VILNIUS UNIVERSITY
BUSINESS SCHOOL

DIGITAL MARKETING PROGRAMME

Zihan Ding

THE FINAL MASTER'S THESIS

Vartotojų atsiliepimų formatų įtaka sprendimui pirkti įvairių tipų produktus internetinėse parduotuvėse.	*The Influence of User Feedback Formats on the Decision to buy different Types of Products in online Stores.*

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SUMMARY

VILNIUS UNIVERSITY BUSINESS SCHOOL

DIGITAL MARKETING STUDY PROGRAMME

THE INFLUENCE OF USER FEEDBACK FORMATS ON THE DECISION TO BUY DIFFERENT TYPES OF PRODUCTS IN ONLINE STORES

Supervisor – Gintarė Gulevičiūtė

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This thesis will examine the effects of User Feedback Formats (ratings, reviews, visual content), Trust in Review Source, Type of Products in Online Stores and Level of Consumer Involvement to the Decision to Buy in the context of online shopping. The main objective is to learn the impact of these variables on the choice to buy, especially the role of various feedbacks and reliance on reviews in consumer behavior.

The method was quantitative with a sample of 209 people who filled a survey on their perceptions of feedback formats on the user, trust of reviews, type of product, and consumer involvement. The relationships between these variables and their effect on the purchase decision were investigated with the help of statistical tools, such as descriptive statistics, correlation analysis, and regression models.

The results of the research indicate that the user feedback formats (ratings, reviews, and visual materials) make a medium impact on consumer trust and purchase likelihood. The moderation effects of product type and consumer involvement were however, not significant as expected. In particular, feedback formats and purchase decisions were poorly correlated in the course of the analysis, which means that such factors as consumer trust do not heavily influence buying behavior. Also, the type of product and consumer engagement did not dramatically change the effect of feedback on buying behaviors, which implies the possibility that the effectiveness of feedback might affect the purchasing decisions across all product categories or levels of consumer engagement.

Keywords： Online Shopping， User Feedback Formats， Online Reviews， Purchase Decision， Consumer Behavior， Product Type， E-commerce.

SANTRAUKA

VILNIAUS UNIVERSITETO VERSLO MOKYKLA

SKAITMENINĖS RINKODAROS STUDIJŲ PROGRAMA

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VARTOTOJŲ ATSILIEPIMŲ FORMATŲ ĮTAKA SPRENDIMUI PIRKTI ĮVAIRIŲ TIPŲ PRODUKTUS INTERNETINĖSE PARDUOTUVĖSE

Supervisor – Gintarė Gulevičiūtė

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Šiame darbe bus nagrinėjamas vartotojų atsiliepimų formatų (įvertinimų, atsiliepimų, vaizdinio turinio), pasitikėjimo atsiliepimų šaltiniu, produktų tipo internetinėse parduotuvėse ir vartotojų įsitraukimo lygio poveikis sprendimui pirkti apsiperkant internetu. Pagrindinis tikslas – išsiaiškinti šių kintamųjų įtaką pirkimo sprendimui, ypač įvairių atsiliepimų ir pasitikėjimo atsiliepimais vaidmenį vartotojų elgesyje.

Metodas buvo kiekybinis, naudojant 209 žmonių imtį, kurie užpildė apklausą apie savo požiūrį į atsiliepimų formatus vartotojui, pasitikėjimą atsiliepimais, produkto tipą ir vartotojų įsitraukimą. Ryšiai tarp šių kintamųjų ir jų poveikio pirkimo sprendimui buvo tiriami naudojant statistinius įrankius, tokius kaip aprašomoji statistika, koreliacinė analizė ir regresiniai modeliai.

Tyrimo rezultatai rodo, kad vartotojų atsiliepimų formatai (įvertinimai, atsiliepimai ir vaizdinė medžiaga) daro vidutinį poveikį vartotojų pasitikėjimui ir pirkimo tikimybei. Tačiau produkto tipo ir vartotojų įsitraukimo moderavimo poveikis nebuvo reikšmingas, kaip tikėtasi. Visų pirma, analizės metu atsiliepimų formatai ir pirkimo sprendimai buvo silpnai koreliuojami, o tai reiškia, kad tokie veiksniai kaip vartotojų pasitikėjimas neturi didelės įtakos pirkimo elgsenai. Be to, produkto tipas ir vartotojų įsitraukimas dramatiškai nepakeitė atsiliepimų poveikio pirkimo elgsenai, o tai reiškia, kad atsiliepimų veiksmingumas gali turėti įtakos pirkimo sprendimams visose produktų kategorijose ar vartotojų įsitraukimo lygiuose.

Raktiniai žodžiai: apsipirkimas internetu, vartotojų atsiliepimų formatai, internetinės apžvalgos, pirkimo sprendimas, vartotojų elgsena, produkto tipas, el. prekyba.

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INTRODUCTION

The Novelty and Relevance of the Topic: The growing popularity of the e-commerce has fundamentally changed the way consumers make their purchasing choices, and the online user feedback can now be seen as a part of the change. Nevertheless, although there is abundant literature on the purpose of customer reviews and ratings, the gap in knowledge remains how the specific formats of the feedbacks affect consumer decision-making with reference to various product categories (Tufail et al., 2022). The uniqueness of this research is in the characteristics of the interaction between different kinds of user feedback formats including text reviews, numerical ratings, and visual feedback (images and videos) and the influence of these factors on the purchase intention of any type of product (Ni et al., 2018). The proposed study by examining this under-researched field attempts to reveal the functioning of the various feedback formats in different contexts, beginning with low-involvement products such as cosmetics and high-involvement products such as electronics or luxury items (Rachmad, 2024). This input is useful since it seals a major gap in the current body of knowledge on how e-commerce platforms can effectively manage user-created content to shape the purchase attitudes in an extremely competitive market (Tufail et al., 2022).

