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Social Influence and Purchase Intention in E-Commerce: The Moderating Role of Privacy Concern

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Abstract. With the rapid development of e-commerce and social media as online shopping channels, social influence has become one of the key factors shaping consumers' online shopping behavior. However, growing concerns about privacy and data risks during transactions continue to affect consumers' willingness to shop online. In this context, this study, based on signaling theory, examines the influence of social influence on purchase intention, both directly and through perceived risk, and investigates the moderating role of privacy concern. The study surveyed 232 consumers in Vietnam through an online questionnaire and analyzed the data using PLS-SEM. The results show that social influence directly affects purchase intention and negatively impacts perceived risk, which in turn negatively impacts purchase intention. Furthermore, privacy concern significantly moderates the relationship between perceived risk and purchase intention, indicating that the impact of perceived risk on purchase intention varies depending on the individual's level of privacy concern. However, this factor does not regulate the relationship between social influence and perceived risk. This research contributes to this area by integrating social factors, risk and privacy into a unified consumer behavior model. Through this, it proposes strategies for e-commerce businesses to combine data transparency with effectively leveraging social influence to build trust and improve positive online shopping experiences.

Keywords: Social influence; purchase intention; privacy concern; perceived risk

1. Introduction

The retail market has been profoundly reshaped by the rapid expansion of e-commerce (Wang et al., 2026), enabling consumers to conduct cross-border transactions with just a few clicks (Zhang et al., 2024). With its ability to facilitate instant, real-time transactions and eliminate geographical barriers, e-commerce has significantly reshaped consumer behavior, enhancing the shopping experience while optimizing time resources. However, due to the lack of direct interaction, the digital environment inadvertently creates psychological barriers because consumers cannot directly control or verify the security of the system. According to Lu (2024), online shopping on digital platforms puts users in a serious information asymmetry situation. In this context, shopping behavior is increasingly seen as an "opaque transaction environment," where risks stem not only from product quality but also from the potential loss of control over personal information. This asymmetry continuously widens the trust gap, hindering the conversion of short-term purchases into long-term customer loyalty (Ashiq & Hussain, 2024). Therefore, barriers to promoting online shopping are emerging due to deep consumer skepticism (Rasty et al., 2021). From a business perspective, without strategic and effective risk mitigation measures, subsequent marketing campaigns may become ineffective, counterproductive, or even perceived as merely reactive.

In the field of e-commerce, perceived risk and purchase intention have long been considered two opposing aspects that directly influence user decisions. In the modern context, risk is no longer considered a vague concept but has evolved into a concrete psychological relationship, closely linked to data privacy and the informational advantage that businesses hold on digital platforms (Handoyo, 2024). This structural asymmetry is further exacerbated by growing concerns about systemic vulnerabilities, which systematically raises the risk barrier and disrupts the continuous flow of online transactions (Alrawad et al., 2023). In the tension between the motivation for ownership and the fear of criticism related to information, social influence is recognized as a crucial prerequisite for resolving this conflict. Through social influence, social evidence is provided, allowing for a reassessment of perceived risk levels and a more positive rebalancing of decisions. However, instead of being considered separate factors, social influence and perceived risk are highlighted as lacking empirical evidence of their interaction within an integrated model. Previous studies (Chen et al., 2021; Hendrajaya et al., 2024) have tended to consider these factors separately, which inadvertently obscures the overall picture of consumer behavioral psychology. Specifically, it remains unclear whether the negative impact of perceived risk is consistently mitigated by social influence, especially when privacy concern is present. Therefore, a significant research gap emerges regarding how these factors function concurrently, as the existing literature has not assessed their combined dynamics within a single empirical framework. This is particularly important in the context of e-commerce service systems, where digital interactions are constant and complex, requiring a deeper understanding of how social signals and privacy concerns together shape risk interpretation and purchase intent within online platforms.

Based on the argument of the tension between benefit and risk, the context of interaction is further broadened through the lens of personalization in this study. In fact, uniform responses to the same information signal are not demonstrated, and in the voluntary shopping environment on digital platforms, trust is considered an intrinsic value that cannot be imposed. In this context, privacy concern is identified as an intrinsic filter that shapes the interpretation of environmental signals. Under the influence of privacy concern, the delicate balance between perceived risk and purchase intention undergoes complex transformations. At higher privacy concern levels, the effectiveness of positive social influence may be diminished, with safety signals perceived as potential threats. Conversely, privacy concern is also seen as an attenuating factor that weakens the negative impact of perceived risk on behavioral intention. By placing privacy concern as a higher-order moderating variable, individual differences in response are more effectively explained, and the fine line between trust and skepticism in the digital data age is more effectively delineated.

