	0.77	-0.54	**0.84**

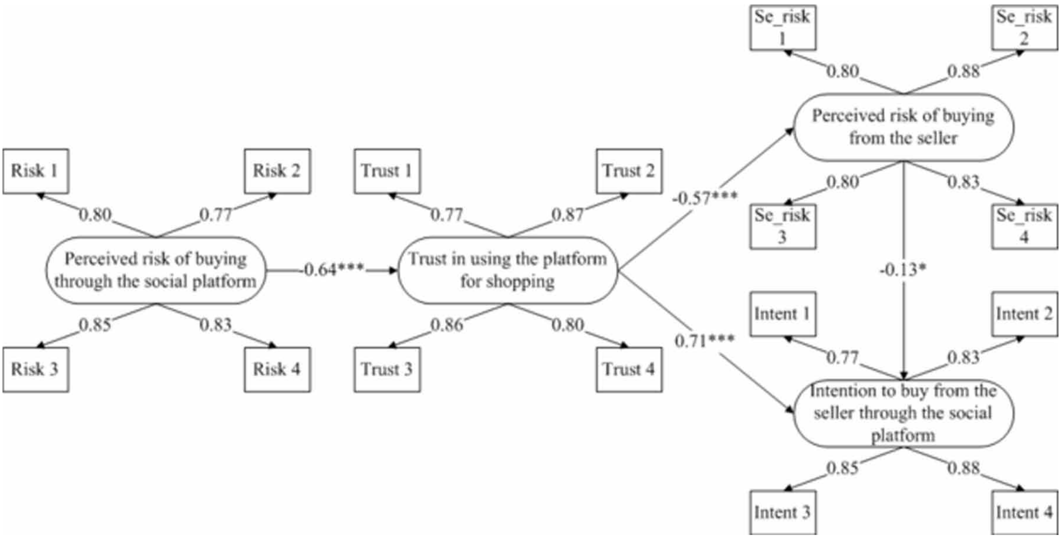
Note: Sub-index “E”: estimation sample; “V”: validation sample; The values along the diagonal line are the square root of the average variance extracted for the construct in the respective column. Below the diagonal line are the correlations between constructs. The negative sign indicates that the two constructs are negatively related.

Figure 2. Standardized parameters between constructs (rounded) for the estimation sample (*: p-value < 0.01; ***: p-value < 0.001) and reflective indicator (in squares) loadings with their respective constructs; all loadings were significant, p-value < 0.001



In addition, a multi-group invariance testing was performed between the estimation and the validation sample to test the generality of the structural model. Following Nien and Duda’s (2008) approach, this test begins by estimating the path coefficients, without any parameter constraints, in the two samples simultaneously. This unconstrained model displayed an adequate model fit (see Table 1, χ^2/d.f.<5, RMSEA<0.8, GFI/CFI/NFI/IFI/TLI>0.9). The unconstrained model, which included no equality requirements, was then compared with the constrained model, in which the parameters relating to our four hypotheses were constrained to be equal across both samples. If the model fit of the constrained model had displayed significantly worse results than the unconstrained model, this could have been a sign of non-invariance; in other words, the results would be indicating that at least one of the constrained parameters was variant across both samples (Nien & Duda, 2008). However, as shown in Table 1, no substantial model fit change was found: ΔCFI$\leq$0.01, ΔTLI$\leq$0.01, and

Figure 3. Standardized parameters between constructs (rounded) for the validation sample (*: p-value < 0.01; ***: p-value < 0.001) and reflective indicator (in squares) loadings with their respective constructs; all loadings were significant, p-value < 0.001



ΔRMSEA$\leq$0.015; see Scherer & Siddiq (2015) for these cut-offs. In sum, no statistical differences in the path coefficients of the hypothesized relationships were found between the estimation sample and the validation sample.

THEORETICAL DISCUSSION

The authors' research concludes that social platform users' direct purchase behaviors are significantly affected by trust- and risk-related variables. Trust is viewed as an underpinning of social commerce (see Farivar, Turel & Yuan, 2017; Hajli et al., 2017; Hansen, Saridakis & Benson, 2018; Lu, Fan & Zhou, 2016; Shi & Chow, 2015; Wang, Min & Han, 2016; Yahia, Al-Neama & Kerbache, 2018), yet few studies have measured consumers' trust in using a social platform for commercial purposes, and therefore the key factor of influence of this construct has yet to be fully explored. As risk is often associated with trust (Farivar, Turel & Yuan, 2017), our study demonstrates a significant risk-trust relationship (H1), in which these two factors are associated with purchasing through a social platform. This finding indicates that a social platform which aspires to win over users' trust in its commercial features must mitigate the generalized perceived risk associated with the platform *per se*. In other words, social platforms need to analyze their platforms in terms of providing solutions to mitigate environmental risks.