Besides the novelty of the topic, the topicality is also conditioned by the increased dependence on online shopping, especially after the COVID-19 pandemic, which considerably contributed to a change in the direction towards an online shop (Ni et al., 2018). The Theory of Planned Behavior (TPB) argues that the intentions of individuals to purchase the product are not only determined by their attitudes to the product but also strongly dependent on social norms and the perceived behavior of other people, especially due to online feedback (Norisnita & Indriati, 2022). The factors used in this research, including the type of feedback (e.g., ratings, reviews, visual content) and the type of products (e.g., low-involvement vs. high-involvement products) are important to grasping the fact that feedback can be used to make consumers act (Ni et al., 2018). With the ongoing evolution of online shopping, the retailers should know what types of feedback are most efficient with particular goods, which will enable them to maximize the user-generated postings in the interest of increased involvement and purchases (Shahzad et al., 2021). The results of the proposed research will help the e-commerce websites to have practical information about the manner in which feedback should be framed and edited to achieve the highest levels of consumer trust and turnover rates (Ni et al., 2018).

The timeliness of the given research project Is further intensified by the fact that there are new online ecosystems built, live-streaming commerce and in-world ministry shopping in the metaverse (Wasilewski, 2024). These contemporary tendencies indicate that the supplementary knowledge is required as to the impact of the format of user feedback on the actions of customers in the context of the Internet (Hadi et al., 2024). The research shall be engaged in exploring the transformation in the feedback forms under the new digital space whether the old-fashioned feedback mechanisms like the stars rating and written reviews remain as useful. Besides it, it will examine whether more interactive feedback methods like (Wasilewski, 2024) live product demonstrations or user-created videos are more persuasive to purchasing intentions and the question of whether product attributes are more pertinent in influencing the intentions to purchase the product toward such industries as electronics or fashion (Zheng et al., 2022). The study can have great importance on the practitioners and the industry analysts who want to understand and be able to exploit the strength of the user commentary in a dynamically developing online market place (Ni et al., 2018).

Problem: How do different user feedback formats influence purchase intentions for different types of products in online stores?

Aim: The aim of this research is to examine the influence of different user feedback formats on consumer purchasing decisions across various product categories in online stores.

Tasks

- To identify and categorize different user feedback formats in e-commerce platforms.
- To assess the impact of feedback formats on purchase intentions for low- and high-involvement products.

- To analyze how product type affects consumer responses to different feedback formats.

Research Methods: The research will be based on the quantitative approach that will be applied through the use of a questionnaire to gather information about online shoppers. The survey will determine the taste of the consumers and their buying intentions to different forms of consumer feedback, including ratings, reviews, and visual materials. The statistical techniques will be applied in data analysis to detect the patterns and correlations.

Limitations: The sampling bias is a limitation as the study participants could be mostly belonging to certain demographic groups, and the research is done on a small number of types of products to capture the whole essence of consumer behavior in all e-commerce industries.

Structure of Thesis

The thesis will be formulated in the following way:

Introduction: Introduction to the research topic, problem statement, aim and objectives.

Literature Review: Existing literature on the user feedback formats and consumer behavior.

Methodology: Statement of the research design, data collection and data analysis procedure.

Results and Discussion: The description of the questionnaire methods results and interpretation.

Conclusion: It summarizes the key results of the study, their implications on the e-commerce sites and advices on future research.

1.0 LITERATURE REVIEW

1.1 Introduction to User Feedback in E-commerce

The online shopping nature has been becoming more dependent on user feedback as one of the key factors. As more websites that deal with online shopping continue to emerge, demand to develop systems that instill confidence between buyers and sellers has never been more heated than ever (Tufail et al., 2022). The star ratings, textual and visual reviews (images or videos left by other customers) are important features of this process of trust-building as user feedback. Such feedback options help to counter the ambiguity associated with not being able to examine products prior to purchase, the core difference between the online and offline shopping experience (Bitaab et al., 2023). The success of such types of feedback in effecting consumer decisions is not simple and depends on product type and consumer profile (Ni et al., 2018). It has been proposed in research that star ratings, even though offering a brief overview of the general quality of a product, do not always provide the amount of information that consumers require when they are making high involvement purchasing decisions such as buying electronics or luxury products. In the case of such products, consumers are more likely to use textual reviews, which give a clearer understanding of the particular product features and experience of using it in real life (Christian & Utama, 2021). Such reviews are particularly harsh in items which are perceived to be more risky and the customers are extra cautious and will feel more assured when they see others who have already bought the product. But there are challenges associated with the use of textual reviews (Tufail et al., 2022). The common problem in this sphere is the abundance of fake or biased reviews that may create a misleading impression of consumers and eventually make them make poor buying choices (Paul & Nikolaev, 2021). This is further aggravated by the fact that most online systems have not put in place sufficiently effective systems to identify and sift through fake content and as a result, consumers take informed choices with the knowledge of fake information (Wasilewski, 2024). Consequently, whereas textual reviews may provide the in-depth information on the quality of a particular product, there is a threat of manipulation, causing the users to lose confidence in the quality of the feedback. This is one of the main areas that should be studied further because to develop better feedback systems and guarantee that online shoppers can make their decision based on precise and truthful reviews, it is essential to understand how people can navigate this problem (Zhou et al., 2018).

