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Breaking the uncertainty barrier in social commerce: The relevance of seller and customer-based signals

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ABSTRACT

Even though the problem of uncertainty in online business is widely discussed, there is still limited knowledge of the mechanisms used by social commerce customers to reduce uncertainty perception. Therefore, this study attempts to bridge this gap by investigating the influence of the number of positive review comments, seller popularity, customer service quality, and return policy on seller uncertainty. A self-administered structured questionnaire was used for data collection. The empirical evidence from 155 social commerce customers shows that the number of positive review comments, seller popularity, and customer service quality has a negative influence on seller uncertainty. Moreover, customer service quality enhances the negative influence of the number of positive review comments on seller uncertainty. Furthermore, the study revealed that the seller that offers a lenient return policy in addition to good customer service quality experiences lower levels of seller uncertainty than the seller that only offers good customer service.

1. Introduction

Social media is increasingly becoming an integral part of people's lives around the world. It is estimated that 3.48 billion people are actively using social media for commercial and non-commercial purposes, which is about 45 percent penetration to Internet users (Hootsuite, 2019). Research has revealed that more than 87% of large firms are using social media for commercial purposes (Maia et al., 2018). Social media commercial use is termed as social commerce or social business (Kim and Park, 2013; Sharma and Crossler, 2014; Maia et al., 2018).

The unprecedented penetration and the popularity of social media in commercial activities is credited to its use of Web 2.0. The features of Web 2.0 allows users to create and share contents, such as purchase experience as well as product and service related information with their online peers (Kim and Park, 2013; Maia et al., 2018; Morris and James, 2017; Ahmad et al., 2019). The benefit is the reduction in information asymmetry and the perceived uncertainty of buying a product online (Öz, 2015). In developing countries, the popularity of social commerce is partly attributed to the advancement in mobile money application that allows customers to pay for their purchases and delivery fee through their mobile phones and have the product delivered to the location of their choice.

Despite the increasing popularity of social commerce and its contribution to reducing information asymmetry, perceived uncertainty remains a major challenge to both online customers and sellers. The present study explores perceived uncertainty from the perspective of customers regarding seller uncertainty in social commerce in a developing/emerging economy context. The negative consequences of increasing uncertainty perception include declining sales (Lee et al., 2015) and low purchase and repurchase intentions (Chiu et al., 2018; Yang et al., 2019). Moreover, some customers tend to limit their purchases to low-value products to reduce possible loss (Maia et al., 2018), and others refrain from online transactions entirely (Vos et al., 2014). As such, focusing on reducing customers' perceived uncertainty about the seller is likely to enhance purchase intentions (Wang et al., 2017), attract more customers, and eventually lead to increased sales revenue.

Several studies have investigated the mechanisms for reducing uncertainty in online business transactions (e.g. Bai et al., 2015; Chiu et al., 2018; Dhanorkar et al., 2015; Dimoka et al., 2012; Hu et al., 2008; Pavlou et al., 2007; Wang et al., 2017). However, most of these have focused on uncertainty in an e-commerce environment, which is significantly different from social commerce. Unlike e-commerce, social commerce has low entry barriers (see Table 1), including low

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Table 1
A comparison of social commerce and e-commerce.

Attribute	Social commerce	E-commerce	Differential rating of attribute(Low, moderate, high) Social commerce	E-commerce	Reference
Level of investment	Low initial investment is required. The seller requires social media presence, internet access, and a smart phone.	High level of initial investment is required to establish own e-commerce infrastructure. However, low investment needed to use third party e-commerce platform.	Low	Low to high	Present study
Social media dominance	Social media dominant/active. Social commerce is part of e-commerce.	Social media may be more/less dominant.Social commerce may/may not be part of e-commerce.	High	Low to moderate	Present study
Social media integration	Full integration of social media and social networking elements with the process of buying and selling of products and services on an online platform.	Social media and social networking elements may be integrated with the process of buying and selling of products and services on an online platform.	High	Low to moderate	Attar et al. (2020)
Entry barrier	Low entry barriers in terms of investment/ operational costs and technical requirements.	High in terms of investment required, operational costs, and technical requirements (asset- specific e-commerce infrastructure).	Low	High	Kim and Park (2013) Ahmad et al. (2018); Present study
Opportunistic behaviour	Relatively high in terms of poor customer service, fraud, late refunds, and inaccurate information. Sellers are likely to avoid costly and easy-to-verify signals.	Relatively low. Sellers are likely to use costly and easy-to-verify signals.	High	Low	Kim and Park (2013); Present study
Level of interaction	Increased interactions with buyer and supplier as well as amongst buyers themselves (both vertical and horizonal interactions).	Trading of goods and services is traditionally based on one-on-one interactions between the buyer and seller (vertical interactions).	High	Low to moderate	Gibreel et al. (2018); Huang and Benyouce (2013)
Use of referral	Even though the customer can be referred to an e-commerce site from a social network, the entire purchase, from searching for the product to its purchase, can still be executed within the social network.	Use referral system to refer customers from social media, social networks, and search engines to other marketplaces such as amazon and the e-commerce webpage of the seller for sellers who are maintaining their own websites.	High	Low to moderate	Gibreel et al. (2018)
Payment options	Price and payment information is placed on the social commerce page without referring the customers. Flexible payment (with or without credit cards) from third party payment systems can be integrated into social commerce. Options for many payment systems (with or without credit cards) from third parties' payment systems can be integrated into the social-commerce platform.	Even though some e-commerce websites have added social commerce features, payment information and payment processes are located on the e-commerce page.Options for many payment systems (with or without credit cards) from third parties payment systems can be integrated into the e-commerce platform.	Relatively high	High	Present study
Mobility and advertising	Peer-to-peer advertising is common.Social commerce relies on socialmedia to carry advertisements.	Can accommodate mobility and peer-to-peer advertising.	High	Low to moderate	Lin et al. (2017): Present study
Use of third party for providing returns	Limit returns through payment structure where the buyer can pay half and pay the remaining after receiving and being satisfied with the product, or paying the full amount after receiving the product.	Provide flexible returns policy through a mediating agent (Gibreel et al., 2020).	Low	High	Gibreel et al. (2020); Present study

operational costs and minimum technical requirements (Ahmad et al., 2018; Kim and Park, 2013). As a result, social commerce has attracted many small firms, both scrupulous and unscrupulous. In the case of the latter, an increasing number of customers are suffering from both passive and active opportunistic behaviours amongst sellers in the form of poor customer service, information misrepresentation (Kim and Park, 2013), fraud (Chiu et al., 2018; Kim and Park, 2013), delivery delays, or defective products (Chiu et al., 2018). Subsequently, opportunistic behaviours (Kim and Park, 2013) and, eventually, seller uncertainty are likely to be higher in social commerce than in e-commerce. Despite the consequences of uncertainty in social commerce and the notable differences between the latter and e-commerce, very few studies (Bai et al., 2015; Wang et al., 2017) have investigated the mechanisms by which uncertainty in social commerce may be reduced.

Previous studies (see Table 2) have examined various antecedents and mitigators of uncertainty, though none have looked at how customer and seller-based cues impact uncertainty directly or interactively. The present study addresses the following research question: how can sellers reduce transaction uncertainty in online social commerce? Consequently, our objective is to investigate how customer and seller-based signals mitigate seller uncertainty. For the purposes of the present study, we define seller uncertainty as the buyer's difficulty in assessing the seller's true characteristics and predicting whether the seller will act opportunistically (Dimoka et al., 2012). The present study complements the information asymmetry literature by using signalling theory to show that customer-based signals such as the number of positive review comments and seller popularity and seller-based signals, customer service quality and returns policies can effectively reduce transaction uncertainty in online business. Thus, the number of positive review comments, seller popularity, customer service, and returns policy can be used as information signals to reduce uncertainty in social commerce transactions. These signals can either attenuate or reinforce desired outcomes (e.g. information asymmetry, purchase decisions, and behavioural uncertainty).

Signalling is an important phenomenon that has been studied in different domains. For example, in health informatics, Yang et al. (2012) and Yang et al. (2014) investigated the harnessing of social media for signal detection of adverse drug reactions. Yang et al. (2012), Yang et al. (2014) based their study on adverse reactions from content contributed by users on social media. Based on the analysis of a sample of online pharmacy websites, Mavlanova et al. (2012) suggested that low-quality sellers were likely to avoid costly and easy-to-verify signals. Hence, they use fewer signals than did high-quality sellers, who use costly and difficult-to-verify signals, such as return policy and website-based content. In bank marketing, Boateng (2019) concluded that banks' use of online relationship activities needs to go beyond the online tools

Table 2
Previous studies on uncertainty in social commerce and e-commerce.

