Who Values E-Opinions Most in the E-Commerce Community?

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ABSTRACT

As online shopping has become ubiquitous in daily life, online communities have emerged where people can easily exchange information and post opinions about specific products, sharing their knowledge and experiences with each other. The issues surrounding online word-of-mouth (WOM) opinions have been extensively studied. Research shows that online WOM is more accepted by consumers, as its influence among peers surpasses those of advertisements. However, products in e-commerce possess different characteristics in terms of tangibility and refundability. This paper first classifies users into four groups based on tangibility and refundability of products. Then this paper adopts the Use Intention Model (UIM) to analyze the intention of referring to opinions in e-commerce communities by the different groups of users. The paper adopts the Delphi Hierarchical Process (DHP) and seven-level Likert scale evaluation to measure the influence degree and agreement degree for each factor in the UIM for different groups of users. This paper conducts a series of experiments to identify which group of users' value opinions the most. The results show that the group of users, if they purchase products being intangible and non-refundable, exhibit the highest intention to refer to opinions, despite the potential presence of biased and faulty opinions in e-forums.

Keywords: E-Opinions; E-Commerce; word-of-mouth; Use Intention Model.

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1. INTRODUCTION

The rapid development of the Internet has spurred the growth of the e-commerce industry, with major platforms such as Yahoo Shopping, Taobao, eBay, Amazon and Shopee leading the way (Bhatia, 2020; Brahma, and Dutta, 2020; Wulandari, and Rauf, 2022). Unlike traditional physical transactions, consumers (note that consumer and user are used interchangeably in this paper) in the online marketplace often seek relevant opinions to boost their confidence in the products they intend to purchase. Research shows that online word-of-mouth (WOM) is more accepted by consumers because its peer influence always surpasses that of advertisements (Atkisson, Górski, Jackson, et al., 2020). According to Karakaya and Barnes (2010), the number of online opinions on e-commerce websites is growing at an explosive rate each year. The quality of these opinions ranges from detailed and excellent to purely promotional or biased. Consumers must sift through this vast array

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of opinions to determine which ones are useful in assessing whether a product meets their needs (Zha, Kou, Zhang, et al., 2020; Qing and Jin, 2022).

Some studies have explored trust in social networks by analyzing the characteristics of opinions to determine their trustworthiness (Al-Oufi, Kim, and El Saddik, 2012; Knoke and Yang, 2019). In practice, consumers often find it challenging to filter out irrelevant opinions, leading to frustration before making a purchase. Even when relevant opinions are found, consumers must still judge their trustworthiness. Compounding the issue, some suppliers pay for biased opinions by hiring bloggers or professional writers to create deceptive opinions that either promote their products or demote competitors' products (López and Sicilia, 2014; Chen, and Lai, 2023). This situation causes consumers to be hesitant about accessing opinions posted in e-commerce communities before making a decision.

Consumers may purchase various types of products online, including tangible items (e.g., clothes, shoes, 3C devices) and intangible ones (e.g., insurance, virtual items in online games). These products can be refundable (e.g., unspoiled products) or non-refundable (e.g., travel tours, hotel bookings, etc. if regretting beyond the cancellation period). Different types of products may influence users' intentions or motivations to browse opinions. Currently, most relevant research on social networks focuses on the characteristics of commenters, their motivations for sharing, factors influencing user acceptance, and marketing perspectives (Hsu and Lin, 2008; Cheung and Lee, 2012; Sukmadewi, Chan, Suryadipura, and Suwandi, 2023). To our knowledge, there is little research discussing which groups of users for different types of products (in terms of tangibility and refundability) place the most importance on opinions before making a purchase. This paper conducts two sets of experiments. The first aimed to explore the influence degree of each construct (or factors) in UIM through the Delphi Hierarchical Process (DHP). The second experiment aimed to score the agreement degree for each factor in UIM using a seven-level Likert scale for the factors in UIM in the viewpoint of different groups of users. By combining the influence degree and agreement degree related to the factors in UIM, this paper can calculate the degree of intention for different groups of user if they purchase different types of products.

2. MATERIALS AND METHODS

E-commerce products can be classified into tangible and intangible types based on their physical nature (Levitt, 1981; Hill, 1999). Tangible products have physical materials, such as food, cars, and 3C devices, while intangible products lack a physical form. Examples of intangible products include downloadable music, mobile apps, and virtual items used in virtual economies or virtual space. Tangible products can generally be directly experienced, touched, or tasted and tested, whereas intangible products, despite lacking physical form, can add significant value to a user. Although tangible products can be touched or experienced after purchase, consumers in e-commerce can only view high-quality images of these products on websites before their arrival to the consumers. Therefore, consumers often consult past users or ask experienced users about the usage and characteristics of the products through forums in e-commerce communities.