If a social platform was able to effectively reduce the perceived risk associated with it, users would acquire more positive trust beliefs and perceive less seller risk (H2), and this would increase intention to purchase from sellers (H3) on the platform. These two findings imply that trust is a cornerstone of s-commerce, and is based on interpersonal relationships. Some social platform users may overlook the role of environmental trust in s-commerce because they can transact with acquaintances, family members and close friends on the platform. But the full potential of social platforms for s-commerce cannot be unleashed as long as so many weak links remain unresolved (Ellison, Steinfield & Lampe, 2007). For this study, the authors created a seller that was completely unknown to all the participants; however, the findings show that users with a positive trust belief in a platform would have a more positive tendency to enter into a transactional relationship with this seller. To summarize, trust in the platform plays a key role in activating a halo effect linking platform-level factors with transaction-level activities.

Seller risk in this paper does not refer to general risk associated with all sellers, but rather to a context-specific perceived risk derived from an unexpected encounter with promotional content. It has been found that seller risk has a significant effect on users' purchase behavior with a seller (H4) on the platform. This finding implies that purchase intentions are affected, not only by platform-level factors, but also by transaction-level or contextual factors. A purchaser on a social platform needs to form an occasion-specific or context-specific (Shankar et al., 2011; Jones & Runyan, 2016) perceived risk associated with the seller before they will eventually conclude a purchase action.

Two relationships (risk → trust → behavioral intention; trust → risk → behavioral intention) have been considered individually in previous research, but few studies have investigated platform risk and seller risk simultaneously, and made connections between them. The main difference between the present study and prior literature is that two influential paths – i.e. platform risk → trust → purchase intention; trust → seller risk → purchase intention – are simultaneously considered in a context in which users make direct purchasing through social platforms with commercial features (see Table 4 in Appendix C for greater detail on the distinguishing characteristics of this study with regard to previous related research).

In a nutshell, the authors present the following major theoretical contributions. When approaching a potential purchase on a social platform, users will first evaluate the purchase risk associated with the platform, then go through a trust-building process based on this risk evaluation, which could eventually affect how a context-specific perceived risk is related to the seller. Trust in the platform for shopping and seller risk jointly affect the extent to which users are willing to eventually enter into direct purchase actions.

MANAGERIAL IMPLICATIONS

The findings of this study have several managerial implications for social platforms wishing to improve their s-commerce performance. Social platforms need to build a safe shopping environment for s-commerce activities, despite the fact that most social platforms have so far kept their distance from transactions between social platform members. This safe shopping environment underpins social platform monetization. Kim (2013) pointed out that social platforms employ three approaches to monetization: sales design, promotion and advertising. But no matter which approach a social platform adopts, a secure and trustworthy shopping environment is the best facilitator of social platform users' direct purchase behaviors, and could also contribute to increasing sellers' sales and boost ad conversion rates, enabling social platforms to make more profit from interactions between sellers and users. For instance, if ad conversion rates were higher, brands would be more willing to spend money on ads. However, most social platforms offer no pre-purchase safeguards or guarantees as traditional e-commerce companies do, probably because, if they provided guarantees (e.g. a money-back guarantee), they would have to dedicate more time and resources to dealing with shopping security and privacy issues.

It can be inferred that social platforms wishing to monetize via s-commerce first need to become actively involved in commercial activities and, most importantly, broaden the scope of their business operations from social business to a hybrid model encompassing social and commercial business. If they fail to do this, it could be very difficult for social platforms to create a safe shopping environment, earn user trust and boost direct sales. Social platform companies can learn from traditional e-commerce companies in this respect. For instance, to reduce platform risk, social platforms may need to offer free returns and a money-back guarantee for direct purchases through the platform, as well as develop a more cooperative partnership with sellers. For example, a seller will need to agree to a safe shopping protocol issued by the social platform, so that the platform can state that free returns and a money-back guarantee are available for this seller. When a social shopper decides to return an item and wants a full refund, the social platform needs to verify whether this request is reasonable. Specifically, the platform can process transaction payments and transfer money to sellers until the buyer has confirmed their purchase. The platform can also require sellers to deposit an agreed amount with the platform as a reserve for refunds, to prevent sellers from refusing refunds. Meanwhile, the platform can consider developing a transaction system to ensure the security of all payments. In consideration of users' privacy concerns, a social platform should put in place a protection mechanism or regulation to prevent sellers from easily accessing and distributing buyers' private information, from their real identity to private photos. In short, a social platform's roadmap to a safe shopping destination could involve considerable effort on its part.