Publication	Main objective	Research setting and methodology	Key constructs	Main conclusion(s)	Current study vs. previous studies
Comparison ofperceived acquisition value sought by online second-hand and new goods shoppers(Fernando et al., 2018).	The study investigates the effect of perceived uncertainty on product value, as well as the effect of product type on perceived uncertainty in the online second hand and new product.	-E-commerce-Online survey (used to collect data from 602 shoppers). The results are based on 481 usable questionnaire returns.	**Endogenous factors:** Acquisition value; e-loyalty; **Exogenous factors:**Perceived uncertainty; Frugality; Product type (new vs. second hand); Product category (search vs. experience)	Perceived uncertainty has a weak negative effect on acquisition value (i.e. the benefit of online purchase), while the perception of uncertainty is higher for online second-hand shoppers than new goods shoppers.	Fernando et al. (2018) categorises uncertainty as an exogenous variable rather than as an endogenous variable. No other variable similar to our study was considered.
The contradiction of trust and uncertainty from the viewpoint of swift guanxi(Chiu et al., 2018).	The study investigates the association between relationship variables (mutual understanding, reciprocal favour, and relationship harmony) with product and seller uncertainty.	-E-commerce-Online survey of Yahoo! Online auction consumers in Taiwan; 864 responses were returned, 455 of which were used for further analysis.	**Endogenous factors:**Product and seller uncertainty; **Exogenous factors:**Trust in vendor; Trust-getting information; Mutual understanding; Reciprocal favour; Relationship harmony	The reciprocal favour effect on product uncertainty is insignificant. All other relationship variables significantly reduce product and seller uncertainties in the online marketplace; that is, they can mitigate uncertainty in the online marketplace.	Chiu et al. (2018) used seller uncertainty as an endogenous variable but none of the exogenous variables are similar to those in our study.
Quality dimensions in online communities influence purchase intentions(Wang et al., 2017).	The study examines how the quality dimensions in independently owned online brand communities influence purchase intentions via uncertainty reduction and the role of involvement.	Social commerceOnline survey, with 243 responses from members of online communities.	**Endogenous factors:** Uncertainty reduction; Purchase intentions, **Endogenous factors:** Information quality; Involvement; Relationship quality	The findings show that for independently owned online brand communities, information quality and relationship quality are effective tools for influencing purchase intentions via uncertainty reduction.	Wang et al. (2017) used uncertainty in general as an endogenous variable but none of the exogenous variables are similar to those in our study.
Effect of social commerce factors on user purchase behavior: an empirical investigation from renren.com(Bai et al., 2015).	The study investigates the influence on social features (social network platform, users, and user generated content) and commercial features (guarantee/ certification by third party) on uncertainty and purchase intention.	-Social commerce-Simulation and online survey. Data were collected from 257 respondents; 212 questionnaires used for further analysis.	**Endogenous factors:**Product uncertainty; Seller uncertainty; Purchase intention; **Exogenous factors:**Social support; Third party infomediaries	The study concludes that product and seller uncertainties have a negative influence on purchase intentions in online social commerce. The uncertainties can be reduced by third party guarantee and social support through comments and experience sharing amongst the social commerce community.	Bai et al. (2015) used seller uncertainty as an endogenous variable but none of the exogenous variables are similar to those in our study.
Repurposing materials and waste through online exchanges: overcoming the last hurdle(Dhanorkar et al., 2015).	The study investigates the factors that reduce buyers' uncertainty and increase sellers' commitment to online material and waste exchanges (OMWE).	-E-commerce-Transaction-level data from an online exchange (MNExchange. org).	**Endogenous factors:**Buyer's uncertainty; Seller's commitment; **Exogenous factors:**Hits on listings; Visual information content; Textual information length; Seller's access to disposal	Greater product and transaction information reduce the buyer's uncertainty and increase exchange success. Both buyers and sellers rely on their prior experience. Higher familiarity between the buyer and seller and familiarity with the OMWE system lead to a greater likelihood of exchange success.	Dhanorkar et al. (2015) used buyer uncertainty as an endogenous variable but none of the exogenous variables are similar to those in our study.
On product uncertainty in online markets: theory and evidence (Dimoka et al., 2012).	The study conceptualises product uncertainty and examines its effects and antecedents in online markets for used cars (eBay Motors).	-E-commerce-Online survey. A total of 331 responses were collected from buyers; 210 unique auctions were identified.	**Endogenous factors:**Product uncertaintySeller uncertainty; Price premium; **Exogenous factors:**Third party assurances; Online product descriptions; Positive ratings; Negative ratings; Dealer vs. individual	The authors propose product uncertainty to be distinct yet shaped by seller uncertainty. Product uncertainty negatively affects price premiums in online markets beyond seller uncertainty. Using the information signalling literature, the authors describe how information signals reduce product uncertainty.	Dimoka et al. (2012) used seller uncertainty in addition to product uncertainty as endogenous variables but none of the exogenous variables are similar to those in our study.
Understanding and mitigating uncertainty in online exchange relationships: a principal-agent	The study uses a principal-agent perspective, information systems, and marketing and psychological theories to investigate the antecedents	-E-commerce-Longitudinal data from 521 consumers of prescription drugs and books.	**Endogenous factors:** Perceived uncertainty; Purchase intention; **Exogenous factors:** Information asymmetry; fear of seller opportunism;	Uncertainty perception is a major impediment to online exchange and is positively influenced by information asymmetry, fear of seller opportunism,	Pavlou et al. (2007) used uncertainty in general as an endogenous variable but none of the exogenous

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Table 2 (*continued*)

Publication	Main objective	Research setting and methodology	Key constructs	Main conclusion(s)	Current study vs. previous studies
perspective(Pavlou et al., 2007)	and mitigators of perceived uncertainty in online exchange relationships.		information privacy concerns; information security concerns; product diagnosticity; website informativeness; trust, social presence; purchase involvement.	information privacy concerns, and information security concerns.	variables are similar to those in our study.

deployed. Banks should use and communicate appropriate and useful signals in order to stimulate customers' online trust and loyalty, as well as influencing their perception and intentions.

The current study investigates seller and customer-based signals from the perception of social commerce users in a developing country context. In most developing and emerging markets, many micro/small businesses and entrepreneurs have taken advantage of social media to reach out to consumers and to transact online. The study provides insight into how in 'less secured' and developing e-business environments, customers reduce the uncertainty associated with online transactions by relying on specific signals or combinations of such signals. While acknowledging that the buyer cannot physically evaluate products prior to purchase in an online business environment, the present study uses signalling theory to extend knowledge on the signals that social commerce customers employ to reduce uncertainty in online purchases. Hence, the study makes several contributions to the literature: (1) we conceptualise and test the 'seller uncertainty model' in a social commerce setting. The model extends knowledge on uncertainty reduction by demonstrating empirically how the number of positive review comments and seller popularity significantly reduce seller uncertainty. In addition, the study provides empirical evidence that shows how customer service quality reduces seller uncertainty, especially when good customer service is coupled with an efficient returns policy or a number of positive review comments; (2) the study highlights the differences between social commerce and e-commerce and provides directions for future studies, especially in a social commerce setting; (3) in terms of analytic techniques, the study provides an evaluative procedure of "predictive consistency" for assessing two analytical research models. This simple procedure will be useful to researchers in assessing two "competing" models; and (4) the study highlights several managerial implications that provide strategic options and new insights for e-commerce and social commerce operators on how to manage the uncertainty problem in online business.

In the next section, we present the literature review and research hypotheses, followed by the research method. After that, we present the data analysis and results. The discussion section highlights the theoretical contributions and managerial implications of the study. Lastly, we end with conclusions, limitations, and future research suggestions.

2. Literature review and research hypotheses

2.1. E-commerce and social commerce

E-commerce is the process by which entities and individuals exchange commodities online using Internet-mediated systems with the support of both the transmission of data between Internet-mediated systems and electronic monetary systems (Wigand, 1997; Gibreel et al., 2018). The growth of e-commerce shows how electronic markets have become part of all aspects of modern economies. According to Alt and Zimmermann (2014), at the early stage, proprietary technologies and solutions existed but were limited to specific application areas and mostly used by big organizations. The Internet became the 'game-changer' as it offered access to information irrespective of the technological platform and interconnectivity across various providers (Alt and Zimmermann, 2014:161).

The role of social media as an 'enhancement' and a platform for e-business became evident during the early digital ecosystem phase (see Alt and Zimmermann, 2014 for details). Social media has created opportunities for new business models and delivery platforms in electronic commerce, referred to as social commerce (Liang and Turban, 2011; Baethge et al., 2016). Social commerce is part of e-commerce, which is an integration of social media in e-commerce platforms. Social commerce is simply a product of social media and e-commerce (Hajli and Sims, 2015). There is no single agreed definition of what social commerce is. However, for the purpose and context of this paper, we will use the broad definition of Zhou et al. (2013: 61). *Social commerce involves the use of Internet-based media that allow people to participate in the marketing, selling, comparing, curating, buying, and sharing of products and services in both online and offline marketplaces, and in communities.* It is a form of commerce mediated by social media that involves the convergence between the online and offline environments (Stephen and Toubia, 2010; Wang and Zhang, 2012). Recent studies (e.g. Benitez et al., 2018; Zhu and Kraemer, 2002) suggest that social media and e-commerce platforms are two IT resources whose degree of investment and deployment may be heterogeneous amongst firms and could be leveraged to provide a competitive advantage. Table 1 presents a comparison of social commerce with e-commerce.

Social commerce websites enable product recommendation, customer review provision, discussion board, and writing and rating a review (Hajli, 2015). The social commerce ecosystem enables customers to have access to social knowledge and experiences that support them in understanding their online purchase intent better and helps them make more informed and accurate purchase decisions (Huang and Benyoucef, 2015). The network of interactions among actors in social commerce is the primary source of value, while in e-commerce, the facilitation of connections among buyers and sellers is the basis for value co-creation (Hajli et al., 2017). Social commerce can be implemented in two different ways: (1) by adding commercial features into social network sites or (2) by adding social network features into traditional e-commerce, such as allowing previous customers to share their experience in traditional e-commerce sites (Tajvidi et al., 2018). Our study focuses on the first approach and examine how sellers can deploy relevant strategies to effectively mitigate perceived seller uncertainty in social commerce. Previous studies have investigated the mechanisms for reducing uncertainty in online business transactions. They have also identified a number of mechanisms for reducing uncertainty in social commerce. These include quality information provided by the seller, the quality of relationship maintained with the buyer (Wang et al., 2017), online social support, and the use of information provided by a third party (Bai et al., 2005). Table 2 shows that previous studies have focused mostly on the broader online business of e-commerce, while only a few have examined social commerce. The present study concentrates on social commerce.

2.2. Signalling theory

In online business, uncertainty refers to the difficulty in predicting the outcome of the transaction (Chiu et al., 2018). It can be related to the product, seller, and selling process (Lee and Ma, 2012). Such a difficult situation is caused by the lack of physical interactions between the seller and buyer (Dimoka et al., 2012; Chiu et al., 2018; Fernando et al., 2018; Chen et al., 2019). Spatial and temporal separation in online business environment, tends to create an information asymmetry problem in favour of the seller (Fernando et al., 2018; Shah et al., 2019) and limits the potential customer's ability to ascertain veracity of the seller' characteristics and evaluate the product physically prior to purchase (Dimoka et al., 2012). Consequently, the customer cannot be sure of the right attributes, features, and functions of the product, such as appearance, performance, and the fit for purpose (Chiu et al., 2018). This situation leads to pre-purchase uncertainties, which are associated with the seller's moral hazard and post-purchase uncertainty associated with adverse selection problems (Fernando et al., 2018).