In e-commerce, another classification of the produces is based on whether the products can be refunded. Refundable products can be returned for a money-back guarantee or exchanged under certain conditions, such as being defective, not meeting the user's expectations, or order canceling within an allowable period. If consumers regret

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their purchase, they can be refunded the amount paid, although some handling charges, like delivery fees, may or may not be reimbursed. For example, clothes and 3C devices are refundable with little loss if returned within an allowable period (e.g., 7 days). Refundable policies are attractive because they make consumers more comfortable and confident about their purchases, especially for online transactions where the products cannot be pretested and consulted about their functions like that in traditional commerce.

However, some products are non-refundable or entail a high loss if the buying decision or experience is regretted. Such types of products are called non-refundable. Examples include products customized or personalized to a user's specific requirements, digital downloads, software, and other virtual products that have no physical item to return and whose value is exhausted once accessed. Additionally, products that come into direct contact with the body, such as cosmetics and underwear, are non-refundable for hygiene and safety reasons. Products requiring booking or custom-made, like airline tickets, hotel bookings, and tour guides, are often non-refundable as they cannot be easily resold or reused if the transaction is canceled beyond the predefined period.

Considering the regret in online purchases, a refundable policy or minimal loss can encourage consumers to make purchases more bravely and actively. However, even if a purchase from a website is refundable or involves minimal cost in case of regret, consumers still seek opinions as the refunding process can be tedious. Conversely, the non-refundable nature or high loss potential in case of regret makes consumers more cautious in making purchases and necessitates careful decision-making. In most cases, consumers thoroughly survey opinions in e-commerce forums to find useful and trustworthy feedback before deciding. The tangibility and refundability of products have different implications for users, and they are sold online with varying distinctions. This paper recognizes these differing features and classifies online products into four quadrants (or types) based on tangibility and refundability. Table 1 shows the classification of online products, numbered from type 1 to type 4, along with their respective examples.

Table 1. Classification of products in e-commercial as well as their examples

classification	Tangible	Intangible
Refundable or with little lose	Type 1: Clothes, devices	Type 2: Cloud storage, virtual treasure in on-line game
Nonrefundable or with high cost	Type 3: Travel tour, hotel, airline ticket (beyond the cancelled period)	Type 4: Download software, e-book, insurance

Currently, users can easily browse opinions in e-commerce communities to assess the suitability, comfort, compatibility, and other characteristics of the products they wish to purchase. Due to the practicality and convenience of web technology, the number of opinion forums has increased significantly, attracting millions of users (Phan, and Nguyen, 2024). These forums allow users to pre-assess whether the products meet their needs, aiding consumers in making appropriate purchase decisions. However, these forums often suffer from information overload, biases, and even false information. Users need to spend considerable time browsing and searching for credible comments for reference. Since products bought from e-commerce can be divided into four types in terms of tangibility and refundability, users naturally have different intentions and levels of

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interest in browsing and considering opinions in e-commerce communities. It remains unclear which group of users care about the opinions the most, i.e., which group of users have the highest user intention to browse opinions.

To evaluate the influence of opinions on the four groups of uses for the four types of products, we adopt the Usage Intention Model (UIM) (Yildirim and Ali-Eldin, 2019; Huang and Chueh, 2022) to compare the intentions to refer to opinions for different groups of users. The UIM, shown in Figure 1, is a psychological model proven to be suitable for describing why and to what degree users adopt certain facilities or products. The model is structured hierarchically with two levels of factors. At level 2, there are three factors: perceived ease of use, perceived usefulness, and perceived risk, which describe the user's perception of the facilities. These three factors contribute to the user attribute factor at level 1 of the model. Many previous research (Huang, and Chueh, 2022; Chueh, and Huang, 2023) on the UIM found that the factors of perceived ease of use and perceived usefulness at level 2 positively influence the user attitude factor at level 1, while the perceived risk factor at level 2 negatively influences user attitude at level 1. Additionally, they found that two factors at level 1—user attitude and reward program—influence the use intention factor at level 0 (i.e., the root). For instance, Davis (1989) conducted an empirical study that concluded perceived usefulness and perceived ease of use were significantly correlated with current usage ($r = .63$ and $r = .45$, respectively) and future usage ($r = .85$ and $r = .59$, respectively); Chueh and Huang (2023) demonstrated that perceived usefulness has a statistically significant positive effect on usage attitude ($\beta = 0.784$, $p < 0.001$), and that usage attitude significantly positively influences usage intention ($\beta = 0.672$, $p < 0.001$); Guritno and Siringoringo (2013) also made empirical study and showed that perceived usefulness and perceived ease of use influence usability attitudes; Guritno and Siringoringo (2013) also provided empirical evidence showing that perceived usefulness and perceived ease of use influence usability attitudes. Furthermore, Choi and Kim (2013) conducted empirical tests concluding that the reward program significantly affects customer willingness (intention) ($t = 7.805$, $p < 0.001$).