It is clear that privacy concern has been identified as a key factor governing the interpretation of perceived risk and social impact on digital platforms, thereby transforming safety assessment into a rigorous individual filtering process. However, in existing theoretical literature, privacy concern is largely viewed as a direct antecedent, rather than a moderating role in responses to systematically considered risks. The value of addressing this gap is demonstrated in two main aspects. From a theoretical perspective, this study shifts the focus from viewing privacy concern as a static barrier to conceptualizing it as a dynamic filtering mechanism, which can explain the differences in the impact of the same positive social signal among different customer groups. Without considering the moderating role of privacy concern, understanding the impact of social influence can be fragmented, which may have been idealized in previous studies. To narrow these perspectives, this study clearly addresses this theoretical limitation by examining the combined impact of social influence, perceived risk, and privacy concerns on consumer decisions. From a practical perspective, this study provides a point of reference for businesses in segmenting customers based on their sensitivity to data, thereby helping to avoid the unintended negative impacts of community-based marketing campaigns, especially when defense mechanisms are inadvertently activated in customer groups with high privacy concern.

Importantly, this integrated model makes a significant contribution to the development of e-commerce service systems by providing deeper insights into how system attributes interact with human psychology. By examining the boundaries of user anxiety and social validation, this study provides valuable insights into tailoring e-commerce service systems, ensuring they are not only technologically efficient but also psychologically aligned with user expectations. Furthermore, the findings enrich the literature on foundational trust by demonstrating that building consumer trust requires more than structural assurances. It requires an adaptive ecosystem where e-commerce service systems can proactively respond to individual risk perceptions (Handoyo, 2024). In terms of privacy governance, this research shifts the model from mandatory regulations to user-centric strategies. By illustrating the complex regulatory impacts of data sensitivity, this study provides a concrete framework for privacy governance, helping digital platforms design more transparent data processing protocols, ultimately bridging the trust gap and fostering long-term consumer loyalty in an increasingly skeptical digital environment.

The introduction presents the context of e-commerce development, identifies research gaps, and sets the objectives. In the theoretical framework, key concepts including perceived risk, social influence, privacy concern, and purchase intention are clarified, followed by a proposed research model and hypotheses. The methods section outlines the data collection process, sampling techniques, and analysis methods using PLS-SEM. The results section provides an evaluation of the measurement model, structural model, and empirically tested relationships. The discussion section summarizes theoretical contributions and managerial implications. Finally, the study concludes by outlining limitations and suggesting directions for future research.

2. Literature Review

2.1. The Signaling Theory (ST)

Signaling theory, originally developed by Spence (1978) and later conceptualized by Connelly et al. (2011), is used to explain decision-making behavior in contexts characterized by information asymmetry. Stiglitz (2000) further emphasizes two key aspects where this asymmetry becomes particularly important: information about quality and information about intent. In the first case, information asymmetry becomes apparent when one party lacks full awareness of the other party's characteristics. In the second case, asymmetry is equally important when one party is concerned about the behavior or behavioral intentions of the other party (Elitzur & Gavious, 2003). This dynamic is particularly relevant in the context of e-commerce, where consumers cannot directly observe the reliability of the seller or the precise mechanisms by which personal data is collected and used. Therefore, observable signals become the fundamental basis for consumer decision-making.

According to Connelly et al. (2011), the essence of ST lies in transmitting observable signals to provide information about unobservable attributes (such as purchase quality and information security). Social influence is expressed through user reviews, comments, and the purchasing behavior of previous consumers, serving as important social signals on e-commerce platforms. These signals help consumers infer the trustworthiness of the platform and the seller, thereby reducing uncertainty during transactions.

However, ST theory still has gaps, as today the effectiveness of signals depends not only on the individual but also on how they are interpreted. Research by Chen et al. (2024) shows that although platform or social signals can reduce perceived risk, consumer responses to signals are still influenced by their subjective assessments. Therefore, ST needs to be expanded by considering the catalytic factors that alter individual perceptions of received signals. This involves conceptualizing privacy concern as a receiver-side interpretive filter, shaping consumer evaluations of social and risk-related signals. By integrating privacy concern into the signaling framework, this research contributes to ST by demonstrating that the effectiveness of signals depends not only on signal quality but also on how the receiver interprets those signals.

