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Mitigating seller uncertainty in social commerce platforms by exploring pre-purchase customer-seller signals

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ABSTRACT

In the growing social commerce landscape, addressing seller uncertainty has become critical for fostering consumer trust and enhancing purchase decisions. Seller uncertainty, often driven by information asymmetry and a lack of trust signals, can significantly hinder transactions on these platforms. This study investigates the mitigation of seller uncertainty in social commerce platforms by exploring pre-purchase customer-seller signals. Utilizing signaling theory, the research examines the role of information quality, positive reviews, seller-reputation, seller-popularity, and return policy leniency in reducing uncertainty. A hybrid SEM-ANN approach was employed to rigorously examine these relationships. Data was gathered from 368 social commerce users, providing robust insights into the factors that most significantly influence seller uncertainty. The findings reveal that all five signals play a significant role in reducing seller-uncertainty, with information quality emerging as the most critical factor. This emphasizes the need for sellers to provide clear, accurate, and comprehensive information to alleviate buyer concerns. The findings contribute theoretically and practically by deepening the understanding of uncertainty reduction mechanisms in social commerce and providing valuable insights for sellers and platform designers.

1. Introduction

The proliferation of social media has fundamentally transformed the digital landscape, with over 5.22 billion users representing 63.8 % of the global population actively engaging on these platforms (DataReportal, 2024). This extensive adoption has catalyzed the emergence of social commerce, where businesses leverage social media platforms for their commercial activities (Nafees et al., 2021; Qu et al., 2023; Sedalo et al., 2022). Social commerce represents a significant evolution from traditional e-commerce, characterized by interactive features, community engagement, and user-generated content that empowers consumers in their purchase decisions (Al-Tahitah et al., 2021; Bazi et al., 2022). The incorporation of social elements into e-commerce has demonstrably enhanced commercial operations globally, creating new opportunities and challenges for both businesses and consumers (Azhar et al., 2023).

However, the distinctive characteristics of social commerce, including lower entry barriers and reduced regulatory oversight, have introduced unique challenges in transaction certainty. Unlike traditional e-commerce platforms, social commerce environments face heightened risks of fraud, service quality issues, and information asymmetry

(Laudon & Traver, 2023; Wai et al., 2018). For instance, buyers or sellers can have multiple social media accounts, which adds another layer of uncertainty to the social commerce experience (Kemp, 2024). In social commerce, information asymmetry occurs when sellers have more information than buyers (or vice versa), creating an imbalance that can lead to various challenges (Yao & Mo, 2022). This asymmetry can affect seller uncertainty (Kanani & Glavee-Geo, 2021). Seller uncertainty, defined as the difficulty potential buyers face in accurately assessing seller attributes and predicting opportunistic behavior, represents a critical barrier to social commerce adoption (Dimoka et al., 2012). This uncertainty often manifests in reduced purchase intentions and limited transaction values, ultimately constraining the growth potential of social commerce platforms (Wang et al., 2017).

While extensive research has examined uncertainty in traditional e-commerce contexts, a significant gap exists in understanding how customer-seller signals can effectively reduce uncertainty within social commerce, particularly in developing countries (Al-Adwan et al., 2022; Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021). The current study advances existing research by integrating customer-based and seller-based signals into signaling theory, providing a more

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comprehensive framework for understanding uncertainty reduction in social commerce. Unlike prior studies that treat signals in isolation, we explore the combined influence of these signals, offering novel insights into their collective impact on seller uncertainty. General aspects, i.e. influence, interaction, support, and social desire are among the main focuses of the current literature (Busalim et al., 2021; Horng & Wu, 2020; Hu et al., 2022), technology adoption (Chen et al., 2019), purchase decision-making (Fang & Li, 2020), and trust building (Guo et al., 2021). Previous studies have investigated how information asymmetry affects uncertainty and trust using various theoretical models. However, seller uncertainty still needs more attention (Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021). Notably, signaling theory has also been used by researchers to investigate different types of e-commerce, such as live-streaming commerce (Mazurek-Kusiak, 2022; Yao & Mo, 2022), website shopping (Li et al., 2019; Oghazi et al., 2018; Pee et al., 2018), and corporate brands (Nyagadza et al., 2021).

In e-commerce, signals are observable features altered by sellers to convey hidden or limited product information to potential buyers (Lu & Chen, 2021). These signals are categorized as (1) seller-based signals, which consist of return policy leniency and information quality, and (2) customer-based signals, which consist of the seller's popularity, seller's reputation, and the number of positive review comments (Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021). Such signals can significantly influence various consumer behavioral outcomes, including trust, purchase decisions, and importantly, seller uncertainty (Miao et al., 2022; Pee et al., 2018; Tandon et al., 2021). In the Arab nations, social commerce is rapidly growing yet remains understudied (Rouibah et al., 2021). Moreover, this study focuses on the underexplored context of social commerce platforms in Palestine, an emerging market with distinct socio-economic and cultural characteristics. By examining this setting, the research contributes novel insights into how signaling mechanisms operate in developing economies, which differ significantly from developed markets regarding consumer behavior, regulatory frameworks, and reliance on social media for commerce. This contextual focus enriches the theoretical and practical understanding of trust-building in global social commerce. Drawing on signaling theory, this research aims to address these gaps through the following objectives:

- To assess the impact of customer-based signals (positive reviews, seller reputation, and seller popularity) on seller uncertainty in social commerce platforms.
- To assess the impact of seller-based signals (information quality and return policy leniency) on seller uncertainty in social commerce platforms.

The remainder of this paper is as follows: Section Two reviews the relevant literature and outlines the research hypotheses. Section Three describes the research methodology used in the study. Section Four presents the analysis of the data and the results. The discussion that follows emphasizes the theoretical and practical contributions of the research. The final section provides the findings, discusses the study's limitations, and suggests directions for future research.

2. Literature review

2.1. Social commerce

E-commerce can be classified based on enabling technology, such as mobile commerce, local commerce, and social commerce (Laudon & Traver, 2023; Mehribioun, 2024). Importantly, social commerce has emerged as a rapidly growing trend, representing a unique style of e-commerce that integrates social media platforms with online transactional capabilities, enabling users to engage in purchasing activities directly within social media platforms, empowering customer engagement, and contributing to a more productive shopping experience (Azhar et al., 2023; Qu et al., 2023; Rahman et al., 2023; Wang & Xie,

2020).

Social commerce is distinguished by two key elements: the impact of social media on digital commerce activities and the integration of various consumer activities such as purchasing, repurchasing, and product usage through social media networks (Valerio et al., 2019; Yadav et al., 2013). These elements create a mutually beneficial ecosystem where businesses gain access to a vast base of potential customers on the one hand. On the other hand, customers gain new ways to interact, share content, and exchange experiences about products and services, enhancing the overall online shopping experience (Attar et al., 2022; Hafez, 2022).

In the e-commerce environment, customers face inherent limitations: their shopping experience relies primarily on textual and photographic descriptions of products without the ability to test items before purchasing, and both buyers and sellers can create unlimited social media accounts (Fu et al., 2016; Yao et al., 2019). These challenges contribute to information asymmetry, a phenomenon where the imbalance of relevant market information between buyers and sellers significantly increases uncertainties in online transactions (Laudon & Traver, 2023; Yao & Mo, 2022). This asymmetry is particularly impactful in social commerce due to spatial and temporal separation in virtual environments, which limits customers' ability to ascertain sellers' credibility and predict opportunistic behavior, a phenomenon known as seller uncertainty. Consequently, this hinders customers' ability to make informed purchase decisions on social commerce platforms (Al-Adwan & Yaseen, 2023; Bleier et al., 2019). In the next section, the related theories will be discussed.