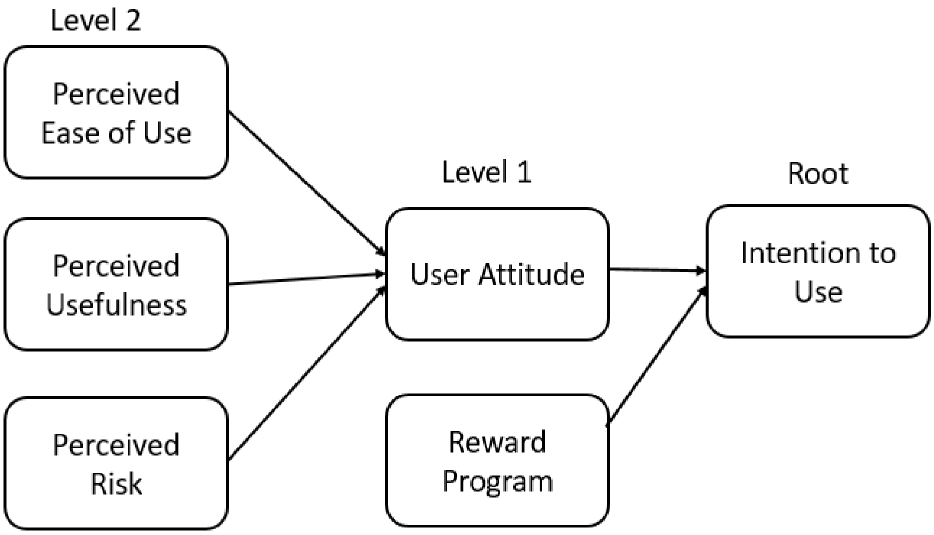

Figure 1. The UIM for consumers referring to the opinions (Huang, & Chueh, 2022).

As previously discussed, the user attitude factor is composed of the three factors at level 2. The reward program refers to a mechanism or policy that incentivizes users with

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rewards for participating in certain activities. In this paper, rewards can be positive or negative; for example, positive rewards include price discounts, bonus points, or other benefits to encourage user engagement, while negative rewards include inconvenience, time costs, or drawbacks that discourage user engagement. The reward program concept remains consistent if negative rewards are counted as negative values. Therefore, the larger the positive (or negative) reward a user encounters, the higher the user intention to engage. The operational definitions of each factor (or variable) in Figure 1 in this paper are as follows:

- Perceived Ease of Use (PEU): The belief of users that they can easily access opinions in the e-commerce community.
- Perceived Usefulness (PU): The belief of users that the opinions accessed from the community are useful;
- Perceived Risk (PR): The belief of users that there is a risk due to faulty, biased, or purposefully misleading opinions when referring to them;
- User Attitude (AT): The consumers' consideration of whether to refer to opinions (i.e., make a decision with or without referring to opinions;
- Reward Program (RP): The rewards provided by the opinion system when users refer to opinions, such as discounts and bonuses as positive rewards, and inconvenience and time costs as negative rewards.
- Intention to Use (IU): The willingness of users to refer to opinions.

The Usage Intention Model (UIM) is considered suitable for representing user behavior and has been validated by numerous researchers whose findings corroborate this relationship (Davis, 1989; Choi & Kim, 2013; Guritno & Siringoringo, 2013; Chen & Lai, 2023; Chueh & Huang, 2023). However, the factors represented in the model exhibit varying degrees of influence on user behavior across different contexts, such as mobile phone purchases, online shopping, innovative app usage, and telemedicine applications. Clearly, the factors in the model shown in Figure 1 have different influences on user intentions to browse opinions. Measuring the influence of each factor in the hierarchical model is challenging due to their psychological nature. This research adopts the Delphi Hierarchical Process (DHP) to measure the influence degree (or weight) of each factor psychologically. A two-phase process is performed to analyze the intention to use for different groups of users:

- The first phase inquires about the influence degree of each factor in the UIM;
- The second phase inquires about the agreement degree of each factor in the model by the four groups of users.

Figure 2 outlines the stages and associated processing under the UIM framework.