In analyzing the effects of the feedback format on consumer behaviour it is important to take into consideration the nature of the product one is buying because that may have a profound effect on the way in which feedback is received and appreciated. Products that are of high involvement like electronics, home appliances and costly clothing items are usually associated with greater consumer research activities since the perceived risk and cost of making the wrong decision is greater (Ni et al., 2018). Under these circumstances, it is important that the feedback offered by textual reviews is as deep as possible since it will provide a more detailed picture of the performance of the product and its durability, which cannot be described by star ratings only. Furthermore, the user-generated images or videos may also contribute to the increased authenticity and credibility of the reviews since these pictures give a potential customer a more realistic perspective on the product in the real-world contexts (Bitaab et al., 2023). Photos and videos especially those displaying the product in action may greatly boost consumer confidence especially products whose appearance or fit is a key concern such as fashion products or beauty products (Esmeli et al., 2023). Nevertheless, even though they may help to build trust, the visual content may not be the most confident predictor of the quality of a particular product, and low-quality photos or false impressions can lead to exaggerated expectations and disappointment (Wasilewski, 2024). As an example, a fashion product might seem flawless in the photo but on the contrary when a consumer sees the actual product at the stores, it will not meet the expectation especially when the photo does not correctly depict the material or fit of the product. This raises a serious issue that e-commerce sites have to deal with since visual content posted by consumers should be genuine and beneficial and not potentially deceitful or falsely leading (Zhou et al., 2018). Although these images can positively influence the entire shopping experience, they should be thoroughly filtered to prevent false portrayals that can lead to customer dissatisfaction or returns (Das & Kumar, 2023). Moreover, the existence of reviews with high-quality pictures or videos may give an illusion of increased transparency, which may consequently result in increased levels of consumer confidence and a higher chance of purchase (Ni et al., 2018).

Nevertheless, the effect of feedback forms is not only limited to the type and the form of the feedback, but also to the features of a specific consumer, including his or her previous experience, expectations, and faith in the platform where the reviews take place (Bitaab et al., 2023). More tech-savvy or online shopping platform-experienced consumers can trust the text reviews or product descriptions more, whereas less experienced or risk-averse consumers may feel more at ease with a simple and immediate star rating (Tufail et al., 2022). The emphasis on the format of feedback can also be affected by the experience of a consumer on the use of the same product or brand; the former may be more inclined to rely on the feedback information that will match the expectations of the former. On the other hand, a consumer who had had a bad purchase previously might be more doubtful of feedback, whichever form of feedback it is and may need more convincing before he or she can make a subsequent purchase (Wasilewski, 2024). Moreover, platform-specific conditions also affect consumer behavior, including the existence of fake reviews or insufficient review control, which can destroy the trust in the entire feedback system (Zhang et al., 2023). The rise of artificial reviews has also turned into a major problem to e-commerce websites, as the consumers have grown sensitive to the possibility of manipulation (Zhou et al., 2018). On one hand, faked reviews might have an unrealistic effect of enhancing the perceived quality of a product but, on the other, this can also backfire as it will develop a feeling of mistrust which will cause the consumers to become skeptical and will even avoid feedback (Hajek et al., 2023). This effect is particularly worrisome in the business divisions where the choice made by customers is most strongly affected by reviews, including consumer electronics or fashion, where the trust in the feedback system may or may not close the deal. Thus, platforms must not only guarantee that the reviews are authentic, but offer consumers ways to determine the trustworthiness of the feedback they are presented with, one of the options being verified purchasing labels or rating systems on the reliability of the feedback they see (Ni et al., 2018).

User feedback formats are known to be critical in making consumer decisions in online stores yet, the success of such formats will be affected by a wide range of factors such as product type, presentation of the feedback, and consumer characteristics (Bitaab et al., 2023). Although star rating is a simple and rapid method of evaluating the quality of the product, it might not provide the level of information needed with high involvement products where consumers tend to pursue more detailed and qualitative information. In those situations, textual reviews and visual materials will become inalienable aids to the consumers, giving them the knowledge they require to make a wise choice (Tufail et al., 2022). Nevertheless, there are also some disadvantages to these types of feedback, especially regarding authenticity, where the presence of counterfeit reviews may harm the consumer base and bias the buying behavior (Roumeliotis et al., 2024). Besides, the manner in which feedback is displayed in the form of star ratings, reviews or pictures should be specific to the requirements of a consumer and the nature of a product under consideration. Those e-commerce sites that fail to respond to these feedback systems risk losing their customers particularly in highly competitive markets where the aspect of trust significantly features in the purchase decision making process (Wasilewski, 2024). Further research is needed in the future to know how the feedback format can be optimized to achieve authenticity and relevance, and this will improve the total suitability of user feedback to influence on online purchase behavior (Zhou et al., 2018). The dynamics play a an important role in the perception of businesses that seek to enhance their customer experience to raise conversion as well as build customer confidence in the fast developing complex and competitive e-commerce environment.