2.2. Theoretical background

Research examining uncertainty reduction in e-commerce has evolved significantly. While extensive literature has documented uncertainty reduction mechanisms in traditional e-commerce contexts (Chiu et al., 2018; Dimoka et al., 2012; Fernando et al., 2018; Pavlou et al., 2007), the emerging field of s-commerce presents unique challenges that warrant specific investigation (Bai et al., 2015; Kanani & Glavee-Geo, 2021; Wang et al., 2017). The complexity of social commerce environments, characterized by the integration of social interactions with commercial activities, has led scholars to employ various theoretical frameworks to understand its distinct characteristics and adoption patterns (Qu et al., 2023). For instance, the Technology-Organization-Environment (TOE) framework has been applied to examine SMEs' behavioral intentions toward social commerce adoption (Abed, 2020), while the Technology Acceptance Model (TAM) has been used to understand consumers' repurchase intentions in social commerce platforms (Anabir, 2023; Nabila et al., 2023; Trenggana et al., 2022). Among these theoretical frameworks, signaling theory has emerged as particularly relevant for investigating s-commerce phenomena, as it provides a robust lens to address the critical challenge of information asymmetry, a pervasive issue in virtual marketplaces. Its focus on how observable signals can convey credible information aligns directly with the dynamics of social commerce, where trust and transparency are often hindered by the lack of physical interaction (Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021).

Signaling theory, developed within economics and communication research, addresses information asymmetry by explaining how parties communicate credible information in markets characterized by uncertainty (Spence, 1978, 2002). In social commerce contexts, sellers can use signals, observable quality indicators that convey meaningful information about their unobservable qualities, to increase buyers' trust and help buyers make more informed decisions (Oghazi et al., 2018; Tandon et al., 2021). These signals can include professional advertising, brand assurance, store reputation, discounts, ratings, product descriptions, and post-sale service (Ballina et al., 2020; S. Wang & Ma, 2023). The categorization of signals into seller-based (e.g., return policy leniency, information quality) and customer-based (e.g., positive reviews, seller

reputation, seller popularity) is grounded in their demonstrated empirical relevance in reducing seller uncertainty across various settings. These signals were selected for their ability to address specific dimensions of trust-building and information asymmetry, particularly in environments where consumers lack direct interaction with sellers (Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021; Luo et al., 2021). Thus, this theoretical framework provides a foundation for examining how various signals can mitigate information asymmetry and consequently reduce various uncertainties including seller uncertainty. Moreover, signaling theory’s adaptability to dynamic and culturally diverse contexts makes it especially relevant for social commerce in developing economies, where structural and regulatory barriers exacerbate the challenges of trust-building.

Signaling theory has been applied in e-commerce contexts across various research settings and objectives, as shown in Table 1. Researchers have applied the theory to examine various types of signals and their effects, trust-building mechanisms in Sweden (Oghazi et al., 2018), website design elements in Australia (Abeysekera, 2019), corporate storytelling in Zimbabwe (Nyagadza et al., 2021), and service quality indicators in Taiwan (Pee et al., 2018). This demonstrates the theory’s robustness in explaining uncertainty reduction mechanisms across diverse cultural contexts.

Recent studies have also begun to explore how signals operate in unique socio-economic environments. For instance, studies in Jordan (Al-Adwan & Yaseen, 2023) and Tanzania (Kanani & Glavee-Geo, 2021) have examined how various signals influence seller uncertainty in social commerce platforms. These studies have highlighted the importance of both customer-based signals such as positive reviews and seller reputation, and seller-based signals such as including information quality and return policy leniency in reducing seller uncertainty.

However, research in the Middle East, particularly Palestine, remains limited. Social commerce in Palestine offers a compelling setting for studying signaling theory due to its unique market conditions. The region’s reliance on social media for commerce, combined with high levels of economic and regulatory uncertainty, amplifies the need for effective trust-building mechanisms. Signaling theory’s emphasis on reducing information asymmetry is particularly applicable here, as consumers often lack sufficient legal or institutional protections and instead depend heavily on trust signals. While Kullab et al. (2022) applied signaling theory in the Palestinian banking sector, its application in s-commerce contexts is scarce. This gap is significant given that social commerce platforms in different cultural contexts may require different signaling mechanisms to effectively reduce seller uncertainty. The unique characteristics of the Palestinian market—its developing economy status, cultural specifics, and emerging social commerce landscape—present an opportunity to extend our understanding of how signals operate in distinct cultural contexts. Furthermore, this research responds to repeated calls in the literature for studies in different cultural contexts, as highlighted in the future research suggestions of multiple studies (Al-Adwan et al., 2022; Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021; Tandon et al., 2021). By addressing these gaps, this study not only contributes to theoretical advancements in signaling theory but also offers practical insights for designing trust-building strategies in similar emerging economies. The findings will enable comparison with existing studies in Jordan and Tanzania, contributing to our understanding of how signal effectiveness varies across different developing market contexts.

2.3. Research model and hypotheses development

2.3.1. Seller-based signals

These signals are directly controlled and managed by the seller on social commerce platforms.

2.3.1.1. Seller popularity and seller uncertainty. The concept of

Table 1
Applying signaling theory in E-commerce contexts.

Study country	Theories	Factors	Contributions
(Oghazi et al., 2018) Sweden	ST & RST	IVs: Return Policy Leniency MED: Consumer Trust. DVs: Online Purchase Decision	Investigated the effect of return policy on future purchase intention, mediated by trust.
(Al-Adwan et al., 2022) Jordan	ST	IVs: Return policy leniency, Cash on delivery, social commerce constructs DVs: Customer trust, Purchase intention	Identified how three signals influence online purchase intention through consumer trust building.
(Abeysekera, 2019) Australia	RBT & ST	IVs: Storytelling material, Website design, Data presentation. DVs: Corporate reputation.	Examined how three website signals influence stakeholder perceptions of SME corporate reputation.
(Nyagadza et al., 2021) Zimbabwe	ST	IVs: Corporate storytelling. Med: Emotional Attachment. DVs: Corporate Brand Perceptions by internal Employees.	Investigated how corporate storytelling signals enhance corporate brand perceptions through emotional attachment among internal employees.
(Pee et al., 2018) Taiwan	ST & ECM.	IVs: Perceived website usability, expected service quality, Perceived service quality. Mod(s): Perceived risk, Prior experience. DVs: Expected service quality, Service quality confirmation, Satisfaction, Repurchase intention.	Analyzed how website usability and service quality signals influence repurchase intention, moderated by perceived risk and prior experience.
(Tandon et al., 2021) India	None	IVs: Virtual try-on technology, return policies, Pay-on-delivery, Vendor-specific guarantees, Free shipping policy. MOD: Perceived effectiveness of e-commerce institutional mechanisms (PEEIM). DVs: Customer trust, Repurchase intention	Investigated how multiple signals influence repurchase intention through customer trust, with PEEIM negatively moderating the trust-repurchase relationship.
(Li et al., 2019) China	MS-HMM & ST.	IVs: Product promotions, Liberal return policies. DVs: Repurchase behavior.	Evaluated how product promotions and liberal return policies influence repurchase behavior across different customer relationship stages using a MS-HMM.
(Lu & Chen, 2021) China	ST	IVs: Physical Characteristic Similarity, Value Similarity. DVs: Trust toward the broadcaster, Product Fit Uncertainty, Product Quality Uncertainty, Purchase Intention.	Investigated how physical and value similarity between broadcasters and viewers influences purchase intention through trust building and uncertainty reduction in live streaming commerce.
(Al-Adwan & Yaseen, 2023) Jordan	ST	IVs: Return policy leniency, Information quality, Seller reputation, The number of positive comments, Seller popularity, Product uncertainty. MED: Seller	Examined how multiple signals reduce product uncertainty through the mediating role of seller uncertainty in social commerce.

(continued on next page)

Table 1 (continued)

Study country	Theories	Factors	Contributions
(Kanani & Glavee-Geo, 2021) Tanzania	ST	uncertainty. DVs: Product uncertainty IVs: The number of positive comments, Seller popularity, Customer service quality. MOD: Customer service quality, Return policy. DVs: Seller uncertainty	Analyzed how positive reviews, seller popularity, and customer service quality reduce seller uncertainty, moderated by return policy and service quality in emerging markets.
(Kullab et al., 2022) Palestine	ACT & ST	IVs: Size, Profitability, Liquidity, Capital adequacy DVs: Bank's pay dividends, Bank's dividend payout ratio.	Examined how bank characteristics influence dividend policies and payout ratios in Palestinian banking sector.
Notes	MS-HMM: Multi-stage hidden Markov model ST: Signaling theory RST: Relational signaling theory RBT: Resource-Based theory ECM: Expectation-confirmation model ACT: Agency cost theory		

popularity within the social commerce domain has been discussed by demarcating it into two main dimensions: seller popularity and post popularity. The amount of followers attributable to a seller is used to measure the seller's popularity as the justifications indicating the act to follow these sellers remain unspecified (De Vries et al., 2012; Lardo et al., 2017; Read et al., 2019). Quite the reverse, a group of engagement metrics is employed to traditionally measure post popularity, including metrics such as the comments, count of views, shares, and likes (Abid et al., 2020; Mukti & Putri, 2021; Oh et al., 2023). The 2-dimension popularity provides key insights into the influence and dynamics of social commerce in the context of individuals and content involved in online social networks.