Social platforms need to work out how the benefits of s-commerce can outweigh such an expenditure of effort. With respect to advertising business, social platforms could command bigger advertising fees from companies operating under a safe shopping protocol. Platforms could apply a brokerage model to merchandising activities in the safe shopping environment, taking a percentage or commission from sellers' sales; they could even consider establishing their own online stores, such as Snapchat's Snap Store, selling directly to their huge user base. As for digital content business such as novels, music and comics, platforms could adopt a subscription model or develop a micropayment system for premium content. It is plausible to develop a profit-sharing mechanism between content creators and participants, as in the case of Weibo mentioned previously.

Brands and retailers should reduce the risk associated with them in order to generate more direct sales. For instance, to demonstrate their business integrity, sellers can carry a security notice declaring that they will apply strict security measures to all purchases, thereby attracting greater user attention and converting traffic into purchases (Vladlena et al., 2015). In a social context, sellers should also take advantage of the social platform to reduce the perceived risk associated with them by buyers. Social platforms are a perfect communication tool for sellers to convey their value to buyers and actively respond to buyers' needs and enquiries. For example, sellers could participate in commercial communities that are regulated and trusted by community members, conducting social interactions with members so that, having developed relationships of trust with sellers through long-term interactions, these members feel less exposed to risk.

Based on the authors' cross-level causal path to purchase, purchase behaviors are determined by platform-level and transaction-level factors. Therefore, it is necessary to find and offer a safe shopping solution that works for all parties. Such a solution would take a synthetic view that integrates a central social platform, brands and retailers, e-commerce sites, transaction and payment institutions, insurance companies and logistics systems. Social platforms may need to take the lead in offering safe shopping policies and procedures, and designate each party's responsibilities in this safe shopping ecosystem which could effectively reduce the risks associated with s-commerce, with the resulting boost to online sales.

LIMITATIONS AND FUTURE RESEARCH

Purchase behaviors among social platform users are an interesting and promising research topic. Researchers could study which purchase behaviors are valuable to a social platform, how a social platform can profit from these purchase behaviors, and the actions a social platform could take to improve its practices. The authors' study was restricted to one direct purchase behavior, which cannot represent all varieties of purchase behaviors. The purchase context varies according to differences in contextual factors (e.g. sellers, products, merchandising approaches). Future research can vary these contextual factors and study whether changes in contextual factors lead to variations in purchase behaviors. The present study is mainly focused on risk-related factors because it is imperative for social platforms wishing to monetize through s-commerce to reduce risk. However, future studies could study other influential factors, such as merchandising approaches, and different purchase behaviors, such as online group buying.

Our study focused on a single social platform: WeChat. Although it is a popular social platform, WeChat is distinct from other social platforms such as Facebook, Twitter, Pinterest or Instagram, among others. A platform's characteristics can positively or negatively affect purchase behaviors and may influence how a social platform is able to capture value from these behaviors.

Future studies may shed light on how social platforms could use updating technologies to facilitate purchase behaviors; for example, how social platform users react to cloud-based shopping apps and AI-driven chatbots, and make more or fewer purchases via interactions with these technologies.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (NSFC) under the grant number 71702064 and the China Scholarship Council.

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APPENDIX A

Figure 4. Pictures used in the survey

APPENDIX B

Scales

Trust in using the platform for shopping (adapted from: Lu, Fan & Zhou, 2016).
(All items are measured by 1: strongly disagree – 7: strongly agree)

1. As an online marketplace, this social platform can be trusted at all times.
2. As an online marketplace, this social platform can be counted on to do what is right.
3. As an online marketplace, this social platform has high integrity.
4. This social platform is a competent and knowledgeable online transaction platform.

Perceived risk of buying from the seller (adapted from: Verhagen, Meents & Tan, 2006).
(All items are measured by 1: strongly disagree – 7: strongly agree)

1. As I consider making a purchase through this social platform, I become concerned about whether the seller will commit fraud.
2. As I consider making a purchase through this social platform, I become concerned about whether the seller will swindle me.
3. As I consider making a purchase through this social platform, I become concerned about whether the seller offers products that will not perform as expected.
4. As I consider making a purchase through this social platform, I become concerned about whether the seller will behave opportunistically.

Intention to buy from the seller through the social platform (adapted from Vendemia, 2017).
(All items are measured by 1: strongly disagree – 7: strongly agree)

1. It is very likely that I would make purchases from the seller through this social platform in the future.
2. Based on the information shown on the seller's post, I would consider buying from the seller through this social platform.
3. I would feel comfortable purchasing from the seller through this social platform in the future.
4. I am willing to buy from the seller through this social platform.

Perceived risk of buying through the social platform (adapted from: Bianchi & Andrews, 2012).
(All items are measured by 1: strongly disagree – 7: strongly agree)

1. I would feel safe making purchases on this social platform using my WeChat Pay. [R]
2. I would feel safe giving my personal details to this social platform if requested. [R]
3. Compared with other ways of making purchases, I think that using this social platform is more risky.
4. There is too much uncertainty associated with using this social platform to make purchases.