Ranking and determining the influence degrees of the factors related to user attitude for opinions can be challenging. To address this challenge, this research employs pairwise comparison to ascertain the influence degrees of the relevant factors. We invited 28 respondents, comprising 12 males and 16 females, who frequently engage in online purchasing, to complete pairwise comparisons of the influence degrees of the factors outlined in the UIM. The ages of the respondents ranged from 20 to 61, reflecting a demographic likely to have a strong interest in reviewing online opinions. Table 2 lists the characteristic distribution of respondents. Prior to taking the questionnaire, we conducted an interview to clarify the goals of the empirical study, ensuring that the respondents possessed relevant online shopping experiences and cognitive abilities. Subsequently, they were asked to complete a questionnaire consisting of the two levels of factors to assess their attitudes regarding the factors included in the UIM. Specifically,

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the respondents were required to evaluate the influence degree of "perceived ease of use" relative to "perceived usefulness" and "perceived risk" at level 1, and then assess the influence degree of "user attitude" relative to the "reward program" at level 2 of the UIM. The influence degree was expressed using a 1-9 scale: from equal importance (score 1), weak importance (score 2), moderate importance (score 3), moderate plus (score 4), strong importance (score 5), strong plus (score 6), very strong importance (score 7), very very strong importance (score 8), to extreme importance (score 9). We finally received 9 consistent complete replies from the pairwise comparisons. Note that Figure 1 depicts a hierarchical structure. To determine the influence degrees of factors in the UIM, we collect the relative influence metrics for each pair of factors level by level, normalize the metrics, and then calculate the influence degrees. The following tables illustrate the calculation process for a respondent's responses. Table 3(a) presents the original replies from one respondent, obtained through pairwise comparison of the three factors at level 2 of the hierarchical structure in Figure 1. Note that the results in Table 3(a) follow the 1-9 scale used in the DHP and have not yet been normalized. To determine the relative influence degree of each factor, we first normalize the pairwise results and then calculate their relative influence degrees. Table 3(b) displays the normalized results, with the summed influence degree of each factor listed in the second to-last column, representing the sum of each normalized influence degree in the same row. The relative influence degree of each factor is shown in the far-right column of Table 3(b).

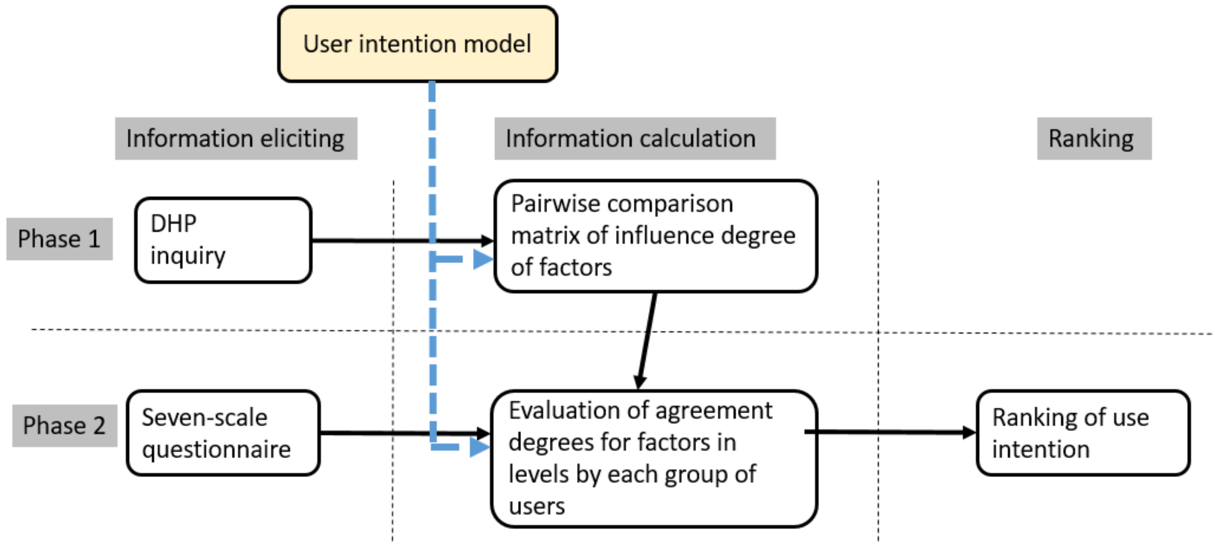

Figure 2. The two phases and their associated processing to rank the use intention for opinions by the four groups users.

Table 2. The characteristic distribution of respondents.