2.2. Hypothesis Development

More importantly, signals do not directly influence decisions but instead operate through the user's cognitive processes, thereby shaping the decision-making process (Kamalul Ariffin et al., 2018). The interpretation of these signals forms perceived risk, an element reflecting consumers' subjective assessment of the potential negative consequences of online transactions, thus influencing the formation of purchase intention. However, the impact of social influence on risk perception is not uniform among individuals, it depends on how each person interprets their concerns about the issue. In this context, privacy concerns act as a crucial boundary condition, governing the interpretation of social signals and the shift from perceived risk to purchase intention in the internet commerce environment. Therefore, ST provides a solid theoretical foundation, explaining the direct and indirect mechanisms involved in shaping customer purchase intention while clarifying individual differences in signal interpretation. Perceived risk is understood as a form of behavioral belief that reflects an individual's subjective assessment of the potential negative consequences of a particular action (Garas, 2025). Based on ST, on e-commerce platforms consumers are aware of potential risks, which directly affects their decision-making process (Alrawad et al., 2023). This perspective also contributes to explaining how consumers process uncertainty and evaluate risk-related information during interactions on online retail platforms.

From a ST perspective, consumers make decisions about their behavior through their cognitive processes (Kamalul Ariffin et al., 2018). Therefore, perceived risk acts as an intermediary mechanism, transforming social signals into assessments of potential negative consequences in transactions on e-commerce platforms, including data leaks, privacy violations, and security attacks (Chen et al., 2024). Concerns about these risks on digital platforms reduce consumers' willingness to engage in online shopping (Pelaez et al., 2019). Therefore, perceived risk is consistently considered a significant barrier to consumer trust (Phamthi et al., 2024). Based on these arguments, the following hypothesis is proposed:

H1: Perceived risk negatively influences purchase intention.

Social influence refers to the psychological process by which an individual's thoughts, attitudes, or behaviors are influenced by the majority through mechanisms such as group identity, social norms, and interdependence (Shah & Asghar, 2023). With the development of digital platforms as they exist today, this process is strongly driven by factors such as information sources, messages, and delivery methods, thereby shaping signals that influence user decision-making (Schweidel et al., 2022). Overall, social influence is a complex process, due to the combined influence of group and media context, particularly in digital commerce service systems where consumers continuously interpret and respond to socially transmitted information.

In the context of e-commerce, social influence plays a crucial role in shaping consumer behavioral perceptions (Mrisha & Xixiang, 2024), stemming from the opinions and evaluations of group relationships surrounding personal life such as friends and relatives. According to ST, information asymmetry leads users to rely on positive, safe information sharing from others, along with successful transactions, as signals to assess the credibility of an internet commerce platform (Wang et al., 2025). Herd mentality also leads them to believe that if the majority are not concerned, then they themselves do not need to be cautious (Xingjun et al., 2024), thereby reducing perceived risk. In addition, social influence also promotes purchase intention with products that are widely supported and perceived as trustworthy, with the "behavioral imitation" effect attracting consumers to popular products (Vahdat et al., 2021). Simultaneously, online social interactions create a ripple effect, making consumers feel connected and validated in their choices. Therefore, social influence both reduces perceived risk and boosts purchase intention leading to the proposal of two research hypotheses:

H2: Social influence exerts a significant positive impact on purchase intention.

H3: Social influence negatively influences perceived risk.

Privacy concern refers to consumers' awareness of the risks associated with sharing and securing information during online shopping, particularly the potential for unintentional data leaks (Yun et al., 2013). This concept reflects the individual's right to control and regulate their personal information, while also expressing concern about unauthorized data breaches (Septiari & Putranta, 2025). In online shopping contexts, privacy concern functions as a cognitive filter through which consumers evaluate information and assess potential threats. Consumers with higher privacy concern tend to pay greater attention to privacy-related issues (Bandara et al., 2021) and engage in more careful information processing before making purchasing decisions (Sengupta & Cao, 2022). As a result, they are more likely to actively evaluate available safeguards and risk-mitigation mechanisms when confronted with potential risks (Lenhart et al., 2023). This heightened vigilance may reduce the extent to which perceived risk discourages purchase intention. Therefore, privacy concern is expected to weaken the negative relationship between perceived risk and purchase intention.

The impact of perceived risk and social influence depends on how individuals perceive and interpret market signals. When privacy concern is high, consumers tend to be skeptical and evaluate signals more rigorously (Panigyraki & Polyportis, 2024), thereby weakening the negative effect of social influence on perceived risk. Conversely, when privacy concern is low, they tend to accept positive signals such as social proof or favorable community feedback, thereby inferring that the platform is safe and willing to share information to receive benefits (Gutierrez et al., 2023). Therefore, privacy concern is expected to weaken the negative relationship between perceived risk and purchase intention while weakening the negative relationship between social influence and perceived risk.

H4: Privacy concern weakens the negative relationship between perceived risk and purchase intention.

H5: Privacy concern weakens the negative relationship between social influence and perceived risk.