1.2 The Role of User Feedback Formats in Consumer Behavior

One finds it hard to disagree with the increasing role the user feedback plays in shaping the consumer behavior of e-commerce and the type of user feedback can be regarded as the deciding factor as to the trust and the purchasing decision. Online reviews, Star rating, and comments have altered the dynamics between the consumer of an item in the digital era even more to the predecessive word-of-the-mouth reasoning but now more to a data based advice (Di Crosta et al., 2021). The effect of a user feedback on the consumer behavior is complex as it depends on multiple factors, such as the type of feedback, the medium on whichh the feedback is posted, and the reasons as to why the consumer has to be interested in such feedback. Consumer behavior studies indicate that user feedback format might have a significant influence on the information processing and consumer purchasing decision (Sundararaj and Rejeesh, 2021). Such reviews as the textual ones, which present a detailed account of a user experience, tend to be more appealing to the consumers as opposed to the bare star reviews since they can give a better insight into the performance, quality, and long-lasting value of a specific product (Lv et al., 2022). Nevertheless, textual reviews may be able to minimize doubt, but can be easily manipulated and biased, which is subject to credibility. Intriguingly, fake reviews, especially, have become one of the most important issues in e-commerce because they undermine consumer trust and can result in negative buying actions (Shahbaznezhad et al., 2021). Therefore, although positive feedbacks posted by users can help the consumers trust the online stores, online platforms must also pay attention to the integrity of the latter as it will help retain the Integrity of the feedback system and not to deceive the potential buyers (Azizah et al., 2022).

In addition, the manner in which feedback is provided and consumed tends to affect consumer behavior. To exemplify, visual feedback formats (i.e. user-posted pictures or videos of used products) have become incredibly popular in the recent years (Fischer et al., 2021). Although visual feedback provides consumers with a more concrete and interpretable depiction of a product, it may significantly increase the perceived value of the product, especially in such a category as fashion, beauty, and home décor (Zheng et al., 2022). Images and videos, in contrast to textual feedback, can be easily used to present concrete evidence of what the product really looks like and what its quality is, as they are especially efficient in diminishing buyer hesitation (Ming et al., 2021). Nevertheless, the usefulness of visual feedback forms lies on a number of issues, such as the quality of the images, the accuracy of the image, and the context within which the images are put. Low quality photos or false images may back-fire and the end result is disappointment on the part of the consumer because the product is not according to their expectation. It follows that consumers usually target feedback that is both visually rich and credible and authentic (Kumar et al., 2022). The significance of visual feedback in consumer behavior explains why authenticity and transparency in e-commerce are critical to the consumer behavior since they tend to respond more to information that connects with their perceptions and experiences (Di Crosta et al., 2021).

The emergence of social media and live-streaming sites has also complicated the contribution of user feedback to the process of influencing consumer behavior. Influencers have emerged on social sites such as Instagram, YouTube, and Tik Tok as a significant force behind consumer engagement and intentions to purchase particular products due to their promotion of them (Hadi et al., 2024). The consumer-influencer relationship has further complicated the conventional type of feedback since the recommendations of influencers tend to incorporate user feedback with advertisements (Lv et al., 2022). Influencer marketing has a special level of influence on consumer behavior, and in the case of impulse buying, consumer purchasing can be easily prompted by the feedback in the form of the opinions of influencers or live-streaming recommendations (Zhang et al., 2023). These platforms enable live response, which confer consumers a feeling of urgency and personal touch that can hardly be achieved with conventional reviews or ratings (Azizah et al., 2022). Particularly, live-streaming commerce has turned out to be a very efficient means of attracting interest and selling impulse actions as consumers tend to be attracted by the dynamics of the live communication and the exclusivity of time-based offers (Shahzad et al., 2023). Nevertheless, the emergence of the influencer-based feedback also throws the question of the authenticity of reviews, as the latter may tend to engage in promoting products in order to be paid, which creates the risk of possible bias in the feedback given by influence (Fischer et al., 2021). This leads to the fact that the consumer behavior is determined by both the content of the feedback itself and the perceived credibility of the source of the one who gives the feedback (Rachmad, 2024). This emphasizes that the platforms should come up with systems that guarantee transparency and authenticity in influencer-created content to avoid losing consumer confidence (Ming et al., 2021).

Besides influencer marketing, artificial intelligence (AI) and machine learning as the factors affecting consumer feedback have become more and more prominent. Recommendation systems powered by AI (user behavior and preferences-driven) and delivering personalized feedback and product recommendations have become a common feature of numerous e-commerce sites (Bag et al., 2022). They are based on massive datasets and algorithms that can forecast which products will be bought by customers the most likely based on their previous activity and communication with the platform. Although AI-based recommendations have the potential of making the shopping experience better, with the suggestions being valuable and timely, it becomes a concern regarding the privacy of data and whether the algorithm is going to be biased (Di Crosta et al., 2021). The introduction of AI in feedback formats also brings about the aspect of automation and customization, which can potentially improve consumer relationships but causes some issues with transparency and equity. It is not always known by the consumers of how their data is being utilized to shape the feedback mechanism that they receive and as such, the ethical aspect of such systems is of concern (Lv et al., 2022). Also, AI-based suggestions might occasionally strengthen the preconceptions in place, with it being prone to suggest a product that is in line with the past interests of the consumers, potentially restricting the exposure to new or varied products (Kumar & Pandey, 2023). Thus, although the aspect of customization and importance of feedbacks might be addressed through AI, it remains to mention that virtual stores will have to address the concerns of the value of AI-rich propositions and the sources of openness and fairness (Azizah et al., 2022).

