"Assessing the impacts of peer-to-peer recommender system on online shopping: PLS-SEM approach"

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ASSESSING THE IMPACTS OF PEER-TO-PEER RECOMMENDER SYSTEM ON ONLINE SHOPPING: PLS-SEM APPROACH

Abstract

Peer-to-peer recommender systems play a critical role in online shopping in Vietnam. This paper aims to identify the relationship between Recommendation Quality and Purchase Intention and the moderating effects of Attitude and Trust on this relationship. Partial Least Squares Structural Equation Modeling was used as a research method. The sample consisted of 365 respondents who frequently use recommender system when shopping online. Data were collected using non-probability sampling method. The questionnaire is delivered to online customers who frequently rely on peer-to-peer recommender systems to make a purchase decision. The results show that Recommendation Transparency, Recommendation Accuracy, Recommendation Novelty, and Recommendation Diversity are positively related to Recommendation Quality. Consequently, Recommendation Quality has a positive impact on Attitude, Trust, and Purchase Intention. Besides, Attitude has a positive impact on online Purchase Intention. Trust also has a positive impact on online Purchase Intention. Practical implications are proposed to improve the impacts of peer-to-peer recommender systems on online shopping.

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Keywords Recommendation Quality, Attitude, Trust, Purchase Intention, PLS-SEM

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INTRODUCTION

In recent years, the outlook of online shopping has undergone a remarkable transformation, with an increasing number of consumers turning to e-commerce platforms for their purchasing. Online shopping has led to a massive influx of products and choices, making it challenging for consumers to navigate the vast array of available options. In response to this challenge, peer-to-peer recommender systems have emerged as crucial tools for enhancing the shopping experience, aiding consumers in discovering products that align with their preferences and needs (Sivapalan et al., 2014). Recommender systems are tools for interacting with large and complex information spaces (Burke et al., 2011). Peer-to-peer recommender systems were introduced to solve this problem, providing personalized product recommendations based on user behavior, preferences, and historical data (Himeur et al., 2022). Peer-to-peer recommender systems utilize various algorithms and techniques to predict and suggest products a user might be interested in. Combining search behavior and shopping cart retention will help the system recommend accurate information (Zhao & Keikhosrokiani, 2022). By presenting product suggestions, these systems facilitate the discovery of items that align with consumers' tastes and preferences (Zhang et al., 2020). The insights into the impact of customer behavior on the recommendation system integration process can result in competitive advantages. Most previous re-

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search has predominantly focused on the quantitative factors that impact Purchase Intention. The qualitative dimension of how consumers perceive and interact with these systems still needs to be explored. Hence, this paper considers the emotional and cognitive responses elicited by personalized recommendations and Attitude and Trust from the quality of information suggested to have different consumer effects towards purchase (Sung et al., 2023). The research question investigates the relationship between perceived Attitude and Trust from receiving information on peer-to-peer recommendation systems on Attitude and Trust responses and long-term implications.

1. LITERATURE REVIEW AND HYPOTHESES

In this study, approaching attitude theory, attitude is defined as customer behavior and attitudes, in which user attitudes are formed primarily based on three aspects: perception, emotion, and behavior (Eagly & Chaiken, 1993). Bagozzi and Warshaw (1992) also view the attitude-behavioral relationship using the variable mediating the emotional response between cognitive assessment and action response. Other related studies have also shown the impact of assessing internal conditions and situations on emotional responses, affecting individuals' activities. The principles of each individual's influence are defined from receiving information to perceiving information to creating adequate levels and implementing behavior. Customer activities on the website or web applications have been recorded in real time. WebQuery 4.0 has been developed, and the process used the SERVQUAL scale service quality to measure the expectations and perceptions of consumers (Parasuraman et al., 1988). Therefore, the hypotheses synthesized from related studies on customer behavior in the web environment are systematized literature reviews. Consumers' evaluation of recommended products is influenced by many factors, including the alignment of suggestions with their preferences, past behaviors, and current needs (Raza & Ding, 2022). Besides, the importance of text mining is increasing in services management as access to big data is increasing across digital platforms, enabling such services (Kumar et al., 2021). A positive perception of accuracy fosters a sense of personalized assistance, leading to increased engagement and potential conversions. Conversely, inaccuracies can lead to frustration and undermine the user experience. Investigating the perceptual gap between the accuracy of recommendations and consumers' subjective assessment offers valuable insights into the psychology of decision-making in the digital shopping outlook.