Characteristic	Item	Frequency	Percentage
Gender	Male	12	42.86%
	Female	16	57.14%
Age	20-29 years	9	32.15%
	30-39 years	7	25.0%
	40-49 years	8	28.57%

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	50 years or above	4	4.28%
Education	High school or less	3	10.71%
	College/university	15	53.57%
	Graduate degree	8	28.57%
	Doctoral degree	2	7.14%

Table 3(a). Pairwise comparison for the factors at level 2 of the UIM without normalization (results from the replies of one respondent)

	Perceived ease of use	Perceived usefulness	Perceived risk
Perceived ease of use	1	1/3	1/4
Perceived usefulness	3	1	1/2
Perceived risk	4	2	1
Sum (in column)	7	3.333	1.75

Table 3(b). Relative influence degree of the factors at level 2 of the UIM with normalization (results from the reply of one respondent)

	Perceived ease of use	Perceived usefulness	Perceived risk	Summed influence degree	Relative influence degree
Perceived ease of use	1/7	0.333/3.333	0.25/1.75	0.386	12.28%
Perceived usefulness	3/7	1/3.333	0.5//1.75	1.014	32.26%
Perceived risk	4/7	2/3.333	1/1.75	1.743	55.46%

Note that the results in Tables 3(a) and 3(b) are derived from the replies of one of the nine respondents. To obtain a comprehensive view, we need to average the relative influence degrees from all respondents' replies. Figure 3 visualizes the distributions of the three factors using box-and-whisker plots, where the boxes represent the central 50% of the influence degrees (i.e., the weights) derived from the respondents' replies. From the box-and-whisker plots, we observe that the range for the perceived risk factor is the smallest, while the range for the perceived usefulness factor is the largest. This indicates that respondents exhibited less variability in their assessment of the influence degree for perceived risk compared to perceived usefulness. It is inferred that the respondents were more consistent in evaluating the weight of risks than in assessing the weight of usefulness. Table 4 presents the average relative influence degree of each factor at level 2 of the UIM, calculated from the replies of all respondents. It is evident that perceived risk factor has the highest average relative influence degree, indicating that most respondents consider risk—associated with biased, faulty, collusive, or advertising opinions—as the most significant factor influencing whether users refer to the opinions.

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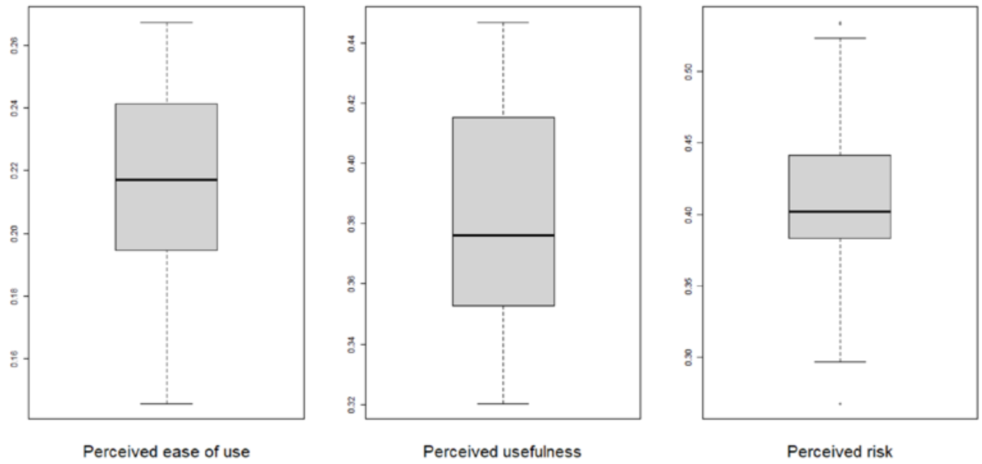

Figure 3. Distribution of influence degrees of the three factors in level 2 from respondents' replies.

Table 4. The average of relative influence degree for the factors at level 2 of the UIM from replies of all respondents.

	Perceived ease of use	Perceived usefulness	Perceived risk
Average relative influence degree	20.93%	37.69%	41.38%

After obtaining the average relative influence degrees of the factors at level 2 in the UIM, the next step in phase 1 is to determine the relative influence degrees of the factors at level 1 in the model. Similar to the process used for level 2, we apply the DHP to the factors at level 1 again. Table 5(a) presents the original replies from one respondent, obtained through pairwise comparisons of the two factors at level 1 of the model shown in Figure 1. The comparison results in Table 5(a) use the 1-9 scale employed in DHP but have not yet been normalized. The subsequent step involves normalizing these pairwise results and calculating the relative influence degree of each factor. Table 5(b) displays the normalized results for each factor at level 1. In this table, the summed relative influence degree of each factor is listed in the second-to-last column, representing the sum of each normalized influence degree within the same row. The relative influence degrees of the factors at level 1 are shown in the far-right column. Similar to the approach used for the factors at level 2 of the UIM, the results in Tables 5(a) and 5(b) are derived from the replies of one of the nine respondents.