The more assertive popularity of the gamification features that were implemented to the e-commerce portals also changed how the consumer feedback is processed. The very concept of gamification is being implemented in order to introduce when one will need to encourage interaction and engagement on the program of consumer feedback by bearing the game like elements, i.e. merrits and rewards, challenges (Shahzad et al., 2023). Based on the example, the sites will be able to encourage someone to leave especially review or respond to the products by taking their feedback as a way of rewarding them and valuing their suggestions. Enlisting gamification may also be a good option, as it may contribute to the rise of the consumer engagement rate and turn the feedback procedure into a more engaging and lively process so as to entice increasing and increasing general reviews (Fischer et al., 2021). In addition, gamified feedback systems may be used to develop a sense of community among the consumers since users will compete to gain rewards or higher ranking due to their participation. The success of gamification in changing consumer behavior, however, is dependent on the implementation of this technology. Gamification elements, in case of improper design, can become manipulative or too commercialized, which can decrease the degree of truth in the feedback and decrease consumer trust in the end (Shahbaznezhad et al., 2021). To be effective, gamification should be consistent with the overall user experience and offer valuable incentives that contribute to the credibility of feedback process instead of damaging it (Ming et al., 2021).

Conclusively, the consumer behavior of user feedback formats is complicated and varies depending on various factors, such as the format of the feedback, the venue on which the feedback is posted, and the motivation of consumers and influencers (Di Crosta et al., 2021). The textual reviews, star rating, and visuals are all used in the formation of consumer perceptions and buying intentions, and this is achieved depending on the authenticity and relevance. With the advent of social media and live-streaming, the concept of the user feedback has shifted to a new perspective, and using influencers is a way to control consumer behavior and buying decision. In the meantime, new opportunities, and challenges are appearing on the e-commerce sites since AI and gamification evolves to change the essence of forming feedbacks and consuming them (Lv et al., 2022). As the consumerism pattern keeps evolving with the digital era, the companies should be sensitive to develop the customer reaction and come up with strategies that would aid in establishing trust, transparency and interaction. A complex interaction between the customer behavior and the feedback will be paramount to the e-commerce sites that become interested in optimizing the feedback system and the consumer shopping experience.

1.3 Types of Products and Their Sensitivity to User Feedback

Feedbacks provided by users are also a critical factor in consumer purchases in digital space in the comprehensiveness of a variety of product-buying (Connell et al., 2018). However, the extent to which different forms of products are responsive to the feedback may vary considerably because it may be influenced by a number of conditions, which include the complexity of the products being purchased, the price of these products, and risk. Consumer decision making is more conscious in the high-involvement products, including electronics, luxury products, and home appliances, and feedback is an important instrument that could be used to evaluate product quality and reliability (Kübler et al., 2018). These products can be associated with increased expectations, both in functionality and life, and users tend to examine various sources of feedback, including textual reviews, ratings, and visual materials before buying them (Pagano et al., 2023). The influence of user reviews on high-involvement products is significant since a consumer considers such products as more risky investments. In this regard, they tend to seek more information to validate their buying choices to have feedback that will provide in-depth information about the performance and usability of the product in real world settings (Mcdonald et al., 2020). Especially, such tools as consumer reviews as detailed narratives or user-posted videos can play an essential role in perceived risk reduction by giving a greater context regarding the quality, functionality, and possible failure of the product (O'Dea et al., 2021). In this respect, goods within such categories are more vulnerable to feedback, where positive reviews would result in greater confidence to buy the product, whereas negative ones would strongly discourage the people interested in buying the product (Følstad, 2017).

Conversely, low involvement products like fashion accessories, beauty products and daily consumables do not respond to user feedback in the same way (Connell et al., 2018). These products have a lower financial risk and are usually bought on impulse and consumers do not take as much time to conduct in-depth research before buying. In this way, the influence of user-feedback is usually weaker than in the case of high-involvement products. This does not however imply that feedback is insignificant in such categories. User reviews and ratings are also a type of social proof that can make buyers feel safer and determine their attitudes toward the quality of a product, even with low-cost products (Farid et al., 2025). E.g., a customer who wants to buy a pair of shoes or a skincare item might use star ratings and short reviews as the main sources of information on the level of satisfaction of former customers. The feedback formats provided in these instances, which provide fast and aggregate summaries, which are ratings or simple thumbs up or thumbs down feedback, were found to be enough to enable consumers to decide (Kübler et al., 2018). However, the conciseness of these formats might not be able to offer the richness needed by more intricate and high-involvement products and, therefore, products with low involvement are less responsive to detailed feedback. Rather, their sensitivity is usually defined by the number and general tone of reviews, where the more positive reviews, the higher the chances of purchasing, whereas even a smaller number of negative reviews can affect the purchase at a disproportionate scale (Roy and Dutta, 2022). Thus, this does not necessarily mean that low-involvement products are not as sensitive to detailed feedback as high-involvement products, but the overall tone of user feedback is an important factor in determining consumer perceptions and decision-making (Mcdonald et al., 2020).