Accuracy is the closeness between a measurement and the actual value (Teller, 2018). The accuracy of recommended products is pivotal in recommender systems' efficacy within B2C e-commerce. Consumers' perceptions of the precision and relevance of these recommendations significantly influence their Trust in the system and subsequent purchase decisions (Zhu et al., 2020). Customers perceive recommendation accuracy in e-commerce platforms. Pecune et al. (2022) explain the perception of how accurately the recommended products align with the user's needs. Chopdar et al. (2022) confirm that customers often search for products, keep products in their shopping carts, and customer perception to which the recommendations are tailored to the individual user's browsing and purchasing history. Zhang et al. (2019) insist on the perception of how closely the recommended products reflect the user's recent browsing and search behavior.

In the rapid development of e-commerce, where consumers are inundated with an abundance of options, the role of recommender systems in aiding product discovery has become paramount. As consumers navigate through the digital aisles of online stores, the perceived novelty of recommended products has emerged as a critical factor influencing their engagement and decision-making. There is research on the complex relationship between perceived recommendation novelty and its impact on the overall recommendation quality within e-commerce platforms. Perceived recommendation novelty refers to how consumers perceive the suggested products as fresh, intriguing, and aligned with their evolving preferences (Luan & Kim, 2022). A novel recommendation captures consumers' attention and suggests that the system understands their interests beyond the obvious choices (Möller et al., 2020). This perception of novelty can lead to heightened user curiosity and prolonged platform exploration, potentially resulting in increased time

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exploration of customers. Simultaneously, new suggestions have brought the shopping experience (Hoyer et al., 2020). Measuring the right balance between novelty and relevance is crucial for enhancing user engagement, Trust in recommendations, and purchase behavior.

Consumers are presented with an abundance of choices, and the efficacy of peer-to-peer recommender systems in guiding purchasing decisions is undeniable (Chiu et al., 2021; Wang, 2023). Among the factors influencing consumer engagement and satisfaction, the perceived diversity of recommended products has emerged as a pivotal dimension. Nguyen et al. (2022) confirm that perceived recommendation diversity encapsulates consumers' belief that the recommended products span a wide range of options, catering to different tastes and preferences. The system suggests similar recommended items of the same acceptable quality level (Pu et al., 2011). Besides, the system suggests products with many standards in terms of specifications and characteristics (Pavlidis, 2019). Diverse recommendations can capture consumer interest, encouraging exploration beyond their typical choices and fostering a sense of discovery. This perception of diversity can enhance user Trust and Attitude, potentially leading to higher chances of purchase conversion.

As e-commerce continues to flourish, the role of peer-to-peer recommender systems in guiding consumer decisions has gained prominence. Among the factors that shape consumers' interactions and decisions, the perceived transparency of recommended products has emerged as a significant dimension (Shin, 2021). Many scholars study consumer perception of recommendation transparency and its implications for the overall recommendation quality within e-commerce platforms (Oliveira et al., 2023). Shin (2021) states that perceived recommendation transparency reflects consumers' understanding of how recommendations are generated and the criteria underlying the suggestions. Transparent recommendations offer consumers insight into why certain products are suggested, instilling a sense of Trust and understanding (Köbis et al., 2021). This perception of transparency improved explained contents show transparency to help customers trust and enhance consumer confidence, leading to more informed choices and fostering a positive relationship with the platform (Wang et al., 2019). The connection between perceived Recommendation Transparency and Quality is multifaceted. While transparent recommendations engender Trust, they must not compromise on personalization and relevance.

The importance of data-driven decisions and support is increasing daily in every management area. The constant access to volume, variety, and veracity of data has made big data an integral part of management studies (Kushwaha et al., 2021). Therefore, the role of peer-to-peer recommender systems in influencing consumer behavior and shaping purchasing decisions is paramount. This study analyses the relationship between consumers' perception of recommendation quality, their attitudes towards the platform, and the level of Trust in recommendation content in e-commerce platforms (Yuwen et al., 2022). When a customer's perceived Recommendation Quality embodies consumers' assessment of the accuracy, relevance, and personalization of the suggested products (Pappas et al., 2017), recommendations quality resonates with individual preferences and needs, enhancing the user's positive Attitude towards the platform (Dwivedi et al., 2021). This perception of recommendation quality can increase engagement and improve customer confidence (Itani et al., 2019). Importantly, positive experiences with quality recommendations can foster favorable attitudes, creating a cycle of Trust (Kemp et al., 2020). Consumers are more likely to trust a recommendation system that consistently delivers relevant and accurate suggestions, as it aligns with customer preferences and improves shopping experience.