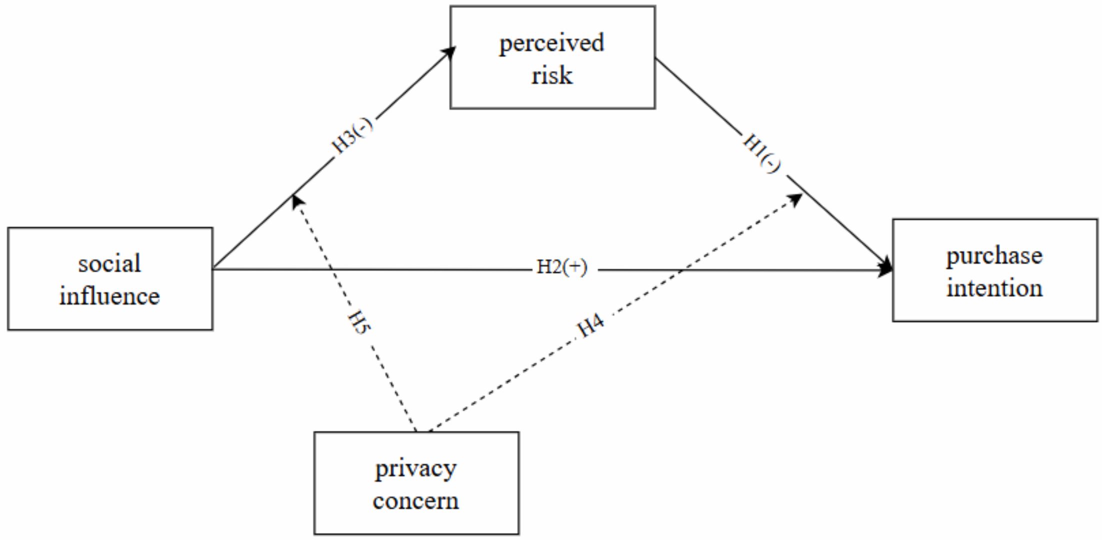

Fig 1: Research Model.

3. Methodology

3.1. Scale

The authors meticulously searched for, constructed, and refined the scales for each variable in the research model (See Appendix). Specifically, the purchase intention scale (3 observed variables) was adapted from Putrevu and Lord (1994). Although the scale was developed in the context of advertising, it has been widely applied in consumer behavior and e-commerce studies due to its general applicability in measuring purchase intention. In this study, the wording of the entries has been adapted to suit the e-commerce environment and the context of online shopping platforms. Social influence (7 items) consisted of 3 items developed by Cho and Chan (2021) and 4 items by Hu et al. (2019). Perceived risk (5 questions) was adapted by Kamalul Ariffin et al. (2018), and privacy concern (5 items) was developed by Yun et al. (2013).

The study used a 7-point Likert scale, ranging from 1 ("Strongly disagree") to 7 ("Strongly agree") and a non-probability sampling method, consisting of two parts: A – demographic information (gender, age, income, shopping platform) and B – measuring four variables purchase intention perceived risk, social influence, privacy concern with content adjusted to fit the e-commerce context.

3.2. Data Collection and Descriptive Statistics

The study used a non-probability convenience sampling method due to limitations in accessibility and time. Data were collected from February to April 2025 through an online survey distributed via social media platforms and online communities related to e-commerce and digital consumption, including Facebook groups, online networks, and messaging platforms.

Next, to ensure relevance, screening questions were included at the beginning of the survey. Participants were asked to confirm that they had previously made online purchases within the last 6 months. Answers indicating no experience or previous online shopping experiences were excluded from the dataset. Additionally, to ensure data quality, inconsistent and invalid answers were also removed before proceeding with the research analysis. Finally, a sample of 232 valid observations was obtained and used for further analysis.

By gender, women accounted for 69% and men for 31%, reflecting the trend that women tend to have a higher level of interest and participation in online shopping compared to men. By age, the 18–

30 age group accounted for 78.9%, mainly concentrated among young, tech-savvy consumers who frequently shop online. Although this characteristic does not represent the entire population due to non-probability sampling, it reflects the characteristics of the target group in the study: young, tech-savvy consumers who frequently interact with e-commerce. (See Table 1). All participants were informed about the confidentiality, ethical considerations, and scientific purpose of the survey. Participation in the study was entirely voluntary, and written informed consent was obtained electronically prior to participation.

Table 1: Descriptive Statistics.