The signalling theory proposed by Spence in 1973 is regarded as an appropriate theoretical lens for tackling the information asymmetry problem in online transactions (Pavlou et al., 2007; Liu et al., 2017). This theory contends that, in order to reduce perceived uncertainty, the seller may send pre-purchase signals (Liu et al., 2017). These are cues that a seller uses to convey information about their trustworthiness and the credibility of unobserved product attributes to the buyer (Li et al., 2015; Liu et al., 2017; Shah et al., 2019). The cues serve as an important means of reducing the information gap caused by the buyer–seller spatial and temporal separation (Li et al., 2015; Shah et al., 2019). Signals may also be conveyed by the customers (Van Nguyen et al., 2020). Some of the customer-generated signals include customer review comments, likes, and ratings.

2.3. Comments and seller uncertainty

Customer comments refer to online customer reviews of the seller, which can be either positive or negative (Casaló et al., 2015; De Pelsmacker et al., 2018; Lee et al., 2012). They provide rich information for decision making that cannot be provided by the seller because they give consumers themselves the opportunity to share their previous experiences of the seller with other potential customers (Lee et al., 2012). Positive comments and positive review comments are used interchangeably with the same intended purpose. Purchase decisions of more than three-quarters of online customers are influenced by other customer reviews (Casaló et al., 2015). Previous research indicates that when customers experience uncertainty in an online shopping context, online review comments from their peer customers are used to reduce risk and uncertainties (Park et al., 2007; Lee et al., 2012). Potential customers tend to find comments from their fellow customers to be more informative, useful, and credible than the seller's comments in forming an opinion about the transaction before purchase (Lee et al., 2012; Casaló et al., 2015). However, negative comments can overshadow positive comments (Lin et al., 2018) and increase rather than decrease uncertainty. Research indicates that people tend to pay more attention and attach more weight to negative information than neutral and positive (Van Nguyen et al., 2020). Thus, when the social media page has a significant number of negative comments, customer decision making becomes more difficult, and the perceived uncertainty of buying from that seller is likely to increase. On the other hand, when the seller has more positive review comments than negative ones, potential customers' perception of seller uncertainty is expected to be low. Therefore, we propose the following hypothesis:

H1: Higher number of positive review comments will reduce seller uncertainty

2.4. Popularity of seller and seller uncertainty

Researchers have described popularity in social commerce in terms of the popularity of the posts or seller's popularity. Post popularity has been operationalised by the number of views, comments, likes, and/or shares (Abid et al., 2019; De Vries et al., 2012; Lardo et al., 2017), while the popularity of the seller is measured by the number of followers regardless of the reason for following them (De Vries, 2012; Du et al., 2019; Lardo et al., 2017; Read et al., 2019). Since our study focuses on the popularity of the seller, popularity is referred to as the number of followers on the seller's social media page. Popularity is often used as a key indicator of online business success (Du, 2013). The successes of online sellers depend on the critical mass of followers to generate sufficient revenue and make a profit. The most popular sellers tend to have a broader base of followers than the less popular ones (Tang and Chen, 2020). Popularity may be gained by demonstrating traits such as delivery reliability, lenient return policy (Lahuerta-Otero et al., 2018), offering a product of good quality, and excellent customer service quality (Wu et al., 2019). These traits can be evident to potential customers through positive purchase experience and comments shared by previous customers on the seller's social media page. As such, the popular seller is less likely to break its promises to customers as it may increase the number of negative comments on its page, tarnish its reputation, and eventually lead to a declining customer base and revenue. Thus, popularity can be used as a signal to gain customer confidence and reduce uncertainty perception. In this regard, we propose the following hypothesis.

H2: Higher levels of seller popularity will reduce seller uncertainty

2.5. Customer service quality and seller uncertainty

Customer service quality refers to the degree to which the customer value the support and services delivered by the seller (Liang et al., 2012; Chen et al., 2016). Customers tend to evaluate sellers as offering excellent service quality if they are helpful, provide on-time services, and respond to inquiries promptly (Chen et al., 2016; Kim and Lennon, 2013; Wolfinbarger and Gilly, 2003). Service quality can play a crucial role in reducing the customer's uncertainty perception. When customers are faced with uncertainty, they may seek to reduce that uncertainty by perusing the firm's social media page or directly communicating with the seller through email, instant chat, direct messaging or by phone to get more information about the product and other services from the seller (Parris et al., 2016). The customer may want to know things such as the weaknesses of the product, how the product works, delivery terms, and payment terms offered by the seller. Thus, the willingness of the seller to provide additional information and provide a prompt response to a customer inquiry is likely to reduce the customer's perception of uncertainty in dealing with the seller. In this regard, we propose the following hypothesis:

H3: Higher levels of customer service quality will reduce seller uncertainty

2.6. Moderation role of service quality

Social commerce's capability of creating and sharing content among customers and between customers and sellers has brought both advantages and disadvantages. While this capability is credited for allowing sellers to share information easily and quickly to a broad audience (Ahmad et al., 2018), it has also brought in the challenge of negative comments. Dissatisfied customers can quickly go to the social media page of the seller and post negative comments with the intention to either harm the seller, obtain emotional relief, or to warn the seller's potential customers. Within a short time, these negative comments reach a broad audience of potential customers, affecting their attitude, buying behaviour (Casaló et al., 2015; Weitzl and Hutzinger, 2017) and increasing their uncertainty perception. Even though potential customers tend to attach more weight to negative comments, the seller can use service quality to signal its reputation, curb the negative consequences of negative customers' comments, and to enhance the influence of positive comments in reducing uncertainty perception. In this regard, we propose the following hypothesis:

H4: Customer service quality moderates the association between number of positive review comments and seller uncertainty.

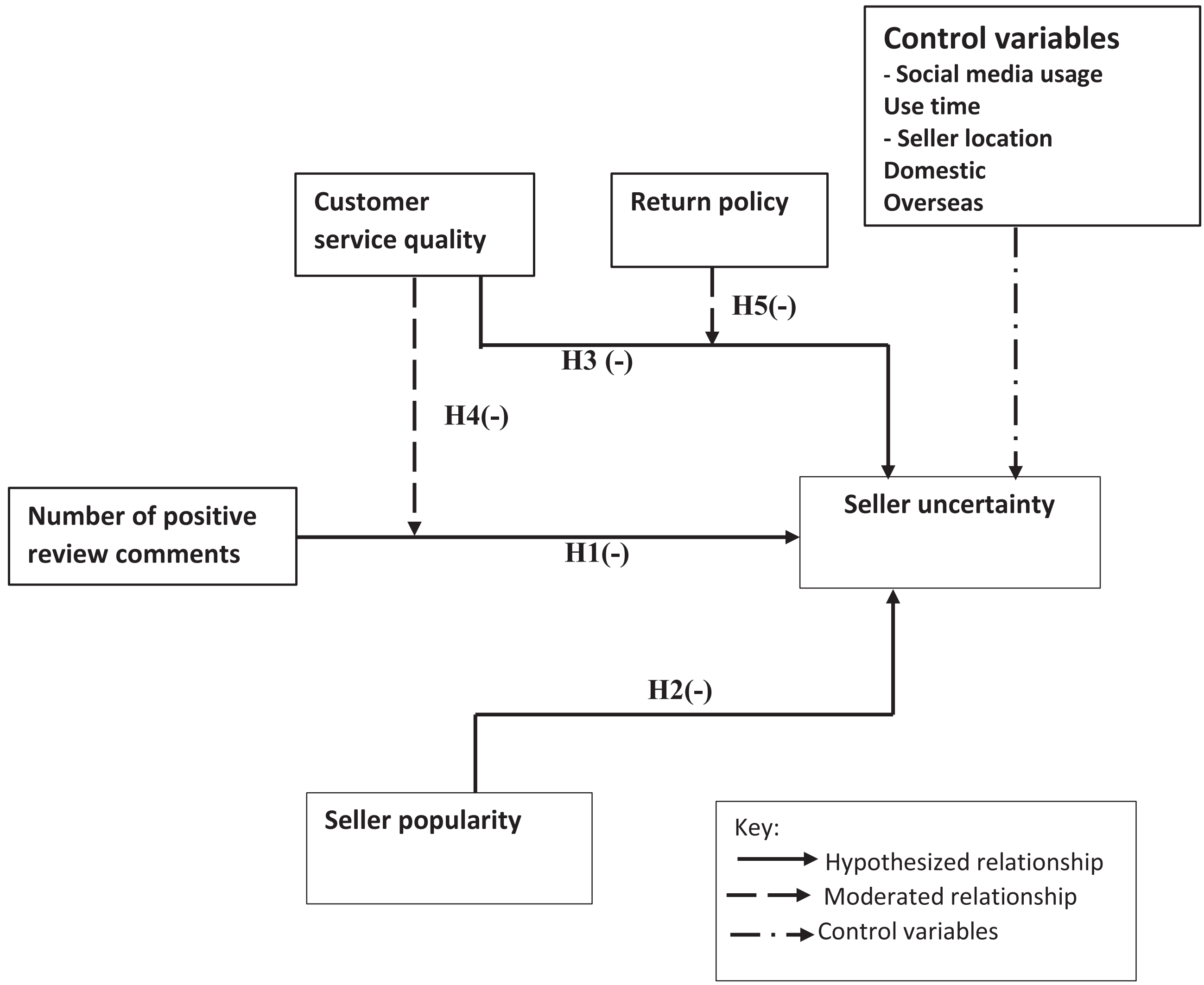

Fig. 1. Conceptual model.

2.7. Moderating effect of a return policy

The return policy is one of the critical tools for most sellers in building customer confidence and gaining a competitive advantage in the marketplace (Mukhopadhyay and Setoputro, 2004; Riasi et al., 2018). Prior research has revealed that more than 70 percent of customers tend to consider the return policy before deciding to buy (Mukhopadhyay and Setoputro, 2004). Thus, firms can use the return policy to influence sales and differentiate themselves from unreliable sellers (Wang et al., 2019). Return policies vary across firms. While some firms have stringent return policies, others offer more lenient policies allowing customers to return the product for any reason and giving a full or partial refund, or the choice to exchange a purchased product (Riasi et al., 2018). The lack of salesperson advice in an online purchase and the fact that the customer cannot physically assess the product prior to purchase, the lenient return policy is likely to curb uncertainty perception and adverse selection problem by reinforcing the perception of high seller reliability (San Martín and Camarero, 2009). An untrustworthy seller runs the risks of losing future sales and tarnishing its reputation (Biswas et al., 2009). In this regard, the customers that shop from sellers that offer high customer service and allow product returns are expected to perceive social commerce transactions to be less uncertain than those who are buying from the sellers that do not allow product returns. In this regard, we propose the following hypothesis:

H5: Return policy moderates the association between customer service quality and seller uncertainty.