In the e-commerce platform, progress from reception of information, perceived contents, effect attitude, affect trust and purchase intention. The interplay between consumer attitudes, trust, and purchase intention has garnered substantial attention from researchers and administrators (Konuk, 2018). Hanaysha (2022) showed that informativeness, perceived relevance, and interactivity positively affect purchase decisions. This relationship is intertwined with a comprehensive understanding of the mechanisms that drive consumer behavior in e-commerce platforms. Consumer at-

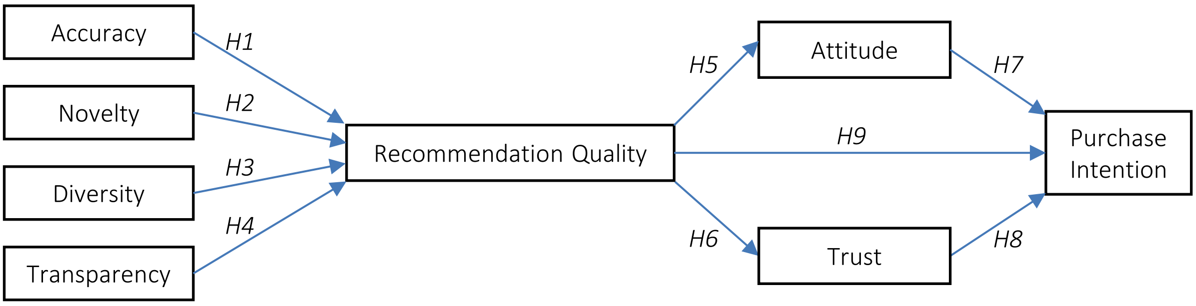

Figure 1. Research model

titudes, reflecting individuals' overall evaluations and perceptions, are pivotal in shaping purchase intentions within e-commerce platforms. Positive attitudes towards the Recommendation Quality translate into favorable perceptions of the shopping experience, product quality, and convenience, all of which contribute to a heightened likelihood of Purchase Intention (Ramanathan et al., 2017). Trust is foundational in fostering a relationship between consumers and Recommendation Quality in e-commerce platforms. Trust is built upon the accuracy consumers have from recommendation's reliability and Recommendation Transparency (Shin, 2021). As consumers perceive Trust influences their Purchase Intention, the Trust established with Recommendation Quality positively correlates with consumers' intention to make purchases (Everard & Galletta, 2005). The relationship between Attitude and Trust is inherently intertwined. Positive attitudes towards recommendation content often stem from establishing Trust (Guttentag, 2019). When consumers perceive the recommendation as trustworthy, their Attitude becomes more favorable, enhancing Purchase Intention (Osei-Frimpong et al., 2019). The interdependence between Attitude and Trust is supported by studies that emphasize the mediating role of Trust in linking Attitude to Purchase Intention (Jadil et al., 2022).

This study aims to assess the impacts of peer-to-peer recommender system on online shopping. The following hypotheses have been constructed in light of a literature review (Figure 1):

H1: *Recommendation Accuracy has a positive impact on Recommendation Quality.*

H2: *Recommendation Novelty has a positive impact on Recommendation Quality.*

H3: *Recommendation Diversity has a positive impact on Recommendation Quality.*

H4: *Recommendation Transparency has a positive impact on Recommendation Quality.*

H5: *Recommendation Quality has a positive impact on Attitude.*

H6: *Recommendation Quality has a positive impact on Trust.*

H7: *Attitude has a positive impact on online Purchase Intention.*

H8: *Trust has a positive impact on online Purchase Intention.*

H9: *Recommendation Quality has a positive impact online Purchase Intention.*

2. METHODOLOGY

The survey questionnaire yielded data in two distinct sections. The first part encompassed inquiries and details related to the respondents' demographic characteristics, including gender, age, and frequency of monthly purchases (Jayasankara et al., 2011). The second part involved five-point Likert scale assessments, ranging from "disagree" to "strongly agree" (Likert, 1932). The survey content is designed on the Google Drive link application. Only customers who agree to participate will receive the survey link. In cross-sectional study design, sample size depends on many factors, such as the degree of certainty of the characteristics of the generalized sample size for the population characteristics, the accuracy requirement for the estimate made from the sample,