Table 5(a). Pairwise comparison for the factors at level 1 of the UIM without normalization (results from the replies of one respondent)

	User attitude	Reward program
User attitude	1	4
Reward program	1/4	1
Sum (in column)	1.25	5

Table 5(b). Relative influence degree of the factors at level 1 of the UIM with normalization (results from the reply of one respondent)

	User attitude	Reward program	Summed influence degree	Relative influence degree
User attitude	1/1.25	4/5	1.689	80.85%

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Reward program	0.25/1.25	1/5	0.40	19.15%

To obtain a comprehensive view, we need to average the relative influence degrees from all respondents' replies. Similarly, Figure 4 visualizes the distributions of the two factors using box-and-whisker plots based on the respondents' replies. We can see the range of the box for the user attitude factor is smaller than that for the reward program factor. This indicates that the respondents exhibited less variability in their assessments of the influence degree for user attitude compared to the reward program. It can be inferred that the respondents were more consistent in valuing the weight of user attitude than the weight of the reward program. Table 6 presents the average relative influence degree of each factor at level 1 of the UIM, calculated from the responses of all respondents. Combining the results from Tables 4 and 6, we can integrate the relative influence degrees into the UIM. Figure 5 illustrates the relative influence degrees of the factors at both levels 1 and 2 of the model. It is evident that the user attitude factor, which is composed of the three sub-factors shown in Figure 5, has the highest influence on use intention to refer to opinions. In contrast, the reward program—encompassing positive rewards such as discounts and bonuses, as well as negative rewards like time consumption and inconvenience—has a lesser influence on use intention.

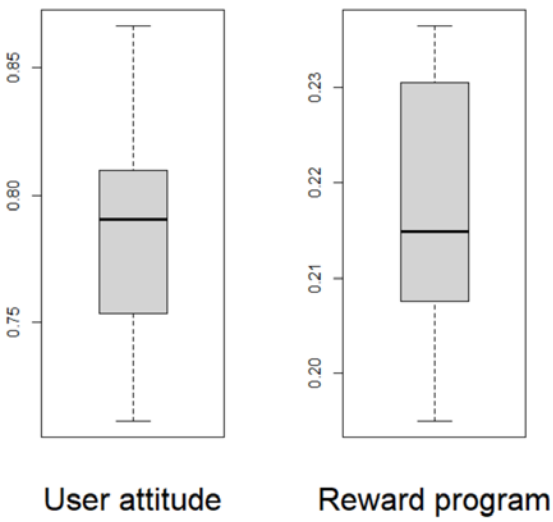

Figure 4. Distribution of influence degrees of the two factors in level 1 from respondent's replies.

Table 6. The average of relative influence degree for the factors at level 1 of the UIM from replies of all respondents.

	User attitude	Reward program
Average relative influence degree	78.34%	21.66%

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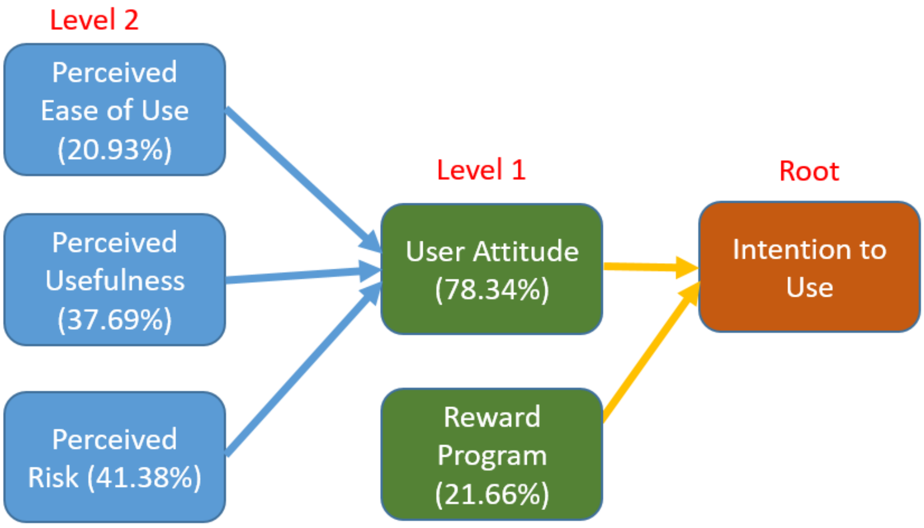

Figure 5. The whole relative influence degrees of factors at levels 1 and 2 of the UIM.