2.8. Conceptual model

The conceptual model in Fig. 1 summarises all the hypotheses in this study and the nature of the relationship among the research variables. Seller uncertainty is the only dependent variable that is negatively influenced by the number of positive review comments, seller popularity, and customer service quality. The model explains further that the interaction of customer service quality and the number of positive review comments and return policy, and customer service quality have a negative influence on seller uncertainty. The model also includes the control variables: social media usage experience indicated by how long the customer has been using social media (use time) and whether the seller is located in the country of the customer (Domestic) or other countries (Overseas).

3. Research method

3.1. Research setting

The context of the present study is Tanzania, a developing country with a population of 58.87 million. Tanzania is one of the 10 African countries that have large numbers of internet and mobile phone users. It has around 25.8 million internet users and 47.7 million mobile network subscribers, who use their mobile phones for communication and conducting commercial transactions. In 2019, it was estimated that 285.2 million mobile financial transactions with a value of around USD34.3 billion were conducted through mobile phones in Tanzania in December of that year alone (Tanzania Communications Regulatory Authority, 2019). Increasing levels of internet penetration and the wide use of mobile phones have contributed to a growth in social media, which, along with the low associated operational costs, have led to the expansion of online-based entrepreneurial activities amongst micro and small firms. Most of these businesses have resource constraints (human, financial, and technical) that limit their ability to invest in e-commerce (Karjaluoto and Huhtamäki, 2010).

Moreover, starting and formally operating a business in a developing country such as Tanzania is difficult and expensive. A recent business report released by the World Bank ranked Tanzania 141 out of 190, far behind other East African countries (World Bank Group, 2020). Given resource constraints and the challenging business environment, commercial use of social media has become an attractive option for micro and small businesses, because they do not have to pay utility bills or incur the other costs that come with owning a physical store. Moreover, social media-based business enables micro and small firms to bypass bureaucratic business regulations and even to avoid paying taxes (in some cases). Such advantages have led a large number of locally and foreign-based Tanzanians to open online-based businesses. These circumstances make the concept of perceived seller uncertainty an interesting area of study. The present study's particular unit of analysis is the relationship between customers and social commerce sellers.

In Tanzania, social commerce sellers conduct a variety of businesses, ranging from food (such as "ready-to-eat" cafes and restaurant services) to clothes, cosmetics, electrical appliances, and electronic equipment. The social media pages of these sellers provide various kinds of information that aid potential buyers in making purchasing decisions (see Appendixes I and II). The information includes the number of followers, descriptions of the products, the location of the seller, price and payment structures, delivery information, and mobile numbers that can be used by the customer to access additional information and to pay for goods payment using mobile technology. The depth of information provided on social commerce platforms varies between sellers. While some of them provide limited information and encourage potential customers to call or send instant messages for more information, others provide detailed information in addition to instant messaging, and offer the option of ringing customer services. Appendix I shows the pages of the social commerce platforms of sellers in the empirical setting. Appendix II shows the social commerce platforms of sellers from a global perspective (see Appendixes I and II).

3.2. Questionnaire development

The present study adopts a survey research strategy with a structured self-administered questionnaire. However, before the development of the questionnaire, structured interviews were conducted with frequent social commerce buyers. The authors adapted the strategy of extending the number of interviews until the saturation point was reached (Cruz-Cárdenas et al., 2019; Glaser and Strauss, 2006). Since the objective of conducting interviews was to acquire an understanding of the research setting and to identify factors that buyers considered before purchasing from social commerce sellers to reduce their uncertainty, the saturation point was reached after four interviews. The number of positive comments, the popularity of the seller, service quality, and return policy emerged as important factors they considered. We adapted the questions and measures used to capture these variables from previous studies, as indicated in the operationalization subsection. Afterward, we used the think-loud technique proposed by Ruane (2005) to discuss the questionnaire with one experienced social commerce buyer and two academicians for face and content validity. These discussions led to minor adjustments in the wording and arrangement of measures, after which we developed the final online questionnaire using Google form.

Table 3
List of measurement items.

Scales	Scale items	Key references
Seller uncertainty (UNCERTAIN)	UNCERT1: I am very doubtful about the terms of sales of this seller UNCERT2: I feel that this seller misrepresented his/her product in social media UNCERT3: I am very doubtful that this seller has fully disclosed specifications of his/her products UNCERT4: I am doubtful that this seller will deliver this product as promised in a timely manner	Dimoka et al. (2012) and Chiu et al. (2018)
Number of positive review comments (COMMENT)	COM1: This seller has a lot of positive customers' reviews COM2: Most of the people I trust provide positive feedback about this seller COM3: Most of my friends provide positive feedback about the quality of product from this seller	Park et al. (2007), Zhang et al. (2014) and Lin et al. (2018)
Customer service quality (SERVICE)	SERVQ1: This seller is always willing and ready to respond to customer needs SERVQ2: This seller always provide customer with information about status of their orders SERVQ3: This seller is very prompt in responding to customers' inquiries SERVQ4: This seller always goes beyond to make sure that customers are informed about the product	Kim and Lennon (2013), Wolfinbarger and Gilly, (2003) and Nadeem et al. (2015)
Seller popularity (POPUL)	Number of followers that the seller has	Yang et al. (2016), Lardo et al. (2016)

3.3. Operationalization of variables

The dependent variable in this study is the customer's perceived uncertainty of the seller (seller uncertainty), while the independent variables are the number of positive comments and seller popularity. The measures for these variables are shown in Table 3. With the exception of seller popularity, we measured the dependent and the independent variables using multiple items on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Seller popularity was operationalized as a single item continuous variable using the number of followers.

We used customer service quality and return policy as moderating variables. The former was measured using a four-item scale adapted with modification from other studies and based on a 7-point Likert scale. We operationalized the return policy as a dichotomy variable whereby the sellers that allow product returns were assigned the value 1. In contrast, those that do not allow product returns were assigned the value of 0. To increase the robustness of our model, we introduced three control variables: the period the social commerce buyer has been using social media (social media usage experience), one dichotomy variable for domestic and another for overseas sellers.

3.4. Sampling and data collection

Data were collected in Tanzania from January 17 to March 30, 2019. The absence of a sampling frame for social commerce customers meant

Table 4
Independent samples *t*-test for comparison of response between online and offline.

Variable	Online Mean	SD	Offline Mean	SD	t-value	P-Value
Seller uncertainty	3.28	1.66	3.47	1.35	−0.73	0.47
Number of positive review comments	4.63	1.65	4.93	1.14	−1.28	0.20
Customer service quality	4.57	1.71	4.96	1.18	−1.58	0.11
Seller popularity	9.35	4.17	9.36	3.78	−0.02	0.98
Return policy	0.74	0.44	0.65	0.48	1.10	0.27
Use time	1.79	0.50	1.60	0.43	2.36	0.02*
Location	0.72	0.91	0.68	0.86	0.27	0.79

that the link to the questionnaire was shared with potential respondents through various WhatsApp groups (after securing the permission of group administrators). This distribution method ensured that all participants were already familiar with social media (Brusch and Rappel, 2020) and maximised the chance of finding people who purchased products via social commerce. Most WhatsApp group members tend to be members of multiple groups. Hence, a snowball sampling technique was used. The group administrators were asked to share the questionnaire link with other groups and to request their members do the same. After every three days, the respondents were given a reminder by sharing the link again. Despite these efforts, the response rate was very low, though this was not surprising, because the distribution of questionnaires online has been shown to be less efficient than the traditional "pencil and paper" method (Anseel et al., 2010). As a result, to gather a large number of responses, a mix of data collection methods was applied (Durst et al., 2019). The decision was taken to administer questionnaires physically to various offices.

Both physically administered questionnaires and online surveys resulted in 188 returned questionnaires. Out of 154 physically distributed questionnaires, 139 questionnaires were returned, representing a response rate of approximately 90%. From the online survey, only 49 questionnaires were returned. After the preliminary screening of the returned questionnaires, we discarded 27 physically administered and six online returned questionnaires for various reasons, including the high level of missing values, respondents' disengagement as well as responses based on e-commerce sites such as Amazon, Alibaba, and Jumia rather than social commerce. We used the remaining 155 completed questionnaires for further analysis.

Since this study used two data collection methods, we conducted a mean difference test to check whether there were systematic differences between responses solicited by the online survey and physical distribution. With the exception of the social media usage time (use-time), which was significant, the results of the test supported the null hypothesis of no difference between the research variables across the two methods (see Table 4). The significant finding for usage time is justifiable in that those who responded online seem to have more social media usage experience than those who responded through a physically distributed questionnaire. To evaluate non-response bias, we compared the early and late responses (Armstrong and Overton, 1977). We found that the mean difference test showed no significant difference across our research variable, confirming that nonresponse is not a problem.

3.5. Common method bias

Common method variance (CMV) is a potential problem in survey research. Reasons why this is so include difficulties in obtaining independent and dependent variable data from the same person and measuring dependent and independent variables in the same location, respondents trying to maintain consistency in their responses, item ambiguity, common scale formats and anchors, and scale length (Podsakoff et al., 2003). Common method variance tends to threaten the validity of conclusions about the relationship between variables by inflating observed correlations and providing spurious support for the hypotheses being tested (Sharma et al., 2009) or by deflating the correlations among variables, thereby rendering the results insignificant (Kock, 2015). We controlled CMV procedurally in the questionnaire design by using simple and clear language, by avoiding double-barrelled questions, and by separating the measurement of independent and dependent variables (Podsakoff et al., 2003).