The essence of the current research lies in examining the concept of the seller-popularity known as the followers' numbers on the seller's social media page. At length, popularity is now an essential and recognized success indicator in online businesses (Du, 2014; Tang & Chen, 2020). Empirically, De Veirman et al. (2017) reveal that several followers can increase a seller's perceived popularity and likability. The victory of online sellers is essentially related to their capability to accumulate a critical number of followers, thus qualifying them to yield substantial profitability and revenues. Tang and Chen (2020) make evident that popular sellers are normally featured with a more wide-ranging follower base in comparison with other less popular peers. Therefore, the followers' number on the seller's social media page demonstrates a crucial role in determining their reputation and success within the landscape of the online business.

Among the findings attained in this research work is that the attainment of popularity among sellers centers on the confirmation of pivotal attributes, together with lenient return policies and delivery reliability along with the delivery of first-rate equality of customer services and products (Lahuerta-Otero et al., 2018; Wu et al., 2019). These attributes evince themselves to potential customers through positive feedback and purchase experiences shared by past consumers on the social media pages of the seller. Popular sellers, therefore, demonstrate a less desire to abandon commitments made to consumers, as these actions might create a huge number of negative comments on the sellers' pages, thereby ruining their social and commercial status and eventually leading to a decrease in their consumer base and revenues. Along these lines, popularity acts as a fundamental signal to instill consumer trust and decrease uncertainty, as expounded by (Lahuerta-Otero et al., 2018; Wu et al., 2019). Given these perceptions, hypothesis (1) is read as follows:

H1. Higher levels of seller popularity are expected to mitigate seller uncertainty.

2.3.1.2. Seller reputation and seller uncertainty. Regarding the sellers, reputation as a concept relates to their responsiveness and trustworthiness to the needs of the consumers. Reputation regularly functions as a tool to evaluate the consistency of the attributes of the seller throughout time (Doney & Cannon, 1997; Herbig & Milewicz, 1993). Foroudi et al. (2016) assert that the perceived reputation encompasses a cognitive image of the previous behaviors of a seller, including qualities such as trust, respect, confidence, and admiration. It, therefore, functions as a reflection of previous performance, current conduct, and the overall image predicted by the seller (Frik & Mittone, 2019). Reputation vitally simplifies online transactions by lessening risks, relieving transaction costs, and ending entry obstacles. Furthermore, it helps to build dependable relationships, improve transparency, and guarantee integrity in ongoing transactions (Chiu et al., 2014; Frik & Mittone, 2019). Additionally, as proved by Al-Adwan and Yaseen (2023), uncertainty in online acts and exchanges is lessened by reputation as a quality indicator associated with the online seller.

Within the post-purchase transactions, the reputation of a company acts as a substantial empirical indicator for consumers to strengthen their trust in sellers with an acceptable image (Eisenbeiss et al., 2014; Kim & Park, 2013). A positive reputation is known for a considerable role in boosting online sellers by enlarging purchase frequencies, decreasing perceived risks, increasing favorable word-of-mouth marketing, and augmenting their follower base (Kanani & Glavee-Geo, 2021; Meilatinova, 2021). Also, seller reputation decreases the market information asymmetry and magnifies customer confidence (Shen et al., 2011; Yahia et al., 2018). Sellers, acquainted with the long-term value of a positive reputation, avoid getting involved in untrustworthy conduct, as this reputation is a sign of a long-term and high-quality asset superseding any short-term achievements resulting from untruthful behavior (Gul, 2014; Kaul et al., 2015).

The vital role played by seller reputation lessens uncertainty and risk in online transactions and acts as an indicator of enriched trustworthiness and quality (Frik & Mittone, 2019; Jadil et al., 2022; Oghazi et al., 2018). Current pieces of research have documented that reputation considerably affects seller quality, perceived trustworthiness, credibility, reliability, and product quality (Al-Adwan & Al-Horani, 2019; Meilatinova, 2021; Oghazi et al., 2018). As asserted by (Punyatoya, 2018), reputation significantly adds a positive effect to the consumers' trust in a corporation and functions as a cognitive trust predictor. In the social commerce context, the sellers' reputation is often assessed to determine the suitability of their services or products and, thereby the level of their trustworthiness (Al-Adwan & Yaseen, 2023; Kim & Park, 2013; Maia et al., 2018). Accordingly, the reputation of a seller is deemed as a gesture of their ethical conduct and empathy. Given these perceptions, hypothesis (2) is read as follows:

H2. A positive seller reputation is anticipated to reduce uncertainty in S-commerce platforms.

2.3.1.3. Positive comments and seller uncertainty. In the domain of consumer comments, online reviews are familiar with their vital role in making the purchasing decisions of the customers by furnishing dynamic insights that cannot be provided by sellers (Shan et al., 2024; Torabi & Bélanger, 2021). With the help of these comments, consumers' experiences are shared with current and future buyers, thus reducing risks and uncertainties related to online shopping (Jadil et al., 2023). It is also important to add that negative and positive review comments are equivalently used and substantially affect more than 75 % of the purchase choices of online consumers (Casaló et al., 2015). Additionally, review comments not only strengthen the credibility of both the seller and the product but also augment the whole appeal of the shopping experience (Cai et al., 2023).

Of note, it is asserted that adverse comments significantly influence customers by possibly increasing the perception of uncertainty and minimizing favorable ones (Wang et al., 2023). Negative information

may have much weight in the customers' eyes and render their decision-making process more complicated (Sadaa et al., 2022). Being flooded with negative remarks, social media platforms incite intensified hesitancy and apprehension among potential consumers. On the other hand, plenty of positive review comments in comparison to negative ones work on alleviating the perceived uncertainty concerning the seller and boosting the confidence of the consumer in their purchasing decisions (Al-Adwan & Yaseen, 2023; Barta et al., 2023). Essentially, consumer comments noticeably influence online shopping behavior with negative comments offering a particular challenge to customers' certainty and trust. Given these perceptions, hypothesis (3) is read as follows:

H3. An increased number of positive reviews is likely to lower seller uncertainty in S-commerce contexts.

2.3.2. Customer-based signals

Unlike seller-based signals, these indicators emerge organically based on their engagement and accumulated experiences from social commerce platforms.

2.3.2.1. Return policy and seller uncertainty. In the same context, return-policies are regarded as strategic procedures utilized to mitigate customer risk and simultaneously motivate customer demand in the retail landscape (Karlsson et al., 2023). The leniency amount within a return policy involves provisions for store credits, exchanges, and refunds, while adding minimal restrictions on customers' engagement in return-related activities (Janakiraman et al., 2016). The appropriation of a lenient return policy is positively associated with an improved possibility of potential customers adhering to purchase decisions (Martínez-López et al., 2022). Importantly, the return policies act as a seller support approach, as their features demonstrate differences across diverse industries (Russo et al., 2022; Salem & Alanadoly, 2024). Sellers occasionally provide a range of return policies, varying in terms of leniency, echoing how these policies affect customers' behavior.

The function of return policy is reflected in an essential tool used by sellers to build consumer trust and take a competitive market advantage (Salem & Alanadoly, 2024). Corporations advantageously utilize their return policies to create sales outcomes and single out themselves from less reliable wholesalers (Al-Adwan et al., 2022). In light of the lack of face-to-face supervision and the failure to physically check products in the online shopping realm, the application of lenient return policies helps to reduce uncertainty and speak of the issue of the adverse selection by strengthening the seller reliability's perception (San Martín & Camarero, 2009). Untrustworthy sellers may experience the risks of loss of future sales and tarnishing of their reputation (Kanani & Glavee-Geo, 2021). Subsequently, consumers engaging in social commerce transactions with online sellers furnishing policies of lenient product return can perceive their transactions as less uncertain than individuals acquiring from vendors with stringent return policies. Given these perceptions, hypothesis (4) is read as follows:

H4. Greater leniency in return policies is predicted to decrease seller uncertainty in social commerce.