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the technique statistical technique that requires the sample size to reach a particular value. In this study, customers who have purchased on e-commerce platforms were selected, data processing was performed using CFA and PLS-SEM analysis. Representative sampling recommendations in PLS-SEM are based on the Ordinary Least Squares (OLS) character. The PLS-SEM approach guidelines use sample sizes, according to Cohen (1992), at least 10 times the formative observatory of measurement for a concept or 10 times the maximum number of paths impacting a concept in a model (Hair et al., 2020). The study had 7 independent measurement variables: the endogenous variable in the structural model with 1%significance level, the detected minimum correlation value of 0.10, statistical sensitivity of 80%, and the minimum sample size of 188. The data acquisition process has a 5% bias. The minimum number of samples for the study is 282 responses. Therefore, to ensure sufficient sample size and follow the principle of sample collection, 400 samples are needed to submit survey content. The result of returned responses is 365, with a return rate of 91.25%.

A comprehensive data screening procedure was used to analyze the data collected via the self-administered questionnaire. Initially, various aspects were evaluated for each item, including missing data, outliers, normality, and inter-item correlations. Subsequently, the sufficiency of covariances and Cronbach's alpha were computed for each construct. Finally, a confirmatory factor analysis was conducted for each construct (Bujang et al., 2018).Following the data screening process, the conceptual model underwent testing through Cronbach's alpha analysis. This testing was divided into the measurement aspect (confirmatory factor analysis (CFA)) and the structural equation modeling aspect (PLS-SEM). To comprehend intricate structural relationships, the model incorporated complex connections among variables. Thus, the utilization of PLS-SEM was deemed appropriate. PLS-SEM facilitates the establishment of coherent relationships between multiple observed structures simultaneously, accounting for measurement errors in the analysis (Hair et al., 2020).

The distribution of demographic traits within the sample with corresponding frequencies and percentages can be found in Table 1. Predominantly, the participant pool consisted of females, accounting for 60.5% of the total. Regarding age distribution, individuals between 30 and 39 years comprised the largest segment, making up 60.8% of the sample. When considering the frequency of monthly purchases, a significant portion, precisely 78.1%, indicated making purchases 1 to 3 times within the given time frame.

Table 1. Characteristics demographics

Variable	Item	Frequency	Percent
Gender	Male	144	39.5
	Female	221	60.5
Age	18-29	95	26.0
	30-39	222	60.8
	39-50	20	5.5
	Older than 50	28	7.7
Frequency of purchases during the month	One time	55	15.1
	1-3 times	285	78.1
	More than 3 times	25	6.8

3. RESULTS AND DISCUSSION

In Table 2, the values reported on the scale reliability test are according to Cronbach's alpha. Internal consistency reliability refers to how consistent the measurements of different indicators are on a scale (Vaske et al., 2017). The main idea behind internal consistency reliability is that these indicators should be closely related to one another, forming a reliable measurement model. It is a positive outcome if the indicators show favorable correlations among themselves (inter-items) (Clark & Watson, 2016). Cronbach's alpha is the most common approach to reliability testing. Cronbach's alpha reflected the degree of correlation in the responses. The smallest Cronbach's alpha coefficient is 0.7, and the significant corrected total correlation is 0.5 (Hair et al., 2020).

Table 2. Cronbach's alpha scale reliability analysis results

Code	Variable	Cronbach's alpha
RA	Recommendation Accuracy	0.82
RN	Recommendation Novelty	0.86
RD	Recommendation Diversity	0.83
RT	Recommendation Transparency	0.86
RQ	Recommendation Quality	0.89
PA	Attitude	0.89
TR	Trust	0.89
PI	Purchase Intention	0.90

Note: RA = Recommendation Accuracy, RN = Recommendation Novelty, RD = Recommendation Diversity, RT = Recommendation Transparency, RQ = Recommendation Quality, PA = Attitude, TR = Trust, PI = Purchase Intention.