4. Data analysis and results

The main goal of this study was to determine factors that can predict seller uncertainty in social commerce transactions. Thus, partial least square structural equation modeling (PLS-SEM) was chosen as an appropriate approach in this situation (see Sarstedt et al., 2017; Hair et al., 2017). Additionally, PLS-SEM has higher statistical power than covariance-based SEM, which can enable us to determine the significant predictors when they are indeed significant. We used the two-stage model build approach proposed by Anderson and Gerbing (1988) in evaluating the measurement model and structural model separately using SmartPLS 3. This approach provides an opportunity to assess measures and constructs comprehensively before the evaluation of the structural model.

4.1. Measurement model validation

To validate our measurement model, we examined the reliability and validity of our measurements and constructs using various criteria. Reliability refers to the consistency or stability of measures and is inversely related to the degree to which the measures are contaminated with random errors (O'Leary-Kelly and Vokurka, 1998). We evaluated reliability through indicator loadings, composite reliability (CR), and Cronbach's alpha (α) coefficients (see Table 5). Standardized loadings of

Table 5
Descriptive, reliability and validity statistics.

Constructs	Items	Mean	SD	Loadings	Indicator variance	AVE	CR	Cronbach'sAlpha (α)
Number of positive review comments						0.782	0.915	0.863
	COM1	4.96	1.385	0.879	0.773			
	COM2	4.93	1.349	0.887	0.787			
	COM3	4.82	1.395	0.887	0.787			
Customer service quality						0.696	0.901	0.858
	SERVQ1	5.13	1.458	0.809	0.651			
	SERVQ2	4.80	1.601	0.836	0.699			
	SERVQ3	4.92	1.449	0.875	0.766			
	SERVQ4	4.73	1.597	0.814	0.663			
Seller uncertainty						0.675	0.893	0.839
	UNCERT1	3.21	1.641	0.811	0.658			
	UNCERT2	3.09	1.923	0.817	0.668			
	UNCERT3	3.37	1.841	0.871	0.759			
	UNCERT4	3.58	1.844	0.785	0.616			

Table 6
Fornell-Larcker discriminant validity criterion.

Constructs	1	2	3	4	5	6	7	8
1. Number of positive review comments	0.884							
2. Domestic	−0.050	1.000						
3. Seller popularity	0.072	−0.248	1.000					
4. Overseas	0.113	−0.481	0.305	1.000				
5. Return policy	0.247	0.007	−0.046	−0.151	1.000			
6. Customer service quality	0.476	−0.173	0.073	0.045	0.380	0.834		
7. Seller uncertainty	−0.448	−0.039	−0.162	0.140	−0.400	−0.582	0.822	
8. Use time	0.074	−0.089	0.170	0.126	0.090	0.144	−0.119	1.000
VIF	1.390	1.406	1.177	1.482	1.288	1.649	–	1.061

Table 7
Measurements model validity assessment: $HTMT_{85}$ Criterion and $HTMT_{inference}$.

Constructs	1	2	3	4	5	6	7	8
1. Number of positive review comments	–							
2. Domestic	0.069[0.005; 0.089]							
3. Seller popularity	0.071[0.014; 0.140]	0.248[0.113; 0.372]						
4. Overseas	0.123[0.056; 0.222]	0.481[0.402; 0.574]	0.305[0.122; 0.469]					
5. Return policy	0.260[0.129; 0.394]	0.007[0.000; 0.009]	0.046[0.001; 0.124]	0.151[0.020; 0.296]				
6. Customer service quality	0.541[0.420; 0.645]	0.190[0.066; 0.314]	0.067[0.009; 0.097]	0.050[0.008; 0.074]	0.399[0.250; 0.537]			
7. Seller uncertainty	0.506[0.373; 0.618]	0.129[0.067; 0.189]	0.174[0.061; 0.274]	0.163[0.082; 0.252]	0.433[0.297; 0.556]	0.649[0.539; 0.742]		
8. Use time	0.142[0.070; 0.216]	0.089[0.010; 0.198]	0.170[0.043; 0.290]	0.126[0.029; 0.229]	0.090[0.007; 0.220]	0.147[0.060; 0.273]	0.127[0.044; 0.232]	–

Note: The values in brackets represent HTMT biased correlated 95% confidence interval.

Table 8
Structural model estimates and tests of hypotheses.

Structural paths	Coefficient (β)	t-values	95% BCa C.I.	f^2	q^2	Decision
Main effects' paths:						
COMMENT → UNCERTAIN (H1)	−0.202	2.165*	[-0.344; −0.037]	0.063	0.039	Accepted
POPUL→ UNCERTAIN (H2)	−0.202	3.220***	[-0.301; −0.099]	0.075	0.031	Accepted
SERVICE → UNCERTAIN (H3)	−0.509	5.807***	[-0.650; −0.367]	0.341	0.162	Accepted
RETURN → UNCERTAIN	−0.187	2.547**	[-0.304; −0.066]	0.059	0.024	Accepted
Moderators' paths:						
COMMENT*SERVICE→ UNCERTAIN (H4)	−0.238	3.343***	[-0.363; −0.129]	0.089	0.021	Accepted
SERVICE*RETURN→ UNCERTAIN (H5)	−0.138	2.451**	[-0.231; −0.047]	0.037	0.006	Accepted
Control variables' paths:						
USETIME → UNCERTAIN	−0.018	0.288	[-0.120;0.082]	0.001	−0.001	
DOMESTIC→ UNCERTAIN	−0.101	1.339^S	[-0.233; 0.018]	0.016	0.004	Accepted
OVERSEA→ UNCERTAIN	0.173	2.257*	[0.048; 0.301]	0.044	0.016	Accepted

R^2(Coefficient of determination)
$R^2$0.539
$R^2_{Adjusted}$0.508
Threshold for R^2 value ≥ 0.25 (weak); $\geq$0.50 (moderate); $\geq$0.75 (substantial)
Q^2 (Model predictive relevance)Stone-Geisser Q2 = 0.329
Threshold for Q^2 value greater than 0 indicate predictive relevance.
Notes: ^{S} $p < 0.1$ (1-tailed); *$p < 0.05$ (1-tailed); **$p < 0.01$ (1-tailed); ***$p < 0.001$ (1-tailed); f^2 = effect size; q^2 = effect size of predictive relevance; BCa = Biased Correlated and Accelerated Confidence Interval based on 5000 bootstrap samples.

all indicators exceeded the acceptable threshold of 0.7, which implies that more than 50% of their variances are explained by their respective constructs (Hulland, 1999; Shook et al., 2004). Moreover, the CR and Cronbach's α values of all constructs exceeded the minimum recommend threshold of 0.7 (O'Leary-Kelly and Vokurka, 1998; Hulland, 1999; Shook et al., 2004; Hair et al., 2017), confirming the reliability of our measurement model. We assessed the convergent validity by examining the average variance extracted (AVE) values of all constructs. These values exceeded the recommended threshold of 0.5 (Kline, 2011; Hair et al., 2017) verifying that all constructs have an adequate level of convergent validity (see Table 5).

The discriminant validity was checked by using Fornell and Larcker criterion, HTMT criterion, and HTMT inference. The results of the Fornell and Larcker criterion presented in Table 6 demonstrated that all constructs are discriminately valid since the square roots of the AVE values presented along the diagonal were higher than inter-construct

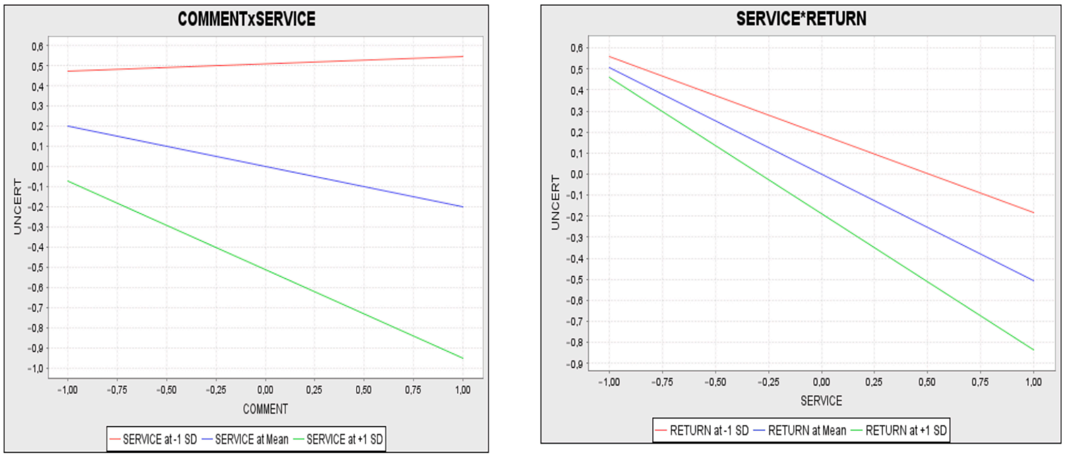

Fig. 2. The effect of positivity of review comments on perceived uncertainty for different levels customer service. (b) The effect of customer service on uncertainty for lenient and non-lenient return policy.

correlations (off-diagonal values). We verified Fornell and Larcker's results by examining the HTMT criterion and HTMT inference presented in Table 7, which are arguably much stronger tests than the Fornell and Larcker test (Henseler et al., 2015). All HTMT values were below the conservative threshold of 0.85, and the confidence intervals did not contain the value of 1, confirming the attainment of discriminant validity requirements.