The sensitivity of the products to the feedbacks of the users could also be observed through the increased influence of user-generated content on e-commerce sites (Følstad, 2017). With the continued rise of social media and live streaming services, they have already begun affecting the behavior of consumers in a new and consequential way. Social media-featured products or those being promoted by social media influencers, in particular, in such industries as fashion, beauty, and lifestyle, were expected to be very sensitive to positive and negative user reviews (Zhu et al., 2023). When it comes to such instances, the feedback is not restricted to conventional reviews but expands to personal views and suggestions of influencers, celebrities, and ordinary consumers who share pictures and videos of the products they wear (Connell et al., 2018). The visual aspect of such feedback, as well as the possibility to personally address influencers in the form of live comments or posts, will develop a closer and more personal contact with the product. It is this immediacy that makes such kinds of products particularly susceptible to feedback since consumers tend to base their purchases decisions on real-time responses by people they trust within their social networks (Bondad-Reantaso et al., 2023). Additionally, the pace at which social media trends change implies that feedbacks on products can result strong and fast influence on the marketability of the products (Kübler et al., 2018). The products that receive good reviews or comments by the influencers or the consumers may see a rise in their numbers, whereas negative reviews, especially when they go viral, may lead to a sudden drop of the consumer attraction to the products in the given category, which hurts the sensitivity of the products placed in these categories to the user feedbacks (Følstad, 2017).

Besides the type of product and its nature, the technological environment where users give feedback also contributes to the sensitivity of the products to the feedback. The popularity of the recommendation systems that use the machine learning algorithms to give the user the personalized feedback according to their preferences has been a typical aspect in the e-commerce sites. These systems are especially effective when it comes to the products that are often purchased along with others or belong to a bigger set, which can be electronics with accessories or the shoes that go with the clothes (Wang et al., 2023). When these systems are more advanced, they can provide feedback recommendations based on the history of a user and thus become more useful in influencing a purchase decision on a large variety of products (Mcdonald et al., 2020). This additional dependence on computer-facilitated feedback, however, is also accompanied by the problem of equity and bias especially in the way such feedback ought to be delivered to their consumers. It also has been documented that research efforts on machine learning models discovered prejudices of algorithms can bring about just biases on deeply representing the products, due to the fact that some of its products are overrepresented and create unwarranted underrepresentations of the rest of its products in the review that consumers are encountering (Pagano et al., 2023). The given feedback in this instance might not represent the entire range of user experience and the concept of the quality of this or that product and its possible functionality will be distorted (Connell et al., 2018). Consequently, any goods having to pass through such unequal systems of recommendation may prove to be less receptive to the trust of the end-user and more susceptible to biases in the algorithms capable of affecting the decisions in the long-term, ultimately impacting the consumer trust. This difficulty raises the question of why e-commerce platforms must make sure that their recommendation systems are transparent and unbiased, as well as offer the consumer a more balanced perspective on what is on offer and the feedback in question (Kübler et al., 2018).

The sensitivity of the various products types to the commentary of users also differs based on the type of market where they are being retailed. When the market is highly competitive and there are many products that are similar in terms of the products provided, the feedback of the users is a more important factor in the differentiation of products. Feedback can play an important role in the market share of a product in such markets because consumers can use reviews and ratings to make a rapid comparison between products (Ahmad et al., 2021). As an example, the smartphone industry is a highly competitive sector with many brands selling similar products, so consumer feedbacks in the form of reviews, ratings, and social media recommendations can also serve as a major point of difference (Mcdonald et al., 2020). Positive feedback may cause the start of a virtuous cycle where more visibility and positive reviews will cause higher consumer interest and sales, whereas negative feedback may cause a drop in consumer interest and sales in a short period. Conversely, in competitive markets that are not as competitive or in products with niche applications, feedback may not be so great of an impact on consumer behavior, as there are fewer products to compare to and fewer sources of feedback to count upon. When this happens, user-generated content might play a secondary role in influencing consumers when compared to the brand or product itself, and the feedback can be regarded as an additional tool that confirms the purchasing decision instead of being the major factor of consumer behavior (Valkenburg et al., 2022). This highlights the need to learn the context within which products are sold and how feedback may change with circumstances in different markets on how it affects purchasing behavior (Følstad, 2017).

To sum up, product sensitivity to the feedbacks received by users greatly depends on the nature of the product, the context of its operation in the market, and the platform on which the product is marketed. The high-involvement products including electronics and luxury products are normally more sensitive to detailed feedback as the perceived risk and investment made by consumer is more sensitive (Connell et al., 2018). Low-involvement products which include fashion and beauty products are likely to be affected more by aggregate feedback and the general sentiment. In addition, goods which are advertised via social networks or live-streaming services are particularly vulnerable to reviews, since the immediate interaction with clients can have a great effect on their buying choices. The technological situation, including the application of recommendation systems, is also significant and may influence the presentation and processing of feedback, and the possible problems are connected with the possibility of algorithmic bias which may impact the correctness and justice of the feedback (Kübler et al., 2018). With e-commerce constantly changing, the study of how various types of products react to user feedback will be essential to both the businesses and the consumers, making sure that the feedback mechanisms are efficient, clear and according to the demands of the consumers.

1.4 Theories and Models

1.4.1 Theory of Planned Behavior (TPB)

A theory of planned behavior, which was first theorized by Ajzen, is one of the most commonly applied theories when analyzing and predicting human behavior. TPB indicates that the intention to perform a behavior is the closest predictor of the behavior and as such, this intention is determined by three important factors namely attitude toward the behavior, subjective norms and perceived behavioral control (Kumar, 2021). Attitudes are a positive or negative assessment of the behavior by an individual, social pressures or influences that can either promote or deter the behavior are known as subjective norms and the perceived behavioral control is the belief that an individual may have in performing the behavior. TPP has over the years found application in various settings whether health related behavior, consumer behavior, to elucidate the manner in which various factors impact on intentions to undertake certain actions (Özel & Çoban, 2023). This model has been very versatile and academicians have usually elaborated on it by adding more variables like risk perception, social influence and environmental conditions (Norisnita & Indriati, 2022). TPB proves quite useful in the framework of e-commerce, with behavioral patterns to purchase a product on-line depending not only on personal views towards the product, the social stigma surrounding online shopping, but also on the perceived control that consumers have over the process of buying products online (Buying & Young, 2018).