APPENDIX C

Table 4. Differences of this study regarding previous related research

Study	Key findings: sequence of relationships	Context	Differences with this article
Kim, Ferrin & Rao, 2008	Trust → risk → purchase intention; trust → purchase intention. Trust negatively affected risk. Risk negatively affected purchase intention. Trust positively affected purchase intention.	E-commerce	These authors studied the trust-risk-purchase sequence in an e-commerce context. However, the present study focused on the specific context of s-commerce, as distinct from e-commerce. In e-commerce, the shopper's mind-set is more commerce-oriented because shopping websites are designed for online shopping. In contrast, social platform users are more social-oriented because the core value proposition of social platforms is to offer online social interactions. This nuance could affect the trust-risk-purchase sequence and warrants particular study in this specific context.
Kim, Prabhakar & Park, 2009	Trust → risk → adoption. Trust influenced adoption through perceived risk.	Online banking	These authors' constructs (trust, risk, and adoption) are related to online banking. The constructs of the present study are different. First, trust in the present article refers to trust in using a social platform for shopping. Second, risk in the present article is associated with a seller. Third, these authors focused on adoption behaviors, whilst the present authors focused on direct purchase behaviors through social platforms.
Kim & Park, 2013	Transaction safety → trust → purchase intention. Transaction safety positively influenced trust. Trust positively influenced purchase intention.	S-commerce	The s-commerce sites studied by these authors, e.g. Groupon (an American e-commerce marketplace), and Coupang (a South Korean e-commerce platform), are different from those studied by the present authors. The present study focused on social platforms endowed with commercial features (e.g. buy buttons), rather than the socialized commercial websites on which these authors focused.
Yang et al., 2015	Risk → trust → usage intention. Risk negatively affected trust. Trust positively affected usage intention.	Online payment	These authors' constructs (risk, trust, and intention) are related to using online payment. The present authors' constructs are different, and related to using a social platform for shopping.
Hong, 2015	Performance risk → trust expectation → purchase intention. Risk positively influenced trust expectation. Trust expectation positively affected purchase intention.	E-tailing	Trust and purchase intention here are related to an e-tailer. Particularly, trust expectation is different to the kind of trust examined in the present authors' study. E-tailing is also contextually different from s-commerce.
Wang, Min & Han, 2016	Trust was negatively related to risk. Trust was positively related to purchase behavior.	Social media platforms and information system	These authors conducted a meta-analysis related to 43 studies in IS between 2006 and 2014. No risk-to-purchase relationships were considered in IS studies during this period. This relationship was highlighted in the present study, however. Moreover, these authors used a broader search scope, including risk- and trust-related studies, e.g. risk or trust issues in information/knowledge sharing on social media. The present authors' study, by contrast, focuses on a context in which social platforms were used for commercial purposes.
Farivar, Turel & Yuan, 2017	Trust → risk → purchase intention; Trust → purchase intention. No significant relationship between trust towards s-commerce site and perceived commerce risk was found. Risk was negatively related to purchase intention. Trust was positively related to purchase intention.	S-commerce	The s-commerce site referred to in these two references is an e-commerce site (Etsy) integrating social media features. By contrast, the present authors focus on social platforms incorporating a commercial feature. S-commerce sites such as Etsy prioritize commercial business. The social platforms in the present study primarily provide social interaction services. Moreover, in contrast to the findings of Farivar, Turel and Yuan (2017)'s work, a significant trust-risk relationship was found in the present authors' study.
Farivar, Turel & Yuan, 2018	Risk → purchase intention. Perceived commerce risk negatively affected purchase intention.		
Meents & Verhagen, 2018	Platform/marketplace risk → seller risk → attitude towards buying. Platform risk positively affected seller risk. Seller risk negatively affected attitude towards buying.	C2C e-marketplace	The present authors' study includes purchase intention when considering platform risk and seller risk simultaneously. This constitutes a major difference from the reference study. Trust is also included in the present model, with the empirical results demonstrating that trust does play a role in influencing social platform users' purchase intentions.
Wei et al., 2019	Trust → Transaction intention; Perceived risk → Transaction intention. Trust positively affected transaction intention. No significant effect of perceived risk on transaction intention was found.	C2C e-marketplace	Although the reference study considered trust- and risk-related factors simultaneously, its aim is to compare the relative influences of risk- and trust-related factors on transaction intention between two samples (buyers and sellers). The present authors' research interest lies only in the purchase behaviors of end users or social shoppers. This constitutes a major difference from the reference study. A significant effect of risk on purchase intention was also found in the present study.

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