4.2. Structural model evaluation

In the assessment of the structural model, we used four criteria, including variance inflated factor (VIF) (Table 6), coefficient of determination (R^2), effect size (f^2), and Stone-Geisser's predictive relevance criterion (Q^2) as shown in Table 8. The VIF criterion indicated the absence of multicollinearity problem since all VIF values were below the threshold of 5 (Hair et al., 2017). R^2 value showed that the variables included in the structural model account for about 0.508% of the variance in the seller uncertainty. This level of R^2 value is moderate,

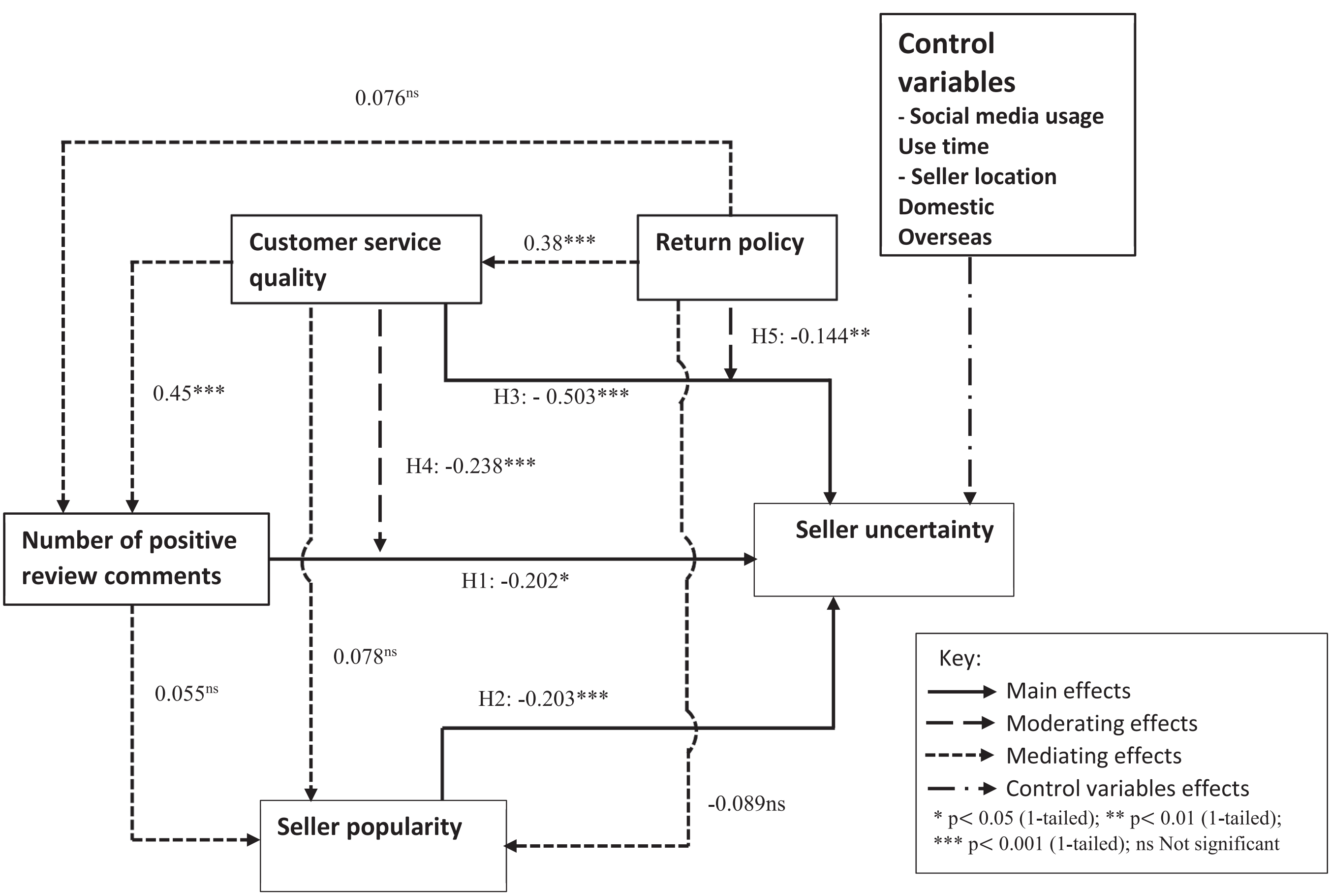

Fig. 3. Structural model results of the alternative model

Table 9
Alternative structural model estimates and tests of hypotheses.

Structural paths	Coefficient (β)	t-values	95% BCa C.I.	f^2	q^2	Decision
Main effects' paths:						
COMMENT → UNCERTAIN (H1)	−0.202	2.139*	[-0.353; −0.049]	0.062	0.032	Accepted
POPUL→ UNCERTAIN (H2)	−0.203	3.248***	[-0.306; −0.098]	0.075	0.032	Accepted
SERVICE → UNCERTAIN (H3)	−0.503	5.620***	[-0.653; −0.354]	0.324	0.150	Accepted
RETURN → UNCERTAIN	−0.191	2.608**	[-0.312; −0.071]	0.060	0.026	Accepted
COMMENT → POPUL	0.055	0.561	[-0.112; 0.215]	0.002	−0.014	
SERVICE → POPUL	0.078	0.844	[−0.073; 0.225]	0.004	−0.011	
RETURN → POPUL	−0.089	1.027	[-0.235; 0.049]	0.007	−0.007	
RETURN → SERVICE	0.380	4.780***	[0.244; 0.509]	0.169	0.105	Accepted
SERVICE → COMMENT	0.450	6.571***	[0.341; 0.566]	0.226	−0.025	Accepted
RETURN → COMMENT	0.076	0.947	[-0.056; 0.213]	0.006	−0.155	
Moderators' paths:						
COMMENT*SERVICE→ UNCERTAIN (H4)	−0.238	3.339***	[-0.352; −0.116]	0.087	0.018	Accepted
SERVICE*RETURN→ UNCERTAIN (H5)	−0.144	2.540**	[-0.239; −0.055]	0.040	0.007	Accepted
Control variables' paths:						
USETIME → UNCERTAIN	−0.018	0.290	[-0.129; 0.079]	0.001	−0.009	
DOMESTIC→ UNCERTAIN	−0.101	1.294^s	[-0.228; 0.025]	0.015	0.004	Accepted
OVERSEA→ UNCERTAIN	0.173	2.254*	[0.048; 0.3030]	0.043	0.018	Accepted

R^2 (Coefficient of determination):
UNCERTAIN:$R^2 = 0.532$; $R^2_{Adjusted} = 0.50$
POPUL:$R^2 = 0.013$; $R^2_{Adjusted} = 0.008$
COMMENT:$R^2 = 0.234$; $R^2_{Adjusted} = 0.223$
SERVICE:$R^2 = 0.144$; $R^2_{Adjusted} = 0.138$
Threshold for R^2 value ≥ 0.25 (weak); $\geq$0.50 (moderate); $\geq$0.75 (substantial)
Q^2 (Model predictive relevance)Stone-Geisser$Q^2_{UNCERAIN} = 0.318$; $Q^2_{POPUL} = 0.029$; $Q^2_{COMMENT} = 0.170$; $Q^2_{SERVICE} = 0.095$
Threshold for Q^2 value >0 indicate predictive relevance.
Notes: ^{s} $p < 0.1$ (1-tailed); *$p < 0.05$ (1-tailed); **$p < 0.01$ (1-tailed); ***$p < 0.001$ (1-tailed); f^2 = effect size; q^2 = effect size of predictive relevance; BCa = Biased Correlated and Accelerated Confidence Interval based on 5000 bootstrap samples.

according to Garson (2016). With the exception of one control variable, the effect sizes of all independent variables were acceptable, since f^2 values were above 0.02 (Sarstedt et al., 2017; Hair et al., 2017). Lastly, Stone-Geisser's value of 0.329 showed that our model is predictively relevant and has a medium degree of predictive accuracy (Garson, 2016).

4.3. Hypotheses testing

We evaluated the hypotheses by examining the significance of the path coefficients and effect size detailed in Table 8. From H1 to H3, we argued that seller uncertainty is influenced by the number of positive review comments (H1), the popularity of the seller (H2), and the customer service quality (H3). In support of H1, the findings showed that the number of positive comments has a significantly negative influence on seller uncertainty (β = -0.202, t = 2.165*). However, its effect size and predictive relevance were small (f^2 = 0.063, q^2 = 0.039) (Garson, 2016; Sarstedt et al., 2017; Hair et al., 2017). Similarly, the results provided support for H2 by showing the negative influence of the seller's popularity on seller uncertainty (β = -0.202, t = 3.220***), but its effect size and predictive relevance were small (f^2 = 0.075, q^2 = 0.031). The findings revealed further that customer service quality has a negative influence on seller uncertainty (β = -0.509, t = 5.807***), supporting H3 with medium effect size and predictive relevance (f^2 = 0.341, q^2 = 0.162).

Table 10
Tests of mediating effects.

Effect	Coefficient (β)	t-values	95% BCa C.I.
Direct Effect:			
SERVICE -> UNCERTAIN	−0.503	5.620***	[-0.653; −0.354]
RETURN->UNCERTAIN	−0.191	2.608**	[-0.312; −0.071]
Specific Indirect Effects:			
SERVICE -> COMMENT-> UNCERTAIN	−0.091	1.984*	[-0.171; −0.021]
RETURN -> SERVICE -> UNCERTAIN	−0.191	3.516***	[-0.290; −0.107]
RETURN ->SERVICE -> COMMENT-> UNCERTAIN	−0.035	1.848 *	[-0.069; −0.008]

BCa = Biased Correlated and Accelerated Confidence Interval based on 5000 bootstrap samples.
Notes: * $p< 0.05$ (1-tailed); ** $p< 0.01$ (1-tailed); *** $p< 0.001$ (1-tailed);

To test the negative moderation effect of service quality on the association between the number of positive comments and seller uncertainty (H4), we ran the interaction effect analysis, and the results provided significant support for this hypothesis (β = -0.238, t = 3.343***) with small effect size and predictive relevance (f^2 = 0.089, q^2 = 0.021). The negative moderation effect of the return policy on the association between service quality and seller uncertainty (H5) was also significant (β = -0.138 t = 2.451**), providing support for H5 (see Fig. 2a and b). Likewise, the effect of the interaction between the return policy and service quality was small (f^2 = 0.037), and its predictive relevance was even smaller (q^2 = 0.006).

To assess the robustness and consistency of the findings, the authors estimated an alternative structural model by introducing new paths. An association between popularity, returns policy, the number of positive comments, and customer service quality in addition to the original structural relationships was proposed (Fig. 1). Customer service quality was proposed to influence the number of positive comments and the popularity of the seller. The returns policy of the seller was proposed to influence customer service quality, the number of positive comments, and seller popularity, while the number of positive comments was proposed to influence seller popularity directly (Fig. 3). These associations are logical; for example, popularity may be gained by

Table 11
Summary of findings and assessment of predictive consistency.