2.3.2.2. Information quality and seller uncertainty. The concept of information quality traditionally pertains to the attributes of information originating from a system, encompassing attributes like accuracy, reliability, currency, conciseness, format, relevance, and timeliness, among others, as elucidated by (William et al., 2003). The quality of information available on a website holds significant importance for users, impacting their assessment of its accuracy, comprehensiveness, and timeliness (Lee & Kim, 2017), and influencing how well the information aligns with their needs and intended use (Jiang et al., 2021).

Online sellers face uncertainty due to their failure to disclose critical details and potential deceptive practices (Nisa & Hutagalung, 2022). However, most strive to maintain accurate and current information

about their products and services, as customer behavior relies on it (Vasić et al., 2019). Transparent and comprehensive information is crucial for customers, as they lack physical inspection during transactions (Leeraphong et al., 2016). High-quality online information fosters trust and enhances customer confidence (Ghose, 2009).

In the social commerce domain, information quality is significant due to sellers' acts of manipulating the information to affect consumer decisions (Ahn & Sura, 2020). Social commerce depends largely on the information provided by sellers' profiles, together with reviews, product descriptions, and comments from other consumers (Appolloni et al., 2023). Understanding the information from diverse sources adds uncertainty to the customer decision-making process (Chen et al., 2016). Research has previously documented that information quality with high levels enhances engagement, consumer trust, perceived usefulness, and satisfaction (Ahn & Sura, 2020; Appolloni et al., 2023). Consumers comprehensively assess the information on user-generated content and sellers' pages before the purchasing decision-making process (Kar et al., 2021). Perceptions of uncertainty and consumer trust are significantly affected by the quality of the aforementioned information. Given these perceptions, hypothesis (5) is read as follows:

H5. Enhanced information quality is expected to reduce seller uncertainty on social commerce platforms significantly.

The current study presents a conceptual framework postulating the presence of two distinct signal categories that impact the seller's uncertainty in the social commerce context, as illustrated in Fig. 1.

3. Research method

3.1. Research design

This study adopted a positivist philosophy with a deductive approach to test hypotheses derived from signaling theory (Saunders et al., 2012). A quantitative mono-method was used, employing a survey strategy to collect cross-sectional data from 368 respondents with experience in social commerce. As illustrated in Fig. 2, the research design framework integrates key components, including the research philosophy, approach, strategy, time horizon, and analytical methods, to ensure a structured and systematic investigation of the proposed hypotheses. The data analysis integrated symmetric Structural Equation Modeling (SEM) and asymmetric Artificial Neural Network (ANN) methods to examine linear and non-linear relationships. The main target population for this study comprised Palestinian individuals who have engaged in online shopping through sellers' social media platforms. The study utilized the nonprobability convenience sample strategy to investigate the proposed framework due to the lack of a complete list of customers on social media platforms and the unknown size of the overall population. We used the G-Power software to determine the requisite sample size. This software was specifically developed to analyze the statistical power widely utilized in social-behavioral investigations. The software offers power analysis tools for commonly utilized analyses, such as correlation and regression. Based on the power analysis, the minimum required sample size was calculated to be 146 respondents, assuming a power of 95 %, an alpha level of 0.05, and a medium effect size of 0.15. The final sample size 368 exceeds this minimum requirement, ensuring statistical robustness. Participants were initially asked a filter question regarding their prior purchases from merchants' social media networks to determine eligibility. Respondents who answered "yes" continued to the further questions, while those who answered "no" were instructed to conclude their participation.

3.2. Scale measurement

With the analysis of the previous pieces of research, the current article comprises six reflective latent variables. Seller popularity was measured using two indicators from extant studies (Al-Adwan & Yaseen,

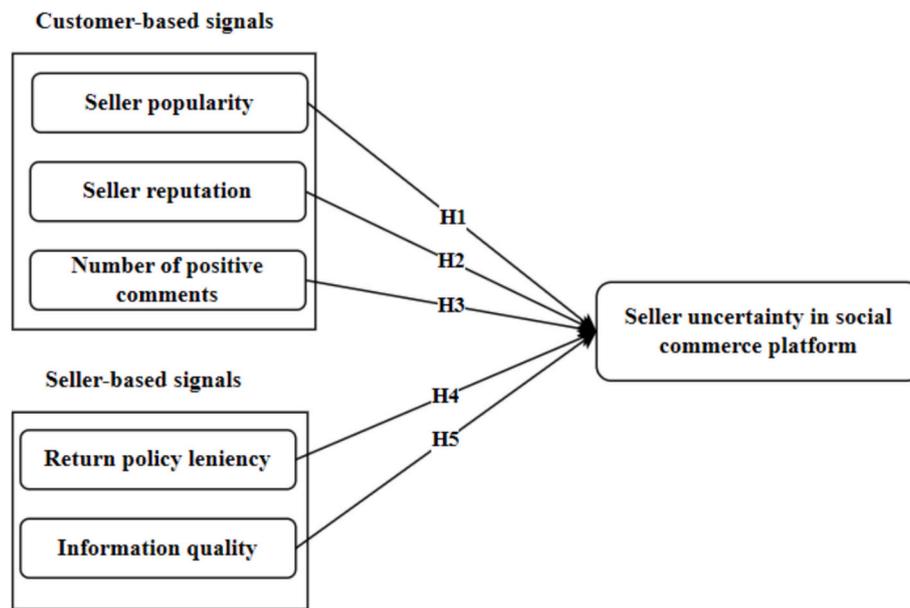


Fig. 1. Research model.



Fig. 2. Research design framework.

2023; Kanani & Glavee-Geo, 2021; Yahia et al., 2018). Seller reputation was evaluated using three items (Al-Adwan & Yaseen, 2023; Meilatinova, 2021). Three indicators were drawn from previous studies to assess several positive comments (Kanani & Glavee-Geo, 2021; Park et al., 2007). Information quality (3 items) and return policy leniency (6 items) were assessed using the past research work (Al-Adwan & Yaseen, 2023; Kanani & Glavee-Geo, 2021; Meilatinova, 2021). Last, four indicators are used to measure seller uncertainty, gleaned from previous studies (Al-Adwan & Yaseen, 2023; Dimoka et al., 2012; Kanani & Glavee-Geo, 2021). The survey items were evaluated on a 5-point Likert scale, ranging from strongly agree (5) to strongly disagree (1). The questionnaire, written in English, was pretested to corroborate the questions and make the instructions easily understandable. Given that the respondents' native language is Arabic, the questionnaire was translated into Arabic to develop their comprehension and simplify quick responses. The complete list of items is provided in Appendix A.

3.3. Data collection and sample characteristics

The study sample comprised 368 social media users in Palestine, all confirming their use of social media platforms. The questionnaires were sent by email, social media sites (including Facebook, Instagram, and WhatsApp), and conventional word-of-mouth means. The collected responses underwent a thorough review process to identify and address any instances of incompleteness or inconsistency, ensuring the validity and reliability of the data. Demographic analysis revealed that male respondents constituted 58 % of the sample, while females represented 42 %. Age distribution showed a predominantly young user base, with 50 % of respondents being under 25 years old. The educational profile indicated that 60 % of participants had completed undergraduate degrees. Regarding digital engagement patterns, the study revealed moderate daily internet usage habits, with 60 % of participants reporting daily internet consumption of 1–4 h. To address concerns about

potential sample bias, the nonprobability convenience sampling method was used to align with the study's exploratory nature and focus on active social commerce users in Palestine. While this approach limits the generalizability of findings, the sample reflects the key characteristics of the target population, ensuring relevance to the research objectives.