Table 3. Discriminant validity for scale measurement of constructs

	CR	AVE	PA	PI	RA	RD	RN	RQ	RT	TR
PA	0.897	0.828	0.910							
PI	0.907	0.779	0.46	0.883						
RA	0.862	0.732	0.162	0.238	0.856					
RD	0.836	0.749	0.084	0.211	0.327	0.865				
RN	0.862	0.783	0.084	0.188	0.336	0.266	0.885			
RQ	0.896	0.759	0.363	0.431	0.392	0.306	0.383	0.871		
RT	0.893	0.788	0.13	0.153	-0.106	-0.008	-0.021	0.242	0.888	
TR	0.902	0.824	0.524	0.461	0.184	0.07	0.056	0.307	0.143	0.908

Note: RA = Recommendation Accuracy, RN = Recommendation Novelty, RD = Recommendation Diversity, RT = Recommendation Transparency, RQ = Recommendation Quality, PA = Attitude, TR = Trust, PI = Purchase Intention.

The values of the fit conformity indicators vary depending on the study in different contexts. Confirmatory Factor Analysis (CFA) considers the assessment of unidirectionality, convergence, and differentiation (Anderson & Gerbing, 1988). Considering how relevant the data obtained is to the analytical model, the indicators include Root Mean Square Approximation Error (RMSEA) smaller than 0.06, the Comparative Fit Index (CFI) larger than 0.95 and Standardized Root Mean Square Residual (SRMR) smaller than 0.08 (Hu & Bentler, 1999). As a result of the analysis, indicators in the range following the recommended value threshold include RMSEA 0.037, CFI 0.97, and SRMR 0.04. However, there is no consistent standard measure in model evaluations. There are relevant studies and recommendations for the validity and relevance of the data obtained to report the study findings (Hair et al., 2020).

The Composite Reliability factor (CR) is a calculation that involves normalized load coefficients and the variability of observed variables linked to an underlying variable (McDonald, 1970). Similar to Cronbach's alpha, aggregate reliability scores range from 0 to 1. A score closer to 1 indicates higher confidence in the measurements. However, if the score exceeds 0.95, there might be an issue of redundant variables, where variables measure the same thing. Conversely, if the aggregate reliability score falls below 0.6, it suggests a lack of inherent consistency in the measurements and requires reconsideration (Hair et al., 2020). Moreover, Average Variance Extracted (AVE) must exceed 0.50 for each structure, and the correlations between variables should not surpass 0.85 (Kline, 2005), following Kline's (2005) suggestion. In this study, the reliability of the measurement structure is evaluated using an aggregate reliability score (CR) higher than 0.70 (Hair et al., 2020).

From the analysis results in Table 3, the value range of composite reliability varies from 0.83 to 0.90. Simultaneously, the value of the average variance extracted ranges from 0.73 to 0.82. This value follows the proposed value thresholds, ensuring reliability for the research results report (Hair et al., 2020).

Table 4. Path coefficient analysis relationship

Hypothesis	Path coefficient	Estimate	P-value	Decision
H1	RA → RQ	0.133	0.000	Accepted
H2	RN → RQ	0.281	0.000	Accepted
H3	RD → RQ	0.184	0.000	Accepted
H4	RT → RQ	0.272	0.000	Accepted
H5	RQ → PA	0.377	0.000	Accepted
H6	RQ → TR	0.286	0.000	Accepted
H7	PA → PI	0.113	0.000	Accepted
H8	TR → PI	0.197	0.000	Accepted
H9	RQ → PI	0.340	0.000	Accepted

Note: RA = Recommendation Accuracy, RN = Recommendation Novelty, RD = Recommendation Diversity, RT = Recommendation Transparency, RQ = Recommendation Quality, PA = Attitude, TR = Trust, PI = Purchase Intention.

The results in Table 4 show that the analytical model identified measurement variables that have a similar-dimensional relationship and are statistically significant. The relationships emerge from access to product information, perception of suggested information, and the degree of influence on attitudes and beliefs so that the individual has a purchase intention. This result is considered in terms of beta estimation coefficients of coefficient paths. When customers receive suggestion information, including Recommendation Accuracy, Recommendation Novelty, Recommendation