Since the UIM effectively describes the psychological conditions influencing whether users engage in an activity, we can assume that the UIM is applicable to user behavior regarding the referral to opinions for purchasing decisions and that the influence degrees of the factors in the model can be generalized to all online purchasing contexts. In this paper, user behavior is classified into four groups of users based on the types of products they intend to buy online, as shown in Table 1. Each user group may exhibit different levels of agreement with the factors in the UIM when referring to opinions. Phase 2 of this research aims to determine the agreement degree of these factors for different groups of users purchasing different types of products.

The UIM is a hierarchical structure of factors, which implies that higher-level factors dominate the factors connected below them in the hierarchy. For example, the user attribute factor includes three sub-factors: perceived ease of use, perceived usefulness, and perceived risk. For such factors composed of several sub-factors, the agreement degree of the influence of the higher-level factor is obtained by summing the agreement degrees of its sub-factors, weighted by their respective influence degrees. Conversely, for factors that stand alone without any sub-factors in the UIM, the agreement degree is determined solely by its own measures. Phase 2 of this research focuses on empirically obtaining the agreement degree for each standalone factor by the different groups of users.

To assess user experiences with referring to opinions, this research conducts empirical studies. A questionnaire was administered to 52 consumers, comprising 30 females and 22 males, who frequently make online purchases and have experience with both tangible and intangible, as well as refundable and non-refundable products. A seven-point Likert scale—ranging from strongly disagree to agree—is used to evaluate the agreement degree with each factor in the UIM. Table 7(a) presents the agreement degrees of the three factors at level 2 of the model, based on replies from the questionnaires, if they purchase the four types of products. Table 7(b) shows the agreement degrees for the standalone factor, reward program, at level 1 of the model, in relation to referring to opinions for the four types of products.

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Table 7(a). Questionnaire results of their agreement degrees to the factors at level 2 of the UIM to refer to opinions by the groups of users for four different types of products.

	Type 1**	Type 2	Type 3	Type 4
PEU*	5.3	5.1	5.5	5.8
PU	4.3	5.3	6.5	5.9
PR	4.2	4.5	5.5	5.7

* PEU: Perceived Ease of Use; PU: Perceived Usefulness; PR: Perceived Risk.
** Type 1: Tangible product with refundable purchase; Type 2: Intangible product with refundable purchase; Type 3: Tangible product with non-refundable purchase; Type 4: Intangible product with non-refundable purchase.

Table 7(b). Questionnaire results of the agreement degree to the standing-alone factor at level 1 of the UIM to refer to opinions by the groups of users for four different types of products.

	Type 1**	Type 2	Type 3	Type 4
RP*	2.7	4.4	2.8	4.6

* RP: Reward Program.

To this point, we have determined the influence degrees of factors (as shown in Tables 4 and 6) and the agreement degrees for these factors across different groups of users for different types of products (as shown in Tables 7(a) and 7(b)). We can now quantitatively calculate the degree of intention to use the opinions by the four groups of users. For each group of users, we first multiply the agreement degree of each level 2 factor by the influence degree of the corresponding factor, and then sum these products. To illustrate, let us use data related to type 1 products to demonstrate this calculation. For type 1 products, the agreement degrees for PEU, PU, and PR are 5.3, 4.3, and 4.2, respectively, as shown in Table 7(a). The corresponding influence degrees for these factors are 20.93%, 37.69%, and 41.38%, respectively, as shown in Table 4. Since these three factors collectively constitute the user attitude factor, the summed product represents the agreement degree of the user attitude factor for type 1 products. This calculation is expressed in Equation (1):

$$5.3 \times 20.93\% + 4.3 \times 37.69\% + 4.2 \times 41.38\% = 4.468 \quad (1)$$

The intention to intention to use factor (i.e., the root of the model) is influenced by both the user attitude and reward program factors. Given that we have calculated the weighted agreement degree for the user attitude factor for type 1 products in Equation (1), we use the agreement degree for the reward program (shown in Table 7(b)) and their respective influence degrees (shown in Table 6) to calculate the final agreement degree for the intention to use.

To calculate this, we multiply the agreement degrees of the user attitude and reward program factors by their respective influence degrees and then sum these products. For type 1 products, this is expressed in Equation (2):

$$4.468 \times 78.34\% + 2.7 \times 21.66\% = 4.085 \quad (2)$$

This value represents the users' agreement degree for intention to use to opinions regarding type 1 products. Following a similar process, we can calculate the agreement

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degrees for the Intention to Use (IU) to opinions for the remaining three types of products, as summarized in Table 8.