3.4. Data analysis

This study used a hybrid approach combining the partial least squares structural equation modeling (PLS-SEM) and ANN to validate the proposed research model. PLS-SEM utilizing Smart-PLS Version 4.0 was used to test the research model. Given the exploratory nature of the study, this method is thought to be the most appropriate (Hair et al., 2011; Hair Jr et al., 2021; Sarstedt et al., 2021). Survey research often deviates from normal distribution, leading to a departure from assumptions regarding the multivariate normality of the data. Consequently, as advocated by Chin et al. (2003) and Sarstedt et al. (2021), the methodology does not presuppose such normality and facilitates evaluating measurement and structural models, even with smaller sample sizes. PLS-SEM was particularly valuable in hypothesis testing, providing insights into the direct relationships between variables and confirming the statistical significance of the proposed paths. However, it is limited to linear relationships and lacks the ability to analyze complex, nonlinear interactions (Arpaci, 2023; Leong et al., 2024a).

To address this limitation, we incorporated ANN analysis due to its ability to outperform traditional statistical methods, including multiple linear regression, binary logistic regression, and SEM, by effectively capturing both linear and non-linear relationships rather than concentrating just on linear interactions (Arpaci, Al-Sharafi, & Mahmoud, 2024; Leong et al., 2023, 2024a). The use of ANN was particularly necessary given the multifaceted nature of seller uncertainty in social commerce, where nonlinear dependencies between variables can play a critical role. ANN's ability to model these complexities ensures that our

analysis captures a broader range of potential interactions, providing a more realistic representation of the data. Moreover, ANN enables ranking input variables based on their contribution to the output, offering insights into the relative importance of different signals. This ranking extends beyond the path significance analysis provided by SEM, enhancing the theoretical and practical relevance of the findings (Al-Momani et al., 2024; Giovanis et al., 2021). Lastly, ANN enhances predictive accuracy, which confirms its reliability and robustness in estimating seller uncertainty (Arpaci, Karataş, et al., 2024; Ng et al., 2022). The hybrid approach was particularly practical for this study, as it allowed us to combine the explanatory power of PLS-SEM with the predictive strength of ANN. This methodological integration ensures that the data's inherent complexities are addressed while offering robust and actionable insights into how trust signals reduce seller uncertainty. By combining PLS-SEM and ANN, the hybrid approach not only strengthens the study's methodological rigor but also provides a more nuanced understanding of how trust signals interact to reduce seller uncertainty.

4. Research findings

4.1. Common method bias

Following the recommendation of Podsakoff et al. (2003), and Rogelberg (2017) Harman's single-factor test evaluates the potential for common method bias. According to (Podsakoff et al., 2003), the first component produced a variation percentage of less than 50 %, corroborating the absence of common technique bias. To strengthen the robustness of this assessment, we complemented it with additional methods, including the full collinearity test and variance inflation factor (VIF) analysis. The VIF values for all constructs ranged between 1.508 and 2.121, well below the recommended threshold of 3.3, further confirming the absence of significant collinearity or common method bias (Hair et al., 2014).

4.2. Measurement model evaluation

Table 2 displays the PLS measurement model results for the thirty-two measured items. PLS factor loadings fall between the range of 0.668 and 0.885; values greater than 0.60 are regarded as extremely good (Henseler et al., 2009). All constructs' average variance extracted (AVE) The values range from 0.556 to 0.750, whereas the composite reliability (CR) values range from 0.829 to 0.900. These values are higher than the minimum requirements of 0.70 for CR and 0.50 for AVE

Table 2
Measurement model assessment results.

Constructs	Items	Factor loadings	CR	AVE
Seller popularity (SEP)	SEP1	0.841	0.829	0.708
	SEP2	0.841		
Seller reputation (SER)	SER1	0.856	0.891	0.732
	SER2	0.824		
	SER3	0.885		
Number of positive comments (NPC)	NPC1	0.858	0.900	0.750
	NPC2	0.877		
	NPC3	0.863		
Return policy leniency (RPL)	RPL1	0.668	0.862	0.556
	RPL2	0.788		
	RPL3	0.783		
	RPL4	0.733		
	RPL5	0.749		
Information quality (INQ)	INQ1	0.833	0.849	0.654
	INQ2	0.875		
	INQ3	0.708		
Seller uncertainty (SEU)	SEU1	0.821	0.886	0.660
	SEU2	0.785		
	SEU3	0.846		
	SEU4	0.797		

(Bagozzi & Yi, 1988; Fornell & Larcker, 1981). These findings demonstrate the high percentage of variance explained by the constructs and the strong internal consistency of the constructs.

Table 3 presents the results of the Heterotrait-Monotrait (HTMT) ratio, and all the values are lower than the threshold value of 0.90, as recommended by (Henseler et al., 2015); hence, the current study does not violate the discriminant validity assumption.

4.3. Structural model assessment

The current investigation employs the bootstrapping technique, utilizing 365 cases and 5000 resamples to assess the statistical significance of the proposed model as per the suggestion outlined by (Hair et al., 2016). The outcomes of PLS-SEM analysis are presented in Table 4 and Fig. 3. Notably, the R-squared values for the endogenous latent variable, namely, seller uncertainty, are 0.550, surpassing the recommended threshold of 0.26 for model adequacy as stipulated by (Cohen, 2013). This implies that the five independent variables explain 55 % of the variance in seller uncertainty. Five specific hypotheses outline the relationships between the variables in the current investigation.

Before conducting the bootstrapping procedure, a collinearity assessment was performed to ensure the robustness of the model. The Variance Inflation Factor (VIF) was examined for each predictor variable, following the recommendations of Hair et al. (2016). As shown in Table 4, all VIF values are below the recommended threshold of 3.3, confirming the absence of multicollinearity issues. Specifically, the VIF values for Seller Popularity (1.551), Seller Reputation (1.220), Number of Positive Comments (1.508), Return Policy Leniency (2.121), and Information Quality (1.865) demonstrate that collinearity does not compromise the structural model's integrity.

A bootstrapping mechanism in SmartPLS was employed to determine the significance of the t-values. Analysis of the samples indicated a two-tailed significance threshold of 0.05, affecting the path coefficient evaluation. Table 4 confirms that t-values greater than or equal to 1.96 are statistically significant at the 0.05 level.

The results show that the seller popularity (SEP) (H1, $\beta = -0.127$, $t = 2.331$), Seller reputation (SER) (H2, $\beta = -0.125$, $t = 2.600$), number of positive comments (NPC) (H3, $\beta = -0.243$, $t = 4.833$), return policy leniency (RPL) (H4, $\beta = -0.200$, $t = 3.221$), and information quality (INQ) (H5, $\beta = -0.276$, $t = 4.635$) have a significant negative impact seller uncertainty (SEU). The research measured the effect size (f^2) by applying the benchmarks set by (Cohen, 2013), with 0.02, 0.15, and 0.35 representing small, medium, and significant effects, respectively. Table 4 shows that the effect size is all small.

The statistical analyses confirmed that all hypothesized relationships were supported. Seller popularity, reputation, positive comments, return policy leniency, and information quality significantly reduced seller uncertainty. These findings highlight the nuanced roles of different signals in trust-building within social commerce. For example, the dominant role of information quality highlights its critical importance in addressing information asymmetry, particularly in the context of social commerce. Similarly, the strong influence of positive feedback and seller reputation shows that peer-generated content and trust markers remain vital in digitally mediated environments. These findings extend previous studies by illustrating how these signals interact in developing

Table 3
Discriminant validity (Heterotrait-Monotrait Correlation Ratio).