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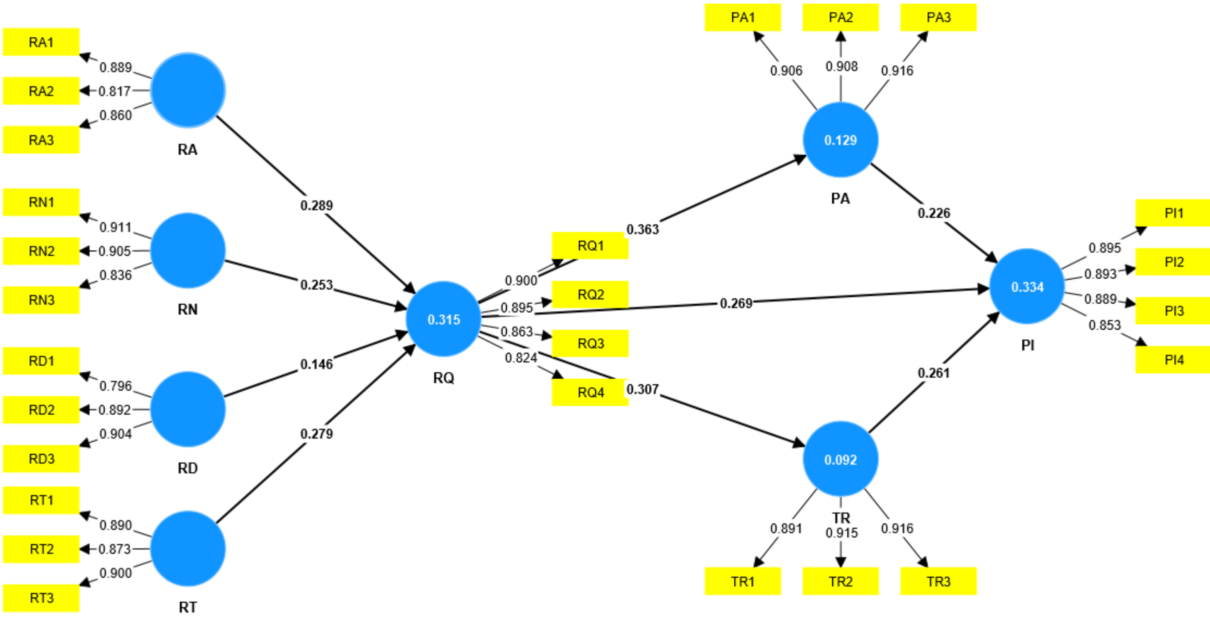

Note: RA = Recommendation Accuracy, RN = Recommendation Novelty, RD = Recommendation Diversity, RT = Recommendation Transparency, RQ = Recommendation Quality, PA = Attitude, TR = Trust, PI = Purchase Intention.

Figure 2. Standardized path coefficient

Diversity, Recommendation Transparency and, Recommendation Quality, there are 3 emotional directions: (1) showing a positive attitude will affect the intent to buy and opposite, (2) expressing positive beliefs also impacts Purchase Intention and the opposite, (3) perception of Recommendation Quality directly impacts Purchase Intention. The study's results on the impact of Recommendation Quality on Attitude and Purchase Intention had the highest beta factor of 0.36. In contrast, the Recommendation Quality's impact on Trust and Purchase Intention had a beta factor of 0.30. Thus, Recommendation Quality impacts Attitude more strongly than the Recommendation Quality impacts Trust. The Recommendation Quality directly impacting the Purchase Intention has a beta factor of 0.26. Therefore, in this study, the perception that Recommendation Quality directly impacts Purchase Intention is similar to the indirect impact of Trust before Purchase Intention.