Sample size N = 232		**Frequency**	**Percentage %**
Gender	Male	72	31.0
	Female	160	69.0
Age	18 - 30	183	78.9
	30 and over	49	21.1

4. Results

4.1. Measurement Model Evaluation

Measurement model analysis using SmartPLS focuses on three main assessments: convergent validity, reliability, and discriminant validity. Table 2 shows that outer loadings (λ) are greater than the threshold of 0.70, ensuring reliability (Garas, 2025). All factor loadings (λ) range from 0.749–0.910, meeting the requirement of adequately reflecting the latent constructs. Initially, the observed variable PC5 had an outer loading lower than 0.70. According to the recommendation of Hair and Alamer (2022), indicators with low outer loadings should be considered for removal to improve the reliability and convergent validity of the scale. Therefore, PC5 was removed from the model. After running the PLS-SEM analysis for the second time, all measurement indicators met the required thresholds, and all remaining outer loadings were above 0.70.

Cronbach’s Alpha ranged from 0.783–0.895. Still, CR is preferred in PLS-SEM because it more accurately assesses scale reliability than Cronbach's alpha. Therefore, Composite Reliability (CR) values from 0.860–0.932 are considered acceptable (Hair et al., 2019). The AVE values are higher than 0.5 (0.605–0.820) further confirm the convergent validity of the model after adjustment.

Table 2: Results of the Reliability and Convergent Validity Assessment.

Constructs	**Items**	**Loadings**	**α**	**CR**	**AVE**
Purchase intention	PI1	0.910	0.890	0.932	0.820
	PI2	0.910			

	PI3	0.897			
Perceived risk	PR1	0.870	0.895	0.923	0.705
	PR2	0.861			
	PR3	0.864			
	PR4	0.803			
	PR5	0.799			
Social influence	SI1	0.758	0.894	0.917	0.612
	SI2	0.795			
	SI3	0.841			
	SI4	0.758			
	SI5	0.807			
	SI6	0.755			
	SI7	0.758			
Privacy concern	PC1	0.787	0.783	0.860	0.605
	PC2	0.781			
	PC3	0.749			
	PC4	0.794			

The Heterotrait–Monotrait Ratio (HTMT) method was used to assess discriminant validity between constructs, due to its stronger ability to detect discriminant validity compared to traditional methods (Henseler et al., 2015). HTMT measures the degree of distinction between constructs, ensuring that the scales represent distinct concepts and enhancing the reliability of the model. Compared to the Fornell and Larcker (1981) method, HTMT is considered more sensitive and more accurate (Hair et al., 2019). As shown in Table 3, all HTMT values in this study are below the threshold of 0.85, confirming that the scales achieve good discriminant validity and supporting the reliability of the conclusions drawn from the model.

Table 3: Discriminant Validity.

	PC	PI	PR	SI
PC	-	-	-	-
PI	0.335	-	-	-
PR	0.207	0.192	-	-
SI	0.486	0.800	0.129	-

4.2. Structural Model Evaluation

The Variance Inflation Factor (VIF) was used to assess multicollinearity among the independent variables. According to Hair et al. (2019), VIF > 5 indicates high correlation that may bias the estimates. In this study, the VIF values ranged from 1.486–2.728, all below the acceptable threshold, indicating that the model did not suffer from multicollinearity (See Table 4). Regarding explanatory power, R^2 represents the proportion of the variance of the dependent variable explained by the model (Shmueli & Koppius, 2011). Based on the criteria of Hair et al. (2011), the model achieves $R^2 = 0.535$ for purchase intention indicating a moderate level of explanatory power, and $R^2 = 0.074$ for perceived risk, which is low but still reflects a certain role of perceived risk in the model. In addition, Q^2 reflects the predictive relevance of the model (Sarstedt et al., 2021). The results show that purchase intention has $Q^2 = 0.503$, indicating good predictive ability, while perceived risk reaches 0.022, although low, it still exceeds the minimum threshold, ensuring the predictive relevance of the model.

Table 4: Structural Model Evaluation Results.

	VIF	**R^2**	**Adjusted R^2**	**Q^2**
PI	2.424 - 2.728	0.535	0.527	0.503
PR	1.913 - 2.681	0.074	0.062	0.022
SI	1.874 - 2.464	-	-	-
PC	1.486 - 1.610	-	-	-

To evaluate the overall fit of the structural model, this study used the SRMR (Standardized Root Mean Square Residual) and NFI (Normed Fit Index) indicators. According to the strict standard of Hu and Bentler (1999), a model achieves good fit when the SRMR value is lower than 0.08. The PLS-SEM results showed that the SRMR value was 0.059, which is below the threshold of 0.08, indicating that the model fits the data well. For the NFI index, the result was 0.822. Although the ideal threshold for NFI is above 0.90, Hooper et al. (2008) suggested that values above 0.80 are still considered acceptable for behavioral research models.

Table 5: Structural Model Fit Assessment Indicators.