Among the most prominent directions in which TPB has been prolonged and implemented, the digital investment sector of cryptocurrency and Non-Fungible Tokens (NFT) markets has been highlighted (Kumar, 2021). These investment opportunities are highly volatile and complicated, and they may introduce a great degree of uncertainty to the investors. TPP in this context must be a valuable tool in shedding light on the motivations behind the urge of an individual to invest in such brand new emergence of digital stocks. Norisnita and Indriati (2022) used the TPB to solve the issue of identifying the factors connected with the decision to invest in cryptocurrencies and introduced the attitudes towards presence and absence of risk and reward of investment as the subjective norms to use a cryptocurrency to perform investment and the perception of the opportunities to control the process of investing in a cryptocurrency as the key predictors of the intentions to invest in a cryptocurrency (Özel & Çoban, 2023). Based on the analysis, the relevance of financial literacy and belief in crypto market make sense of the decision in becoming an investor of the crypto market, as the simple paradigm of TPB is multiplied by the introduction to the outside elements that affect behavior in the digital market. Providing a more precise evaluation on the discussed matter, Albayati et al (2023) refined their TPB model to review various elements of engagement practices in the sphere of newly developed, rapidly changing world, NFTs and metaverse. They also find out that the attitude towards virtual experiences is not the sole factor which predetermines the consumer presence in the metaverse, but social effects do take place as well, including the behavior of the peers and a sense of control over cooperation in these virtual worlds (Buying & Young, 2018). The marketplace of digital investment and the virtual form of engagement uses functions to this set of TPBs as it demonstrates how the theory could be incorporated into the modern environment, specifically, when the propensity to new technologies and cyber societies can influence the consumerism (Kumar, 2021).

TPP usage is also common in the environmental behavior specifically in pro-environmental intentions. Using the TPB, the authors of the interpretation Gansser and Reich (2023) analyzed the relationship between the environmental issues and the attitudes with the environment and the pro-environmental behavior with recycling and sustainable consumption (Özel & Çoban, 2023). They discovered that perceived control and subjective norms of behaviors that were deemed to be long term sustainable are vital predictors of pro environmental intentions. In this respect, the TPB model demonstrates the suitability of the societal needs and individual enablements in influencing the environmentally healthy behaviors (Buying & Young, 2018). This comes with the reality that the people will feel like doing things that they think are accepted within the society and that they have the capability of doing so. Besides this, the paper revealed that a close relationship existed between the attitude toward the environmental concern like the change in climate as well as the conservation of the resources and intention by the individual to participate in the pro-environment business (Kumar, 2021). It emphasizes the way that the TPB concept is so flexible, facing the perception of the other than consumer buying behavior that extends to an extent of initiating actions with social and environmental implications so much greater. Moreover, it further indicates that TPB might be employed to implicate policies and strategies involved in the popularization of the eco-friendly approaches, and even more, the encouragement of connotive sentiment and the establishment of a presumed agency over the overall environmental practices may be salient policies to the similitude of environmental-sensitive practices (Özel & Çoban, 2023).

Another place where TPB has been widely used is in transportation choices, specifically in the desire to use a public transportation. In the city, the choice that people have to take in terms of taking the other means of transport is subject to factors like convenience, affordability, and environmental issues (Buying & Young, 2018). Ali et al. (2023) used TPB to foresee the behavioral intentions of the people regarding using public transportation in Japan, focusing on the influence of the attitudes to the convenience and environmental advantages of the use of public transport, as well as subjective norms about sustainable travel, on the choice to use transportation (Kumar, 2021). It was also established in the study that the perceived behavioral control including the ease of accessing public transport and availability of other alternatives played a significant role in influencing intentions of people to use public transport. The use of TPB in this manner shows the significance of perceived barriers, including accessibility and convenience, to promote the use of public transport (Özel & Çoban, 2023). Furthermore, it implies that the perception of control can be positively affected by interventions that will be undertaken with the purpose to make the public transport infrastructure more convenient and appealing to users in order to achieve an increase in the rates of the latter. In city planning and policy making, it is important to learn the determinants that shape transportation choices as a means of encouraging sustainable travels and TPB is a useful tool of forecasting and manipulating these actions (Buying & Young, 2018).

TPB has also been extensively used in regards to health related behaviour e.g. exercise and food consumption whereby it assists in the elucidation of the intentions of adopting healthy behaviours. Sujood et al. (2022) used TPB to explore behavioral intentions to travel during the

COVID-19 pandemic, investigating the effects of the attitudes to health risks and perceived safety on the travel intentions (Kumar, 2021). The researchers concluded that conventional TPB elements like attitude and subjective norms were useful in influencing the intentions of people, but also perceived risk and fear of infection were other influential elements that affected the choices individuals made to travel. This use of TPB extension illustrates how any external issue, in this case, a global health crisis, can seriously influence the conventional components of the theory (Özel & Çoban, 2023). The intentions of people were influenced in the pandemic more by the consideration of health risks rather than social pressure or individual attitudes towards travelling. On the same note, Azhar et al. (2023) expanded TPB and investigated travel intentions after the pandemic, in this case, considering rural locations. Their research discovered that together with their attitudes to travel and environmental issues, other aspects like perceived safety and confidence to health protocols became important predictors of travel intentions (Buying & Young, 2018). These instances of TPB use to describe health and travel behavior in the pandemic and post-pandemic demonstrate how the theory can be adjusted to consider exceptional situations, and it is flexible in explaining the behaviors that are determined by real-life events.