Associations	Sign	Original model (1)	Alternative model (2)	Overall findings	Predictive consistency#:(1) versus (2)
Direct effects					
Number of positive review comments → Seller uncertainty (**H1**)	–	Accepted	Accepted	Supported	Yes
Seller popularity → Seller uncertainty (**H2**)	–	Accepted	Accepted	Strongly supported	Yes
Customer service quality → Seller uncertainty (**H3**)	–	Accepted	Accepted	Strongly supported	Yes
Return policy → Seller uncertainty	–	Accepted	Accepted	Supported	Yes
Number of positive review comments → Seller popularity	+	None	Insignificant	Not supported	None
Customer service quality → Seller popularity	+	None	Insignificant	Not supported	None
Return policy → Seller popularity	+	None	Insignificant	Not supported	None
Return policy → Customer service quality	+	None	Accepted	Strongly supported	None
Customer service quality → Number of positive comments	+	None	Accepted	Strongly supported	None
Return policy → Number of positive comments	+	None	Insignificant	Not supported	None
Moderated effects					
Number of positive review comments* Customer service quality → Seller uncertainty (**H4**)	–	Accepted	Accepted	Strongly supported	Yes
Customer service quality* Return policy → Seller uncertainty (**H5**)	–	Accepted	Accepted	Supported	Yes
Mediated effects					
Customer service quality → Number of positive review comments → Seller uncertainty	–	None	Accepted	Supported	None
Return policy → Customer service quality → Seller uncertainty	–	None	Accepted	Strongly supported	None
Return policy → Customer service quality → Number of positive review comments → Seller uncertainty	–	None	Accepted	Supported	None
Control effects					
Use time → Seller uncertainty	–	Insignificant	Insignificant	Not supported	No
Domestic → Seller uncertainty	–	Accepted	Accepted	Supported	Yes
Overseas → Seller uncertainty	+	Accepted	Accepted	Supported	Yes

Notes: #Predictive consistency is evaluated with a rule of thumb: 'yes' if the original model result is significant and supported by the result of the alternative model and 'no' if not. 'None' not applicable when the path in the alternative/respecified model is not in the original/initial model and hence no need for assessing predictive consistency.

demonstrating traits such as delivery reliability and lenient returns policy (Lahuerta-Otero et al., 2018), offering a product of good quality, and excellent customer service quality (Wu et al., 2019). The analysis reveals that all the additional structural paths in the alternative model were insignificant, except the association between customer service quality and the number of positive comments ($\beta = 0.45$, t = 6.571***) and between returns policy and customer service quality ($\beta = 0.38$, t = 4.78***). The two moderating effects and all the hypothesised associations were significant and consistent with the original model. The structural model results of the alternative model is illustrated in Fig. 3 and more details of the analysis are shown in Table 9.

In addition, while the present study did not propose any mediating hypothesis, various mediating relationships resulting from the alternative structural model were analysed. The results of 5000 bootstrapping subsamples revealed three significant paths, since the confidence intervals of these paths did not contain zero values (Table 10). In particular, the results demonstrate that the number of positive comments negatively and significantly mediated the effect of customer service quality on seller uncertainty (β = -0.091, t = 1.984*). Similarly, the influence of returns policy on seller uncertainty was significant and negatively mediated by customer service quality (β = -0.191, t = 3.516***). Furthermore, customer service quality and the number of positive comments mediated the effect of returns policy and seller uncertainty (β = -0.035, t = 1.848*). The significance of the direct relationship between customer service quality and seller uncertainty and between returns policy and seller uncertainty in the mediated model (alternative structural model) indicates that all mediating relationships were partial. A summary of the study's findings is provided in Table 11. The "predictive consistency" of the two models was evaluated using a simple rule of thumb: *yes* if the original model result was significant and supported by the result of the alternative model and *no* otherwise. The evaluation shows that eight paths out of the nine in the original model were significant and supported in the alternative model, demonstrating that the original model was consistent and robust in predicting the targeted construct. In addition, the main target construct, seller uncertainty, had the adjusted R^2 for both the original model and the alternative model as 0.508 and 0.50, respectively, showing consistency in predicting the target construct (Table 11). Though the objective of this assessment was not to show which model was "better" than the other, the first model was simple (parsimonious) while the alternative model was more complex and "enriching". While the second alternative model provided new insights through the additional paths, the first, simpler model answered the research question.

5. Discussion

5.1. Theoretical contributions

As highlighted in the introduction, perceived uncertainty poses various challenges in online businesses. Some of these challenges include deterring potential customers from participating in social commerce, increasing the tendency of buying low-value items, declining sales, as well as lowering purchase and repurchase intentions. While acknowledging these challenges, this study empirically investigated the signals used by the customers to reduce uncertainty perception. We argue from a signalling theory perspective and we have considered four signals, namely the number of positive review comments on the seller's social media page, the quality of service offered by the seller, popularity of the seller, and the return policy.

Several earlier studies have investigated the signals mentioned above (e.g., Park et al., 2007; Liang et al., 2011; Utz et al., 2012; Nadeem et al., 2015; Wang et al., 2019; Ladhari et al., 2020). Nevertheless, the empirical evidence on the impact of these signals on the perceived uncertainty is mostly absent. Thus, this study extends knowledge of signalling theory by examining and providing empirical evidence on the influence these signals on customers' perceived uncertainty in the social commerce setting.

First, there is a rich body of knowledge on the influence of customer reviews on online transactions. For example, Choi et al. (2018) investigated the valence of comments and revealed that positive comments have a positive effect on the level of sales. Cheung et al. (2014) demonstrated the positive influence of consumer reviews on the purchase decision. This paper extends knowledge on the influence of customers' comments by demonstrating that when the number of positive comments increases, customer's perception of uncertainty in dealing with the seller diminishes.

Second, the contribution of this study lies in the association between popularity and seller uncertainty. Most of the earlier studies on online business has shown the positive influence of the popularity signal on purchase intentions (e.g., Park et al., 2007), purchase frequency (Ladhari et al., 2020) and sales volume (e.g., Choi et al., 2018). Our study extends the knowledge about the popularity signal further by revealing the presence of a negative association between seller popularity and seller uncertainty, which suggests that the increase in the popularity of the seller, measured by the number of followers, can significantly reduce customers' perceived uncertainty in online business.

Third, this study has revealed that customer service quality reinforces the effect of the number of positive reviews in reducing seller uncertainty. That is, as service quality increases, the effect of the number of positive review comments on seller uncertainty becomes more negative. In connection with this contribution, the study further revealed that the influence of the number of positive comments on seller uncertainty becomes more negative when the seller increases customer service quality.

Fourth, the findings of this study have shown that the effect of customer service quality on seller uncertainty is more negative for sellers that allow customers to return products, (purchases for different reasons) than for the sellers that do not offer product returns. Lastly, the present study contributes to the literature with empirical evidence to emphasize that consumers seek out cues to reduce the uncertainty of online transactions by relying on either seller or customer-based signals. However, for the 'bundling effect' (a term we coined to describe the combination of 'discrete' elements), to stimulate the desired outcome (e.g., reinforce a favourable outcome or attenuate an unfavourable outcome), consumers rely on combinations of several reinforcing or attenuating elements to reduce behavioural uncertainty of the seller and to improve the certainty of the desired outcome.

Fifth, although the present study did not propose any mediating hypothesis, the findings of the mediation analysis shown in Table 10 contributes to an understanding of the effect of customer service quality and returns policies on seller uncertainty. The first indirect path indicates that, while customer service quality directly reduced seller uncertainty, it did so partially by increasing the number of positive review comments from previous customers. The second and third indirect paths demonstrate that a good returns policy had the effect of reducing seller uncertainty directly and partially through improving customer evaluation of sellers' service quality only through improving both customer evaluations of sellers' service quality and the number of positive comments from customers. Returns policies are an excellent signal for the level of customer service quality in reducing uncertainty in online business. However, they pose challenges for managers.

5.2. Managerial implications

Like any other online business, social commerce businesses suffer from various kinds of uncertainties ranging from product, seller to process uncertainty (Bai et al., 2015; Chiu et al., 2018). Since customers cannot physically assess products prior to purchase, signals play a key role in reducing uncertainty. Thus, sellers with a better understanding of the signals used by the customers to reduce uncertainty are better positioned to reduce perceived uncertainty and eventually attract more customers and increase sales revenue. This study has examined four signals, namely the number of positive review comments, the popularity of the seller, service quality, and return policy. However, online businesses do not have direct control over two of the signals (positive review comments and popularity of the seller/online retailer). The implication is that although online businesses may not have much control over the factors mentioned above, social commerce businesses can still indirectly influence these factors.

Social commerce businesses need to note that their customer service influences the positivity of comments. Customer service elements such as a prompt response to customer inquiries, willingness to provide additional information for customers who are not satisfied with the information provided on their social media page, as well as updating customers with information about their order status are critical. Thus, online retailers/sellers that offer good customer service are likely to receive more positive reviews and eventually reduce customers' perception of seller uncertainty. This assertion was demonstrated by the interaction effect of the number of positive review comments and customer service on perceived uncertainty (revisit Fig. 2a).

Consumer reviews and comments are useful for designing customer service protocols. However, another challenge for businesses is the large number of these data generated in recent times (the 'big data problem') (Yang et al., 2010; Baesens et al., 2016; Wang et al., 2016). The management implication is the need for information systems developers to develop efficient and effective easy to use sentiment analysis techniques that can help management decision making. For marketers, these techniques can help in understanding the complex consumer behaviour associated with online-offline customers. For example, product feature extraction is critical for sentiment analysis (Wei et al., 2010). Techniques capable of extracting products and other related information from consumer reviews can help in extracting positive sentiments from the negative. The extraction outcomes can help inform the design of customer service protocols for online/offline 'frontline' marketing and customer service staff. These implications are critical as positive comments are closely linked to the quality of customer service in reducing seller uncertainty. Customer service quality leads to a higher number of positive reviews, while customer service impact in reducing seller uncertainty is through the number of positive review comments.