	INQ	NPC	RPL	SEP	SER	SEU
INQ						
NPC	0.591					
RPL	0.847	0.663				
SEP	0.741	0.611	0.760			
SER	0.400	0.359	0.431	0.526		
SEU	0.789	0.684	0.761	0.736	0.483	

Table 4
Results of the hypotheses testing

H	Structural Paths	Path Coefficient	T-Value	p-value	f ²	VIF	Decision
H1	Seller popularity (SEP) -> Seller uncertainty (SEU)	-0.127	2.331	0.020	0.023	1.551	Supported
H2	Seller reputation (SER) -> Seller uncertainty (SEU)	-0.125	2.600	0.009	0.029	1.220	Supported
H3	Number of positive comments (NPC) -> Seller uncertainty (SEU)	-0.243	4.833	0.000	0.087	1.508	Supported
H4	Return policy leniency (RPL) -> Seller uncertainty (SEU)	-0.200	3.221	0.001	0.042	2.121	Supported
H5	Information quality (INQ) -> Seller uncertainty (SEU)	-0.276	4.635	0.000	0.091	1.865	Supported

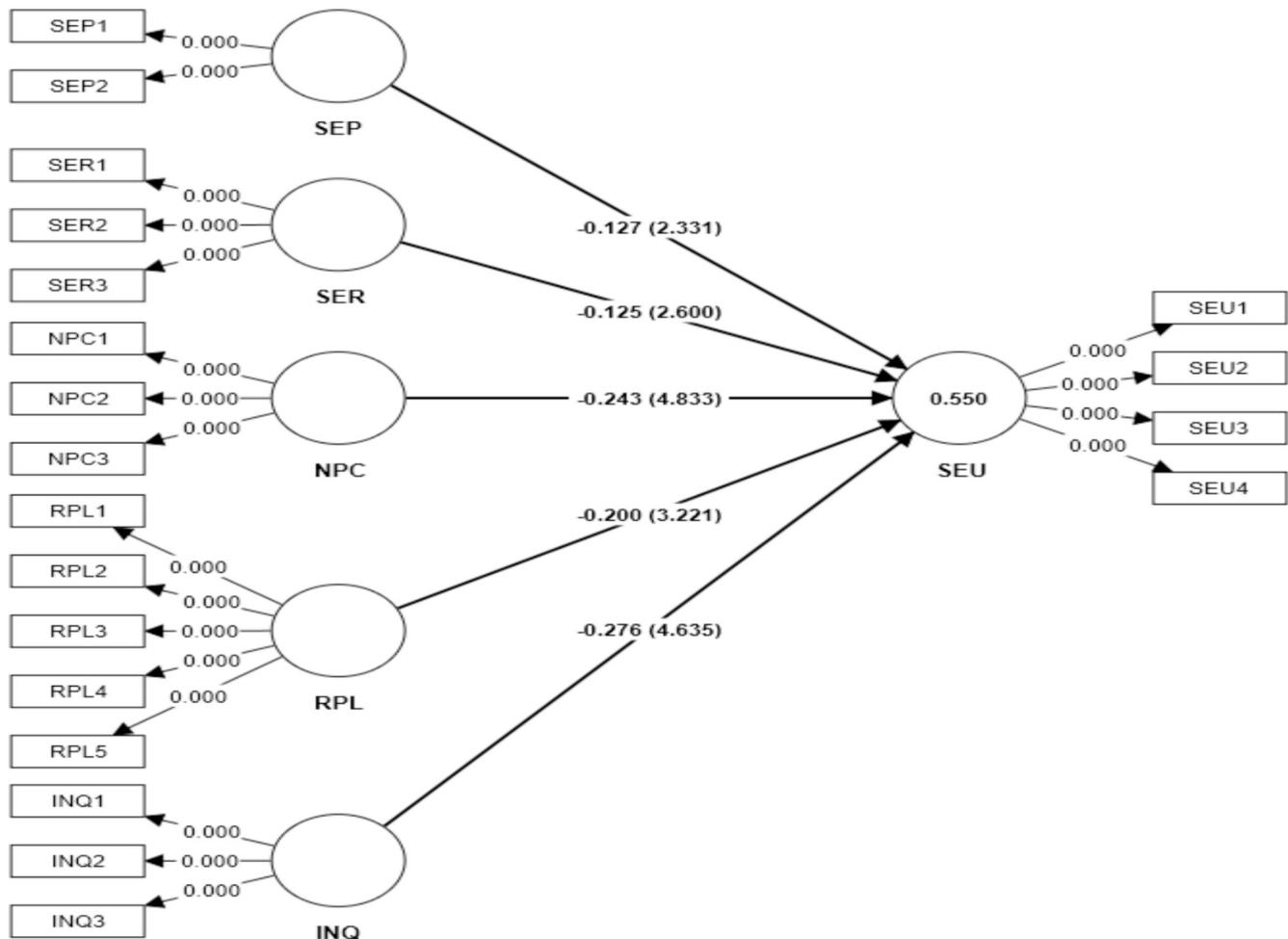


Fig. 3. Results of PLS-SEM analysis.

economies, where consumers rely heavily on such mechanisms due to limited regulatory oversight.

4.4. Goodness of fit (GOF) indexes

The model fit was established by a largely adequate method, i.e. “standardised root mean square residual” (SRMR), where the SRMR value should be less than 0.08 (Hair Jr. et al., 2017). The outcomes revealed the value of SRMR is 0.065, suggesting our model is quite well. Secondly, we also calculated GOF using the formula ($GOF = \sqrt{AVE \times R^2}$) (Wetzels et al., 2009). In our model, the GOF is 0.610, demonstrating the model fulfils the large criteria.

4.5. Artificial neural network analysis

In the first phase of this study, PLS-SEM was used to assess the hypothesized relationships and identify the factors influencing seller uncertainty in e-commerce transactions. In the second phase, an analysis

was employed to further evaluate and rank these factors (AlShamsi et al., 2024; Al-Sharafi et al., 2023; Herzallah et al., 2023; Leong et al., 2024b). This research’s neural network structure comprises an input layer, two hidden layers, and an output layer (refer to Fig. 4). The sigmoid activation function was used for the hidden and output neurons, facilitating smooth transitions among input values. To enhance performance, the neuron values for the input and output were normalized to a range of [0,1], consistent with recommendations from previous studies (Al-Sharafi, Al-Emran, et al., 2022; Kalinić et al., 2021; Nguyen et al., 2022; Thabet et al., 2023). To avoid overfitting, a ten-fold cross-validation technique was adopted, using 90 % of the data for training and the remaining 10 % for testing (Al-Momani et al., 2024; Leong et al., 2024b). The developed neural network model in this study involves multiple constructs influencing seller uncertainty. As visualized in Fig. 4, the ANN model contains five input nodes, representing exogenous variables, including seller-popularity, seller-reputation, number of positive comments, return policy leniency, and information quality. The model also includes one output node for seller uncertainty. The ANN

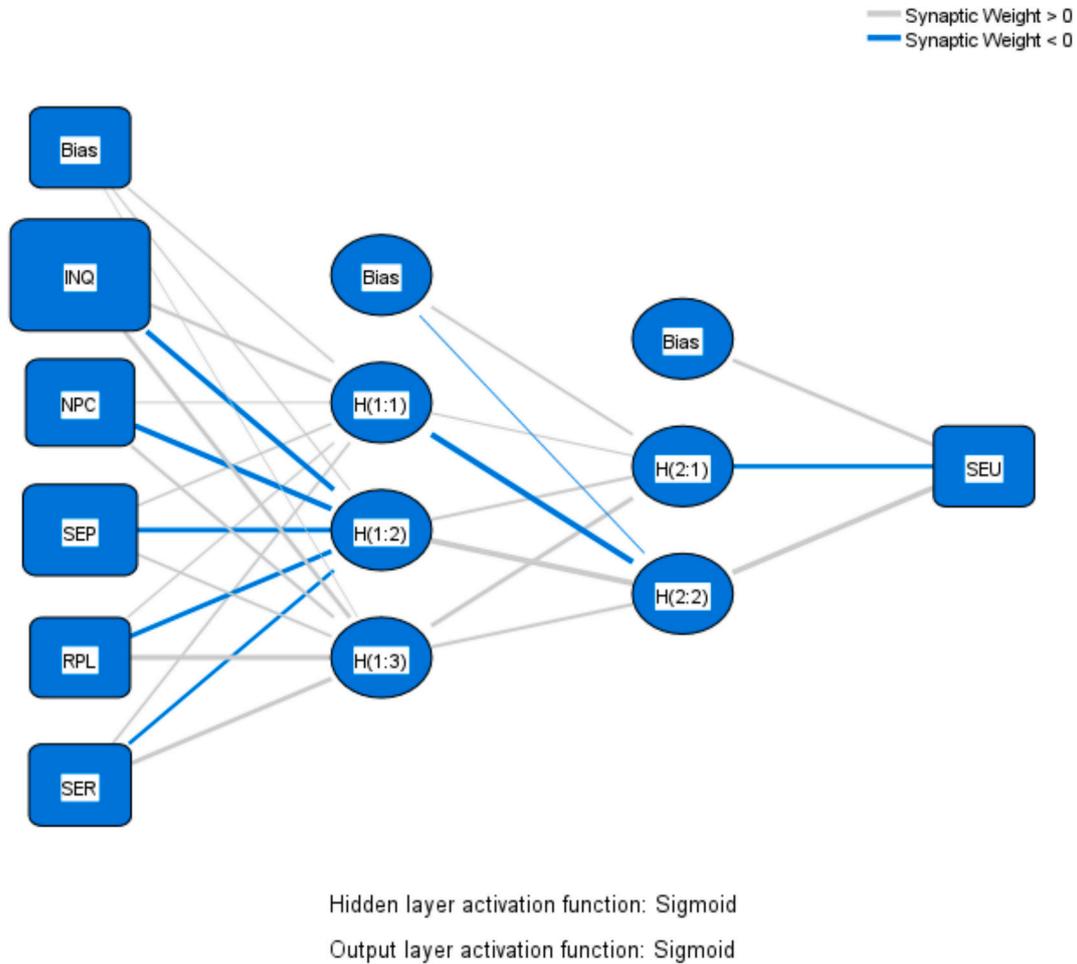


Fig. 4. ANN model.