Conformity Assessment Index	**Estimated model**
SRMR	0.059
NFI	0.822

To increase methodological rigor and test the stability of the linear relationships, this study conducted a confidence interval analysis using the bootstrapping technique (N = 5,000). The 95% bias-corrected confidence interval results are presented in Table 6. The results show that most hypotheses were supported, except for H5. Social influence has a negative impact on perceived risk ($\beta = -0.232$, $p < 0.05$), indicating that stronger social influence reduces consumers' perceived risk in e-commerce transactions, thereby reducing hesitation in purchase intention ($\beta = -0.090$, $p = 0.032$). At the same time, social influence also has a positive effect on purchase intention ($\beta = 0.708$, $p < 0.05$), emphasizing its role in promoting consumer behavior. Privacy concern moderates the relationship between perceived risk and purchase intention ($\beta = 0.068$, $p = 0.023$), reducing the negative impact when concern increases. However, H5 is not supported ($\beta = -0.028$, $p = 0.693$), indicating that privacy concern does not affect the relationship between social influence and perceived risk.

Table 6: Hypothesis Testing Results.

Hypothesis	**β**	**T-value**	**P-value**	**f^2**	**2.5%**	**97.5%**	**Result**
H1: Perceived Risk → Purchase Intention	-0.090	2.140	0.032	0.02	-0175	-0.012	Accepted
H2: Social Influence → Purchase Intention	0.708	11.101	0.000	0.855	0.575	0.822	Accepted
H3: Social Influence → Perceived Risk	-0.232	4.057	0.000	0.047	-0.348	-0.121	Accepted
H4: Privacy Concern x Perceived Risk → Purchase intention	0.068	2.268	0.023	0.03	0.017	0.136	Accepted

H5: Privacy Concern x Social Influence → Perceived Risk	-0.028	0.394	0.693	0.001	-0.166	0.108	Rejected

To reduce the possibility of Common Method Bias (CMB), which may affect and distort the relationships in the model, this study applied the Full Collinearity Assessment technique using Inner VIF values, following the recommendation of Kock (2015). The detailed results from the Inner Model List in SmartPLS are presented in Table 7. The Inner VIF values of all structural relationships ranged from 1.038 to 1.323, which are all lower than the threshold value of 3.3 (Kock, 2015). These results indicate that the model is not affected by Common Method Bias (CMB), and the data have sufficient reliability for further analysis (Table 7).

Table 7: Inner VIF Results for Common Method Bias Assessment.

Path	**Inner VIF**
PR → PI	1,079
SI → PI	1,260
SI → PR	1,233
PC x PR → PI	1,038
PC x SI → PR	1,106

To evaluate the out-of-sample predictive power of the structural model, this study applied the PLSpredict procedure with k-fold cross-validation following Shmueli et al. (2019). The results showed that all Q^2 values were greater than 0, confirming the model's predictive relevance. In addition, 7 out of 8 indicators had lower RMSE values in the PLS-SEM model compared to the Linear Model (LM), while only PI3 showed a slightly higher RMSE value. Based on the guidelines of Shmueli et al. (2019), since most indicators performed better than the benchmark model, the study concludes that the model has medium predictive power. This result indicates that the proposed theoretical model is not only statistically significant but also has practical value for predicting consumer behavior in new samples (Table 8).

Table 8: Out-of-Sample Predictive Power Assessment Results (PLSpredict).

Observable	**Q^2 predict**	**PLS-SEM_RMSE**	**LM_RMSE**
PI1	0,408	1,218	1,273
PI2	0,407	1,219	1,245
PI3	0,416	1,235	1,213

PR1	0,035	1,778	1,785
PR2	0,008	1,768	1,793
PR3	0,001	1,873	1,909
PR4	0,026	1,861	1,869
PR5	0,017	1,771	1,772

5. Discussion

In the context of increasingly widespread technology, research on purchase intention plays a pivotal role in explaining online shopping behavior and guiding business strategy. The results indicate that perceived risk has a negative effect on purchase intention ($\beta = -0.090$, $p = 0.032$) which is consistent with prior studies identifying perceived risk as a psychological barrier to consumer trust in e-commerce (Majeed et al., 2024). Accordingly, consumers tend to avoid purchasing behaviors when they perceive the possibility of loss or uncertainty. Therefore, consumers often remain concerned because they cannot directly verify the processes and may feel a lack of control (Handoyo, 2024), even though platforms have invested substantially in security measures. From Signaling Theory's perspective, doubts about transparency in protection or incident handling tend to increase due to information asymmetry related to privacy policies between sellers and buyers (Wang et al., 2025). Perceived risk is constantly being amplified based on negative experiences or feedback, leading consumers to rely on subjective reviews despite technological advancements.