This study is similar to many other studies. The results obtained may be the same or different from previous studies. The presentation focused on key findings to address the purpose of the study. The demographic breakdown of the study sample reveals a few key insights. Most participants were female (60.5%), suggesting that this gender may represent a more extensive consumer base or market preference. This finding could warrant further investigation into gender-based shopping behaviors or marketing strategies. The age group 30-39 was the most represented (60.8%), indicating a focus on understanding this age group's preferences, spending patterns, or needs. This result was also found in another related study on purchasing behavior (Burke, 2002). For frequency of purchases, 78.1% of participants reported making 1-3 monthly purchases, suggesting that most of the sample engages in moderate shopping activity. This finding could affect inventory management, demand forecasting, and marketing strategies. The research findings reveal significant insights through an analytical model that uncovers interconnected measurement variables where recommendation quality exerts a more potent influence on both Attitude and Purchase Intention compared to the impact of Trust on these variables. This phenomenon can be attributed to several underlying factors. First and foremost, in the modern outlook of information abundance and digital commerce, consumers increasingly rely on peer-to-peer recommender systems to guide their purchasing decisions (Heinrich et al., 2022). When these recommendations demonstrate high accuracy, novelty, diversity, and transparency, they inherently enhance the perceived value of the suggested products or services (Elahi et al., 2022). This positive reinforcement cultivates a favorable attitude towards the recommendations and the products they endorse. Moreover, recommendation quality directly aligns with value alignment and resonance with the consumer's preferences (Supapon & Sukhawatthanakun, 2023). As consumers perceive the recommendations to be tailored to their needs and preferences, a stronger emotional connection is established, amplifying their positive attitude and fueling the intent to purchase (Sahoo et al., 2022). Furthermore, while Trust undoubtedly plays a pivotal role in influencing purchase decisions, its impact might be more indirect. Trust often develops over time through consistent positive experiences and interactions with a brand or platform, whereas recommendation quality offers a more immediate and tangible effect on perception (Tseng et al., 2022; Palmer, 2010). Consequently, the pronounced influence of Recommendation Quality on Attitude and Purchase Intention can be attributed to its ability to provide immediate value, align with preferences, and elicit a positive emotional response, all of which synergistically contribute to its stronger impact in comparison to Trust (Lis & Fischer, 2020; Jiang et al., 2023).In this study, the perception that recommendation quality directly impacts purchase intention is similar to the indirect impact of Trust before Purchase Intention. The implications stemming from these research findings hold significance across practical, societal, and research domains. From a practical perspective, businesses and marketers can leverage the understanding that recommendation quality plays a pivotal role in shaping consumer Attitude and Purchase Intention. Investing in refining and enhancing recommendation algorithms to ensure accuracy, novelty, diversity, and transparency can yield substantial benefits by increasing immediate sales and fostering long-term customer loyalty (Zaizi et al., 2023). Furthermore, the insight that Recommendation Quality directly impacts consumer behavior more than Trust underscores the importance of personalized and relevant recommendations in today's competitive marketplace (Amoako et al., 2023). On a societal level, these findings underscore the power of technology-driven recommendations in shaping consumer choices. As these peer-to-peer recommender systems become increasingly integrated into daily life, society must know the potential influence these algorithms wield (Bonicalzi et al., 2023). Striking a balance between personalized suggestions and maintaining individual agency over decision-making becomes crucial, particularly as recommendation algorithms gain prominence across various sectors. This study's results open avenues for further exploration into the intricate dynamics between Recommendation Quality, Trust, Attitude, and Purchase Intention. The researchers can delve deeper into the psychological mechanisms that drive these connections, examining cognitive biases, emotional responses, and the interplay between rational and emotional decision-making processes (Wang et al., 2023). Additionally, comparative studies across different industries and cultural contexts can provide a nuanced understanding of how these relationships may vary and offer insights into cross-cultural consumer behavior. Ultimately, this research contributes to the broader discourse on consumer behavior in the digital age and encourages ongoing investigations into the multifaceted interplay between technology, psychology, and commerce.

CONCLUSION

This study aims to assess the impacts of peer-to-peer recommender system on online shopping. In the research, the sample's demographic characteristics also open avenues for further inquiry into the implications of information demographics., analyzing the descriptive statistics of gender focus females, aged 30-39, and frequency of purchases during the month of 1-3 times. It can illuminate consumer cluster insights with practical implications for various sectors, from retail to marketing to consumer research. The research findings illuminate a comprehensive understanding of the intricate relationships among measurement variables within a concept framework, establishing their statistical significance through an analytical model. The sequential emergence of relationships, from access to product information to the nuanced interplay of attitudes and beliefs, underscores a cohesive journey that culminates in the formation of Purchase Intention.

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The results of customer responses to suggestion information encompass dimensions like Recommendation Accuracy, Novelty, Diversity, Transparency, and Recommendation Quality. Notably, the positivity in Attitude and Trust influences Purchase Intention, presenting a multi-faceted emotional continuum. The direct impact of perceived recommendation quality on Purchase Intention is of particular significance, exemplifying the immediate sway that a well-executed recommendation can exert on consumer decision-making.

AUTHOR CONTRIBUTIONS

Conceptualization: Cuong Nguyen.
Data curation: Ninh Nguyen.
Formal analysis: Ninh Nguyen.
Funding acquisition: Cuong Nguyen.
Investigation: Cuong Nguyen, Ninh Nguyen.
Methodology: Cuong Nguyen.
Software: Cuong Nguyen, Ninh Nguyen.
Supervision: Cuong Nguyen.
Validation: Ninh Nguyen.
Visualization: Ninh Nguyen.
Writing – original draft: Ninh Nguyen.
Writing – review & editing:Cuong Nguyen.

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