model’s performance was assessed through the Root Mean Square Error (RMSE) during the training and testing phases (Leong et al., 2024b; Qasem et al., 2020). RMSE is a widely accepted metric to assess the predictive accuracy of ANN models. Based on the results shown in Table 5, the average RMSE for the ten neural networks was 0.09518 during the training phase and 0.09806 during the testing phase. The relatively low RMSE values indicate that the ANN model is effective and demonstrates strong predictive accuracy in estimating seller uncertainty, confirming that the model is both reliable and robust.

4.6. Sensitivity analysis

In this section, sensitivity analysis was conducted to assess the

Table 5
RMSE values of ANN model.

Network	RMSE (training)	RMSE (testing)
1	0.085	0.092
2	0.093	0.094
3	0.099	0.112
4	0.095	0.093
5	0.088	0.096
6	0.097	0.094
7	0.098	0.103
8	0.099	0.086
9	0.094	0.105
10	0.103	0.106
Mean	0.09518	0.09806
Standard deviation	0.00529	0.00808

relative importance of each input variable in predicting seller uncertainty in social commerce (Al-Sharafi, Al-Qaysi, et al., 2022; Leong et al., 2024b). The analysis examined five factors: INQ, NPC, SEP, RPL, and SER. The goal was to determine how each of these factors contributes to the overall reduction of seller uncertainty. As shown in Table 6, the results of the analysis show that Information Quality (INQ) emerged as the most influential factor, with a mean importance value of 0.3295 and a normalized importance of 98.82 %. This underscores the critical role that clear, accurate, and reliable information plays in mitigating uncertainty about sellers on social commerce platforms. The next most influential factor was the Number of Positive Comments (NPC), with a mean importance of 0.2236 and a normalized importance of 69.04 %.

Table 6
Sensitivity analysis results.

Network	INQ	NPC	SEP	RPL	SER
1	0.386	0.201	0.169	0.155	0.089
2	0.271	0.220	0.153	0.207	0.149
3	0.346	0.254	0.046	0.146	0.208
4	0.273	0.252	0.088	0.220	0.168
5	0.381	0.186	0.051	0.141	0.240
6	0.296	0.229	0.132	0.185	0.159
7	0.403	0.237	0.118	0.148	0.094
8	0.253	0.255	0.060	0.287	0.145
9	0.381	0.218	0.156	0.098	0.147
10	0.305	0.183	0.205	0.150	0.158
Mean importance	0.3295	0.2236	0.1177	0.1737	0.1555
Normalized importance %	98.82 %	69.04 %	36.18 %	55.05 %	48.01 %
Ranking	1	2	5	3	4

Positive feedback from previous customers appears to significantly enhance trust and reduce uncertainty for future buyers. Return Policy Leniency (RPL) ranked third, with a mean importance value of 0.1737 and a normalized importance of 55.05 %. This suggests that sellers who offer flexible return policies are better able to alleviate concerns about transaction risks. Seller Reputation (SER), with a mean importance of 0.1555 and normalized importance of 48.01 %, also contributed to reducing seller uncertainty, though to a lesser extent than the top three factors. Finally, Seller Popularity (SEP) was found to be the least influential, with a mean importance of 0.1177 and normalized importance of 36.18 %. Despite being a commonly recognized metric in online platforms, SEP was less effective in reducing uncertainty compared to the other factors. Overall, this sensitivity analysis provides valuable insights into which factors are most effective in reducing seller-uncertainty in S-commerce settings, highlighting the paramount importance of information quality and positive customer feedback.

5. Discussion

This study examines the role of customer- and seller-based signals in reducing seller uncertainty in social commerce platforms, providing both theoretical and practical insights. The results confirm all hypotheses, indicating that proposed signals directly affect seller uncertainty, addressing both study objectives. Our results confirmed the support for H1, revealing a negative influence of seller popularity on seller uncertainty. In the realm of social media-driven business, the increase in sellers' popularity leads to a decrease in customers' uncertainty. Having a substantial number of followers signifies that a vendor is authentic and reliable, hence enhancing their credibility and instilling confidence in clients. This outcome aligns with the findings of a study conducted by (Kanani & Glavee-Geo, 2021).

Beyond this, the findings underscore the unique dynamics of social commerce compared to traditional e-commerce, highlighting the heightened importance of trust-building in less-regulated, community-driven environments. The analysis reveals that hypothesis H2 is upheld, indicating a significant negative influence of the seller's reputation on seller uncertainty. Within the context of S-commerce, although the relationship between seller reputation and seller uncertainty has not been explored, prior research has shown a significant positive effect of seller reputation on customer trust (Jiao et al., 2024; Meilatinova, 2021). This finding suggests that customers tend to depend on the reputation of sellers on social media to mitigate transaction-related risks (such as non-delivery or fraud), thus diminishing their uncertainty regarding sellers on these platforms.

The data analysis results indicate that an increase in positive comments from other consumers on social networks has a detrimental impact on sellers' uncertainty. This implies that as the number of positive comments about the services and products offered by sellers on social commerce platforms increases, customers become more confident in their reliability. This outcome aligns with the findings of prior studies (Al-Adwan & Yaseen, 2023; Attar et al., 2022; Kanani & Glavee-Geo, 2021; Meilatinova, 2021). This confirms the third hypothesis. Such findings reinforce the importance of leveraging user-generated content as a core element of trust-building, particularly in developing economies where formal regulatory protections are limited. Feedback from past customers plays a crucial role in guiding online consumers in the realm of social commerce. Comments generally provide buyers with valuable insights that allow them to familiarize themselves with unfamiliar sellers and products, thereby fostering a positive perception. People consider reviews or buying experiences about sellers or products to be reliable. Nevertheless, remarks regarding sellers or products typically encompass both favorable and unfavorable aspects. Positive remarks bolster customers' confidence in sellers or items, and negative comments engender skepticism toward the products or vendors. As a result, providing favorable remarks as a form of social support can effectively mitigate the dangers and uncertainties associated with sellers or items.

An abundance of favorable remarks enables clients to familiarize themselves with unknown sellers and products, fostering a positive perception of them.

The study confirms that return policy leniency negatively impacts seller uncertainty, despite previous research showing that such policies positively affect customer trust in online sellers (Al-Adwan & Yaseen, 2023; Oghazi et al., 2018). Despite the lack of comprehensive exploration in social commerce and e-commerce, customers often feel uncertain about sellers on social media platforms, as they are often unofficially registered and lack physical stores. This uncertainty increases the risk of receiving low-quality or non-existent products. By demonstrating that clear and lenient return policies significantly reduce uncertainty, the findings provide actionable recommendations for sellers to prioritize transparent and customer-centric policies to enhance trust. To ensure credibility, customers rely on clear return policies, which can increase trust and encourage sellers to meet customer demands. The researcher believes that whenever a clear and flexible return policy is provided to customers through the sellers on SNSs, the uncertainty about the seller decreases, and this result is consistent with a study (Riasi et al., 2018; Rintamäki et al., 2021).