Furthermore, social influence helps reduce perceived risk ($\beta = -0.232$) and increase purchase intention ($\beta = 0.708$). This effect stems from belief in the community, social support, and the sharing of experiences within relationships. When faced with uncertainty, individuals tend to rely on the behavior and opinions of others as a cognitive shortcut in decision-making. Therefore, relationships with friends, family, or interest groups create a layer of psychological safety (Wang et al., 2021), and social consensus helps promote the herd effect (Vahdat et al., 2021). This leads consumers to trust and follow popular choices even without direct experience, as they view widespread acceptance as an implicit signal that risk can be managed. Furthermore, positive online reviews act as social proof (Senali et al., 2024), increasing trust and perceived usefulness, thereby reinforcing and driving purchase decisions.

At the same time, privacy concern moderates the relationship between perceived risk and purchase intention ($\beta = 0.068$, $p = 0.023$), extending the approach of previous studies (Chaudhuri et al., 2023; Phamthi et al., 2024). Although high perceived risk increases anxiety, when the perceived benefits are attractive enough, consumers tend to reduce risk rather than abandon the transaction. The psychological phenomenon of effort justification makes consumers less willing to give up after spending time selecting products, reading reviews, and comparing prices. They feel that they have already invested effort, making it difficult to cancel the transaction and return to the starting point (Park & Hill, 2018). Therefore, when privacy concern is high, consumers respond positively to security measures. Since these concerns mainly come from the feeling of losing control over personal data privacy, consumers choose behaviors that help them regain control, such as checking security features, selecting payment methods, or limiting information sharing (Wang et al., 2025). As the feeling of control increases, although high perceived risk reduces purchase intention, security measures can help reduce anxiety and maintain purchase intention.

Conversely, privacy concern does not significantly moderate the relationship between social influence and perceived risk (H5). This result contradicts previous studies by Neves et al. (2024), which suggested that privacy concern may weaken the impact of social factors on online behavior. In other words, when individuals lose control over the amount of information, they activate defense mechanisms. Under the moderating role of privacy concern, they become more sensitive to risk and proactively seek security measures. However, this study shows a different model, indicating that academic views remain divided on the moderating role of privacy concern.

Instead of allowing personal data protection (privacy concern) to mitigate the impact of social influence, consumers seem to prioritize social validation and specific benefits over concerns related to personal data. In this context, perceived risk manifests itself in various aspects such as information risk, counterfeiting, financial risk, delivery risk, and psychological risk, leading consumers to opt for cash-on-delivery (COD) or to consult reviews and compare prices across multiple platforms before making a purchase decision. Simultaneously, in collectivist cultures where the influence of friends and community plays a prominent role (Buck & Smith, 2015), consumers are willing to trade personal data for specific benefits, and they tend to prioritize collective validation of a transaction over personal concerns about data exposure. Therefore, consistent with the arguments of Dinev and Hart (2006) and Taddicken (2014), online behavior is shaped by the balance between benefits and risks rather than solely by privacy concern, making privacy concern insufficient to moderate the relationship between social influence and perceived risk.

6. Conclusion

This study aims to clarify the interactive relationships between perceived risk, social influence, privacy concern, and purchase intention in the context of e-commerce. Specifically, the study examines whether social influence can mitigate the negative impact of perceived risk and whether privacy concern plays a significant moderating role in this process. The PLS-SEM results show that perceived risk negatively impacts purchase intention, while social influence both reduces perceived risk and strongly promotes purchase intention, thus confirming social influence's contribution to reshaping risk perception. Privacy concern moderates the relationship between perceived risk and purchase intention (Liao et al., 2021) but does not moderate the impact of social influence on perceived risk. This suggests that in a collectivist culture context, social influence can still dominate perceived risk even in the presence of privacy concern.

6.1. Theoretical Implication

This study redefines social interactions as essential quality signals that help mitigate information asymmetry, thereby expanding the application of signaling theory in e-commerce environments. The main contribution lies in demonstrating that social influence is not only a direct motivator but also a reliable source of information that compensates for unobservable deficiencies, allowing consumers to reassess perceived risk before making transactional decisions.

Furthermore, the study clarifies the role of privacy concern as a boundary condition that controls the level of risk influencing purchase intention. Rejecting the moderating role of privacy concern in the relationship between social influence and perceived risk (H5) opens a potential new avenue of discussion. In the digital age, social proof signals can exert overwhelming power, which is enough to neutralize individual defense mechanisms and redirect purchasing behavior even when data-related concerns persist. These findings provide a comprehensive theoretical framework to explain the consumers' psychological journey, in which the tension between risk and benefit is resolved through social interactions and individual control thresholds.