Table 8. The agreement degree of the intention to use to refer to the opinions by the group of users of four types of commodities in e-commercial.

classification	Tangible	Intangible
Refundable or little lose	Type 1: Clothes, devices, etc. IU = 4.085	Type 2: Cloud storage, virtual treasure in on-line game, etc. IU = 4.812
Nonrefundable or high cost	Type 3: Travel tour, hotel, etc. IU = 5.21	Type 4: Download software, e-book, insurance, etc. IU = 5.537

3. DISCUSSION AND RESEARCH LIMITATIONS

This research classifies online products into four types based on their tangibility and refundability and then classifies the users into the four groups according to the products they intend to purchase. The paper utilizes the Unified Intention Model (UIM) to understand users' intentions to refer to opinions in e-commerce. The Delphi Hierarchical Process (DHP) was employed to measure the psychological factors within the UIM.

Findings and Interpretation

From the analysis presented in Figure 5, it is evident that perceived risk, among the three factors at level 2, has the highest influence on user attitude factor. This indicates that concerns about biased, faulty, or misleading opinions are the most significant barriers to users referring to opinions. Perceived usefulness ranks second, highlighting that users often refer to opinions to gain valuable insights into products, despite the potential for misleading information. Perceived ease of use ranks third, reflecting the common occurrence of user-friendly interfaces on platforms that facilitate easy access to opinions. At level 1 of the model, user attitude factor significantly outweighs the reward program factor. This suggests that the intrinsic value of user attitudes and the perceived usefulness of opinions are more influential than external rewards such as discounts or bonuses. The reward program alone does not sufficiently drive users to engage with opinions.

The paper also reveals variations in use intentions against the different groups of users. For example, the group of users if purchasing tangible and non-refundable products, such as travel tours and hotel bookings, exhibit that they consider the opinions as the highest perceived usefulness. This may be due to their high expectations and lower tolerance for risk, making them more reliant on user opinions for informed decision-making. Conversely, the group of users if purchasing intangible and non-refundable products, such as digital downloads and insurance, show their highest concern for perceived risk. This concern is likely due to the inability to physically assess these products before purchase and the potential for significant loss if the purchase turns out to be unsatisfactory. The intention to use opinions is higher for non-refundable products, regardless of their tangibility. This is particularly true for intangible and non-refundable products, where such group of users are most cautious due to the inability to return the

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product and the potential for substantial loss. Users of these products are more likely to seek out and rely on opinions to avoid regret and mitigate the risk of dissatisfaction. In contrast, the reward program did not significantly affect user engagement, as indicated by consistently low agreement scores across all groups of users.

Conclusion

This paper explores how different types of products in e-commerce influence users' intentions to refer to opinions in online communities. By classifying the users by the products properties of tangibility and refundability, and employing the Unified Intention Model (UIM), we analyzed user behaviors and preferences regarding online opinions for different groups of users.

Key findings include:

- Classification of Users: Users were divided into four groups based on the product properties of tangibility and refundability they purchase. This classification provided a framework to understand user intentions across different groups of users.
- Application of UIM: The UIM was utilized to model user behavior in referring to opinions. We applied the Delphi Hierarchical Process (DHP) to determine the influence degrees of various factors within the model, and used a seven-point Likert scale to measure user agreement levels for each factor by the groups of users.
- Influence and Agreement Degrees: By combining the influence degrees from DHP with the agreement degrees from questionnaires, we calculated the final degree of intention to use opinions for each group of users. The results revealed that users across all types of products value opinions, but those groups of user purchasing intangible and non-refundable products exhibit the highest intention to seek out and rely on opinions before making a purchase.
- Practical Implications: The findings suggest that sellers should prioritize the organization and presentation of opinions about their products. This is particularly crucial for intangible and non-refundable products, where consumers of these products are more likely to seek opinions to mitigate risks and make informed decisions.

Research Limitations

- Limited Classification: The paper classifies products into only four types. Future research could benefit from a more granular classification that includes additional factors, such as whether the purchase is for personal use or a gift for others, or the refund policy duration.
- Bios and Faulty Opinions: The research does not address how to discriminate between biased and faulty opinions. Future studies could explore methods for identifying and mitigating the impact of such opinions on user decision-making.

Overall, while the UIM effectively captures user intentions regarding opinion referral, further research could refine the model by incorporating additional factors and addressing the limitations identified in this paper.

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