The study supports the idea that information quality significantly reduces seller uncertainty in social media-based commerce. Consumers are more inclined to trust vendors who offer comprehensive, precise, dependable, beneficial, and enough information regarding their products or services. While the relationship between information quality and SNSs-based seller-uncertainty has rarely been examined, previous research has demonstrated the significant positive impact of information quality on online customer trust such as (Alzaidi & Agag, 2022; Meilatinova, 2021). The findings emphasize that providing accurate, reliable, and comprehensive information is critical for sellers in building trust and mitigating uncertainty, especially in social commerce settings where physical product evaluation is not possible. Customers trust information provided by the seller, including product and service descriptions, return policies, and ratings, feedback from other customers. The more abundant information in online stores through social networks, the lower the percentage of distrust (Al-Adwan & Yaseen, 2023).

6. Conclusion and implications

This study has explored the factors that influence seller uncertainty in social commerce platforms by focusing on both customer-based and seller-based signals. The findings demonstrate that key signals, including information quality, number of positive comments, seller-reputation, seller-popularity, and return policy, significantly reduce seller uncertainty. The integration of signaling theory and the use of PLS-SEM and ANN approach offer a comprehensive understanding of how trust can be built and uncertainty mitigated in social commerce. These results provide both theoretical and practical insights that are valuable for sellers, platform designers, and researchers interested in the dynamics of online commerce in developing economies.

6.1. Theoretical implications

This study makes several key theoretical contributions to the literature on social commerce, particularly in the context of reducing seller uncertainty. First, it advances signaling theory by demonstrating its nuanced application in social commerce. Unlike traditional e-commerce, social commerce involves higher levels of consumer interaction and community-driven content. This study identifies and empirically validates the distinct roles of customer-based signals (e.g., positive comments, seller reputation, seller popularity) and seller-based signals (e.g., information quality, return policy leniency) in mitigating uncertainty. This provides a more granular understanding of how signals function in environments characterized by dynamic consumer participation and peer influence. This deeper understanding enriches signaling theory, offering insights into how trust-building mechanisms operate in

highly interactive, peer-influenced environments.

Second, the study critically evaluates the differential effectiveness of trust signals, thereby addressing a significant research gap. While prior studies often treat seller trust as a monolithic construct, this research shows that different signals exert varying degrees of influence on reducing seller uncertainty. For example, the results highlight the dominant role of information quality compared to seller popularity, challenging conventional assumptions about the importance of social metrics in building trust. This critical evaluation enriches existing theories by delineating the contextual relevance of specific signals. Third, the study contributes to the emerging discourse on social commerce in developing countries. Existing research has largely focused on developed markets, neglecting the unique challenges and opportunities presented by emerging economies. By examining seller uncertainty in a developing country context, this study sheds light on the role of cultural and contextual factors in shaping consumer behavior on social commerce platforms. This expands the theoretical scope of social commerce literature and offers a culturally grounded perspective that was previously underexplored. Lastly, the integration of PLS-SEM and ANN provides a significant methodological contribution. This hybrid approach bridges the gap between linear and non-linear analyses, enabling a deeper exploration of complex relationships between signals and uncertainty. By ranking the relative importance of predictors, the study offers new methodological insights for understanding the dynamics of uncertainty reduction. This contribution extends the applicability of these techniques to future research in social commerce and related fields, offering a framework for analyzing multi-faceted phenomena in online marketplaces.

6.2. Practical implications

This study offers several important practical contributions, particularly for practitioners and platform designers in the field of social commerce. First, it provides actionable insights for social commerce sellers on how to reduce uncertainty and build trust with potential customers. By demonstrating the critical role of information quality, the study highlights the importance of providing clear, accurate, and comprehensive product information. Sellers should prioritize providing high-quality, transparent, and accurate information about products and services, as information quality emerged as the most critical factor in reducing uncertainty. Comprehensive and up-to-date product descriptions are essential for gaining customer trust. Second, the research underscores the value of positive customer feedback in shaping trust and reducing uncertainty. Sellers are encouraged to actively seek and promote positive reviews from their customers, as these reviews significantly reduce perceived risks for future buyers. Implementing strategies that encourage satisfied customers to leave positive feedback, such as follow-up requests or incentives, can enhance customer confidence and boost sales conversions. Third, the study highlights the value of lenient return policies in mitigating buyer hesitation. Social commerce sellers should adopt customer-friendly return policies and communicate them clearly. Flexible return policies not only alleviate buyer concerns but also differentiate trustworthy sellers from riskier ones, ultimately enhancing trust and increasing purchase intentions. Additionally, seller reputation continues to play a pivotal role in reducing uncertainty. Sellers are advised to cultivate and maintain a strong reputation by delivering consistent quality and fulfilling their promises. The research

Appendix A

shows that customers tend to rely on seller reputation when making purchase decisions, which means that building a credible brand identity through consistent performance is essential for long-term success in social commerce. Finally, this study offers key recommendations for platform designers and social commerce managers. Platforms should prioritize interface designs that enhance the visibility of trust-building signals, such as clear product information, accessible customer reviews, seller ratings, and transparent return policies. These features can create a more trustworthy environment, reduce seller uncertainty, and improve the overall consumer experience. This focus on trust-building mechanisms can significantly enhance platform adoption and loyalty in developing economies.

6.3. Limitations and future research

While this study offers valuable contributions, it is not without limitations. First, the study is conducted within the setting of a developing country using a nonprobability convenience sampling technique, which may limit the generalizability of the findings to other regions with different social commerce dynamics. The sample reflects the characteristics of active social commerce users in Palestine, but caution should be exercised in extrapolating the results to broader populations or diverse market contexts. Future research could examine the same variables in other geographical and cultural settings to validate the universality of these findings. Second, this study focused on a limited set of signals (customer-based and seller-based) and did not explore other potential factors that may influence seller uncertainty, such as social influence or peer recommendations. Future studies could incorporate additional signals or expand the model to include other elements that may affect consumer perceptions and trust in social commerce platforms. Third, the cross-sectional nature of the data limits the ability to examine changes in seller uncertainty over time. Longitudinal studies could provide deeper insights into how seller uncertainty evolves with prolonged customer interaction and reputation-building efforts. Lastly, as the social commerce landscape continues to evolve with new technologies and business models, future research should also consider investigating the impact of emerging trends, such as AI-based customer service systems or blockchain-driven transparency, on reducing seller uncertainty.

CRediT authorship contribution statement

Fadi Herzallah: Writing – original draft, Data curation. **Mohammed A. Al-Sharafi:** Writing – review & editing, Project administration, Formal analysis.

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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Construct and sources	Code	Item
Seller popularity	SEP1	"This social commerce seller has a large number of followers"
	SEP2	"This social commerce seller receives many likes on his page"
Seller reputation	SER1	"This social commerce seller is well known"
	SER2	"This social commerce seller has reputation for being honest"
	SER3	"I am familiar with the name of the page of this social commerce"
Number of positive comments	NPC1	"This social commerce seller has a lot of positive customers' reviews"
	NPC2	"Most of the people I trust provide positive feedback about this social commerce seller"
	NPC3	"Most of my friends provide positive feedback about the quality of product from this social commerce seller"
Return policy leniency	RPL1	"This social commerce seller returns the goods in original price under any circumstances"
	RPL2	"This social commerce seller promises an easy return mode"
	RPL3	"This social commerce seller takes charge of the shipping fee of returning the commodities under any circumstances"
	RPL4	"This social commerce seller accepts the returns of promotion items"
	RPL5	"This social commerce seller accepts the returns due to consumers' preferences or inconsistent expectations."
Information quality	INQ1	"The page of this social commerce seller provides accurate information on the item that I want to purchase"
	INQ2	"The page of this social commerce provides reliable information"
	INQ3	"The page of this social commerce seller provides sufficient information when I try to make a transaction"
Seller uncertainty	SEU1	"I feel that this social commerce seller may have misrepresented the products in its page description"
	SEU2	"I am doubtful that this social commerce seller will deliver the products as promised in a timely manner"
	SEU3	"I am afraid that this social commerce seller may attempt to defraud me"
	SEU4	"I feel that dealing with this social commerce seller involves a high degree of uncertainty about the sellers' quality"

Data availability

Data will be made available on request.

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