6.2. Practical Implication

This study suggests that e-commerce platforms should shift from a purely formal approach to transparency to mechanisms that directly intervene in consumers' privacy perceptions. Platforms could implement viable solutions such as clearly displaying collected data and its intended use at the time of transaction. This allows users to easily control personalization options and standardizes the review system through buyer authentication and review content control. Simultaneously, integrating trust-building signals, such as commitments to privacy or guarantees against sharing data with third parties, directly into the purchase interface could help reduce ambiguity and increase the sense of security.

For businesses, instead of simply complying with legal requirements, they need to implement proactive privacy policies such as opt-in mechanisms, allowing users to control (access, edit, or delete) personal data they have consented to or declined for collection. This ensures transparency in determining the purpose of data collection and use. Simultaneously, providing simple explanations for content personalization can increase transparency, thereby strengthening consumer trust.

At the regulatory level, regulations on data transparency and oversight facilitate consumer awareness of how, by whom, and for what purpose their data is used. When businesses are required to disclose how they collect and use data, consumers can easily assess the level of security before making purchase decisions. Simultaneously, accountability and violation handling mechanisms provide consumers with a basis for complaints and protection when their privacy is violated, thereby increasing user trust in online transactions.

7. Limitations and Future Research Opportunities

Despite its contributions, this study has several limitations. First, the sample size is relatively narrow, primarily reflecting young consumers, and thus does not fully encompass other age groups with varying behaviors and risk perceptions. Second, the study employs a cross-sectional design, meaning it cannot track behavioral changes over time. Future studies should expand the sample to be more diverse in terms of age, occupation, and region, and incorporate a longitudinal research design with multiple data collection methods. Finally, the integration of alternative behavioral theories is recommended to enrich the analytical framework and improve predictive capabilities.

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Appendix

Construct	Code	Measurement Item	Adapted form
Perceived Risk	PR1	I feel that my credit or debit card details are not secure when shopping on e-commerce platforms.	Kamalul Ariffin, S., Mohan, T., & Goh, Y. N. (2018). Influence of consumers' perceived risk on consumers' online purchase intention. *Journal of Research in Interactive Marketing*, *12*(3), 309–327. https://doi.org/10.1108/JRIM-11-2017-0100
	PR2	E-commerce platforms may not provide a secure shopping environment.	
	PR3	Online shopping platforms may disclose my personal information without my consent.	
	PR4	I may receive unwanted contact from other companies after shopping online.	
	PR5	Information provided by online shopping platforms may be insufficient regarding how personal data is handled.	
Social Influence	SI1	When making online shopping decisions, I often consult other people for useful information.	Cho, V., & Chan, D. (2021). How social influence through information adoption from online review sites affects collective decision making. *Enterprise Information Systems*, *15*(10), 1562–1586. https://doi.org/10.1080/17517575.2019.1651398
	SI2	When making online shopping decisions, I often search for online reviews.	
	SI3	When making online shopping decisions, I frequently gather information from others.	
	SI4	I often consult other people on e-commerce platforms to help choose the best products.	Hu, X., Chen, X., & Davison, R. M. (2019). Social support, source credibility, social influence, and impulsive purchase behavior in social commerce. *International Journal of Electronic Commerce*, *23*(3), 297-327.
	SI5	I frequently gather information from e-commerce platforms before purchasing products.	
	SI6	To make sure I buy the right product or brand, I often observe what other users on e-commerce platforms are buying and	

		using.	https://doi.org/10.1080/10864415.2019.1619905
	SI7	If I have little experience with a product, I often ask others on e-commerce platforms about the product.	
Purchase Intension	PI1	It is very likely that I will purchase products from this online shopping platform	Putrevu, S., & Lord, K. R. (1994). Comparative and noncomparative advertising: Attitudinal effects under cognitive and affective involvement conditions. *Journal of Advertising*, *23*(2), 77–91. https://doi.org/10.1080/00913367.1994.10673443
	PI2	I intend to purchase from this online shopping platform the next time I need a product.	
	PI3	I will definitely consider purchasing from this online shopping platform in the future.	
Privacy Concern	PC1	I am concerned that online shopping platforms collect too much personal information about me.	Yun, H., Han, D., & Lee, C. C. (2013). Understanding the use of location-based service applications: Do privacy concerns matter? *Journal of Electronic Commerce Research*, *14*(3), 215–230.
	PC2	I am concerned that online shopping platforms may not take sufficient measures to prevent unauthorized access to my personal information.	
	PC3	I am concerned that online shopping platforms may store my personal information inaccurately in their databases.	
	PC4	I am concerned that online shopping platforms may share my personal information with other parties without my permission.	
	PC5	Overall, I feel unsafe providing personal information when shopping on e-commerce platforms.	