Furthermore, consumers have traditionally made purchase decisions at the store shelf, giving institutional brick-and-mortar retailers great power to learn about and influence their behaviours and preferences. However, the rise of e-commerce, mobile shopping, and recently, smart technologies, has not only exposed established industry players to new competitors but has also made the customer purchase decision-making problematic especially in less secured online environments and markets. 'Power' has shifted from businesses to consumers. Negative word of mouth (e-WOM) and reviews can 'make' or 'unmake' a company by a click of a button, the use of emoticon, or tweet. Customers are becoming better connected to companies, more knowledgeable about products and/or service selections, and more powerful in buyer–seller relationships (Shaikh et al., 2018). Negative online consumer reviews result in negative consumer attitudes due to the conformity effect (Karakaya and Barnes, 2010). However, positive reviews and comments can be overshadowed by negative comments and reviews (Lin et al., 2018), which can cause an enormous challenge to businesses.

The integration of social media with commerce provides opportunities to businesses for increased interactions. The implication is that businesses can leverage social commerce inherent functionalities as a source of value creation and competitive advantage. For example, Papa John's is an American restaurant franchise and a leading firm in the pizza industry that simultaneously leverages social media and its e-commerce platforms to improve digital customer experience (Benitez et al., 2018). The benefits of the convenience of online transactions (e.g., ease of doing online business), good customer service and experience coupled with customer feedback, reviews and comments provide businesses ‘strategic options’ on which to capitalize to become more competitive.

Additionally, social commerce sellers need to be aware that the role of good customer service in reducing uncertainty perception can be increased significantly by offering a lenient return policy. This assertion was demonstrated by the interaction effect of service quality and return policy on seller uncertainty shown in the graph (revisit Fig. 2b). For the seller that offers both good customer service and a lenient return policy, the line graph shows that the effect of customer service on seller uncertainty becomes more negative than for the seller that offers only good customer service (but does not allow customers to return a product). However, a return policy can be problematic for retailers.

A return policy can ‘stretch’ the already limited resources of small companies and can be a ‘nightmare’ for even large companies such as multinational enterprises (MNEs). Online purchases are almost three times more likely to be returned than purchases from bricks and mortar retailers. Generally, retailers lacked the systems needed to deal with the ‘highly complex’ challenge of reverse logistics (Gray, 2019). The implication is that a return policy should be used more as an uncertainty reduction safeguard, that is, ’a means to an end’ rather than as ’an end’ in itself. Online businesses can use return policy statements ’strategically’ to signal the safety and security of online transactions without any adverse effect while providing customer experiences and support that limit the actual return of products/goods except when most needed or warranted. Besides, firms could reconfigure and realign logistics processes to better manage the reverse flow of goods more efficiently.

6. Conclusions, limitations and future research

Despite the presence of a rich body of knowledge on social commerce, this study has put forth several unique theoretical and managerial contributions that are worth noting. Theoretically, this study has first confirmed the negative influence of the number of positive review comments, the popularity of the seller, and customer service in reducing seller uncertainty. Second, the study has shown that when the seller offers excellent customer service, the negative influence of the number of customer review comments on seller uncertainty is more pronounced. Lastly, the study has demonstrated that when good customer service is coupled with a lenient return policy, seller uncertainty is likely to diminish significantly.

Managerially, the study has emphasized the need for understanding the signals used by the customers to reduce perceived uncertainty. Even though the sellers may lack direct control in some of the signals, such as review comments and popularity, they can indirectly influence them through the use of other signals such as customer service quality. Moreover, the study has underscored the need for using return policy signal cautiously due to its cost implications. When opting for this signal, the seller must put effort into maximizing customer experience in order to minimize the likelihood of returns.

Despite offering valuable insights, this study has several limitations that offer avenues for further research. The causality relationship between our independent and dependent variables cannot be claimed. This is because of the cross-sectional nature of the data used. Thus, a future study should consider the longitudinal data to add more validity to our findings. The context of the study was a developing market where many small businesses and entrepreneurs have taken advantage of social media to reach out to consumers. The study looked at the perception of customers regarding buyer–seller transactions and relationships in social commerce. Future studies could consider buyer–seller transactions from the perspective of the sellers using qualitative studies with a focus on social commerce website characteristics and their impact on transaction uncertainty.

Studies regarding customer perceptions of social commerce involving medium-sized and large firms could have different outcomes. Customer feedback and return policy are considered as difficult to verify and low-cost signals (Mavlanova et al., 2012). Large firms may have much more secure websites integrating social commerce and e-commerce platforms that use high cost and easy to verify signals such as third-party seals, domain-specific seals, and electronic payments. Future studies could investigate how other low-cost signals but difficult to verify signals (contact details, credit card logos and privacy policy, security policy) impact transaction uncertainty of social commerce in other developing and emerging economies. Our results also showed that transaction uncertainty increases when the seller is located in one country while the customer is in another. Comparative studies based on customers from developed and developing countries and sellers from developed and developing countries could provide insightful mechanisms on home-host country social commerce business-to-consumer (B2C) relationships and transaction uncertainty.

Research has shown that product familiarity and reputation are likely to affect the usefulness of a review. A positive review is likely to be less useful to customers who are familiar with the product and when dealing with more reputable products (Casaló et al., 2015). Thus, the investigation of the interaction effect of these variables with positive comments on seller uncertainty is likely to add valuable insights. Several other factors that were not considered in the present study could be integrated with the constructs examined. For example, trust in the community of sellers and familiarity with the system can influence the purchasing of goods and services online (Gibreel et al., 2018). Moreover, some social commerce sellers own physical stores in addition to online shops and offer friendly payment terms. The customer can then make a partial payment—as a show of commitment prior to the delivery of the product—or a full payment after the delivery of the product. Future researchers might investigate the influence of these signals on seller uncertainty and their interaction with other signals.

Finally, the COVID-19 pandemic caused disruptions in local, national, and global supply chains. The pandemic led to increased demand for some services and goods (e.g. hand sanitizers, toilet rolls, protective face masks) and the associated opportunistic/panic buying and hoarding. Many governments all over the world introduced several measures to tackle the spread of the disease. Social distancing was one of the options. The need to keep physical and social distance became the norm such that online businesses and e-commerce filled in the void. Future research may investigate how social/e-commerce with the associated uncertainty and risk brought about by the pandemic helped businesses and consumers to overcome the challenges.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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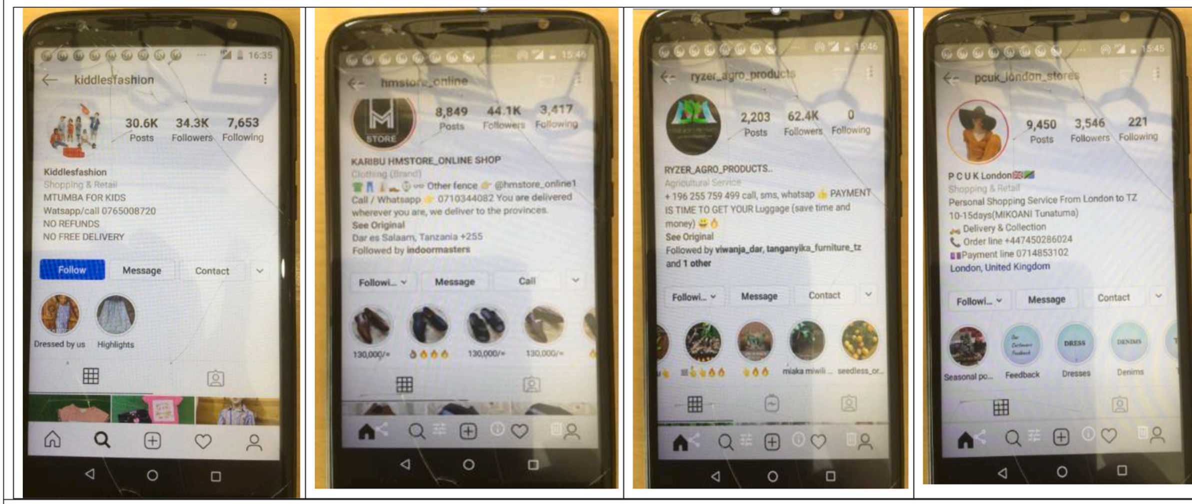
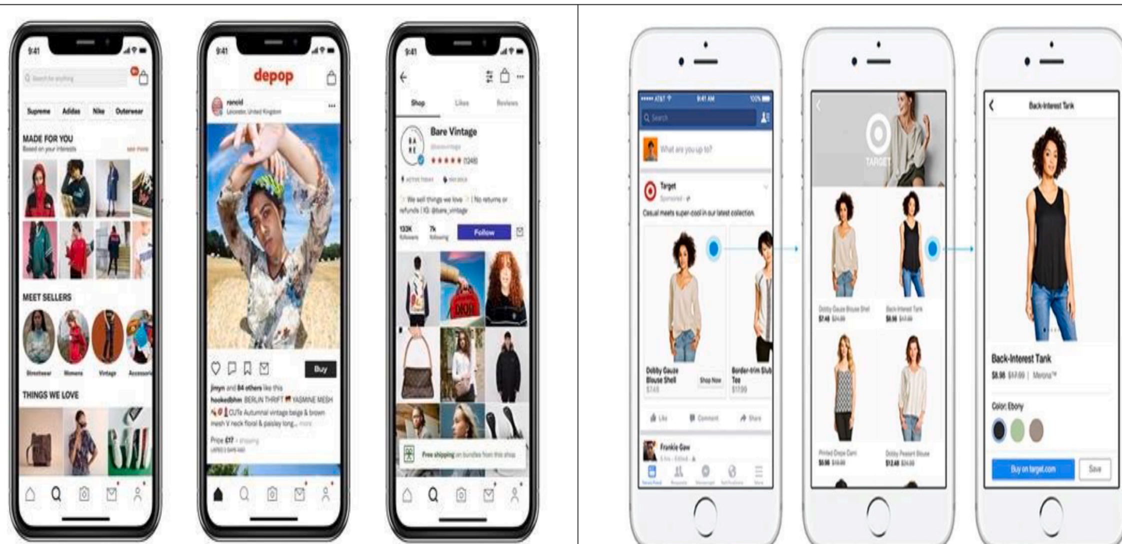
Appendices I & II



Source: Authors' own exhibit of specific sellers from the empirical context

Appendix I. Social commerce platform with products, number of followers among other information from the context.



Source : https://www.raconteur.net/social-commerce/

Source : https://www.futurepay.com/
https://alistemarketing.com/blog/social-commerce-trends/

Appendix II. Social commerce platform with products and other information from a global perspective.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.elerap.2021.101059.

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Further reading

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