1.4.2 Social Influence Theory

Social Influence Theory has been a staple of comprehending human behavior both offline and on-line especially regarding consumer decision making. According to the theory, the behavior of individuals can usually be influenced by the presence of others, their behavior, or anticipation, either in personal interactions, peer pressures or by observing the social norms. Social Influence Theory has become highly applicable in e-commerce and the online consumer behavior context because consumers are always exposed to various influences in the digital space by their peers and brands (Sharipudin et al., 2023). This influence is of different types and includes user reviews, social media endorsement, influencer marketing as well as peer feedback, which all can direct the consumer decision (Oliveira et al., 2025). The rise in the use of social networking sites and online communities has increased the effects of social influence since people are not only subjected to immediate feedbacks of their close social group but also of those who are far away and who are most times unknown to them (Purohit & Arora, 2022). Social influence, in e-commerce contexts, can be divided into informational influence, in which people consult the experience of other people, and normative influence, in which individual behavior is caused by a need to be accepted into a group or gain approval (Rachmad, 2025). These two categories of social influence play a critical role in the attitudes and behaviour of the consumers in the digital market developing where choices are becoming more of a community involvement as opposed to a solitary decision making process (Sharipudin et al., 2023).

The social influence aspect in influencing consumer behavior has especially been keen in the emergence of virtual influencers in online marketing campaigns (Oliveira et al., 2025). The virtual influencers, usually AI-generated figures or digital personas, have already gained a considerable role in influencing online consumer behavior as they apply the concept of Social Influence Theory to influence the intention to purchase and mold the brand image. Research shows that virtual influencers do not work differently than human influencers, basing their social influence on their perceived credibility and relatability to motivate consumer behavior (Davlembayeva, Chari, and Papagiannidis, 2025). These fictional characters are positioned strategically on the social media platforms where they communicate with their followers, promote products, and make them feel part of the social groups they have in the online platforms. Just like traditional influencers, virtual influencers are trusted, having a steady and relatable content, but the difference is that the former is completely controlled and designed by brands, which creates a more focused and steady messaging strategy (Purohit & Arora, 2022). Their success can be explained by the similar mechanisms of social influence that influence traditional instruments of influencer marketing, such as conformity, admiration, and the urge to achieve social validation, which makes them an ever-growing instrument among the marketers who target to reach younger and digitally-native consumer groups (Sharipudin et al., 2023). Their increasing power, notwithstanding, the authenticity and emotional resonance that virtual influencers are able to provide is a controversial issue, especially compared to the human nature that can create more consumer loyalty and engagement (Hazari, Talpade, and Brown, 2024). However, the further development of virtual influencers provides a promising chance to learn more about the ways in which digital characters and social impacts are capable of influencing consumer behavior (Oliveira et al., 2025).

The concept of social Influence has also been addressed in the context of social media channels, specifically in the context of brand influencers on such applications as Tik Tok. The social influence is on a scale never seen before due to the algorithm of the platform that values the engagement of users and the popularity of the content. Influencers on Tik Tok, such as an example, can have a significant influence on consumer behavior by utilizing their mass audience to market products, trends, or challenges that others can follow (Purohit & Arora, 2022). This type of influence has no causal implications of the authorities but it brings forth social conventions that arise through the usage and interaction within the platform (Spears, 2021). This type of influencers can be theorized to give rise to information that contributes to the social evidence among users through basing their behavior and ideas of those they follow on their behavior and thoughts (Sharipudin et al., 2023). It was also released that the Tik Tok influencer power is highly high in terms of being perceived as relatable and authentic and significantly enhances their normative power among the followers. Once the social influence, interaction with peers, and available contents in the Tik Tok combine to create such a convergence state, the consumer behavior becomes highly networked in terms of action of other people coupled with what they perceive (Oliveira et al., 2025). This underscores increased extrapolation of the application of the Social Influence Theory in general in the way social media is invigorating consumer decision making process in the sense that it is an inherent fact that people have to decide whether to balance the peer influence (in relation to peer influence) between the influencer recommendation and peer influence toward the social norms (Purohit & Arora, 2022).

Besides the virtual and brand influencers, the social influence is also a powerful contributor to the consumer behavior when it comes to providing a recommendation on a product, as well as online reviews (Sharipudin et al., 2023). Considering that consumers consider the experience of other consumers when choosing products in an online setting, the comments of former buyers are a vital part of the social power mechanism, and user-generated content can play a crucial role in the process. Online reviews can be considered as an informative and normative tool as people seek the experiences of others to determine the quality of a service or a product, as well as fulfill the social norms about what is acceptable or desirable (Oliveira et al., 2025). It has proven that the perceived credibility of reviews, the quantity of reviews, and the social confirmation provided by affirmative reactions can greatly enhance the possibility of a consumer purchasing a product (Liang et al., 2021). As an illustration, a product that has many positive reviews may cause a bandwagon effect where one may buy more often due to the popularity or social validation of others. The success of this social influence is, however, determined by the perceived credibility of the review source. Although the opinion of experts and verified customer reviews can be regarded as more important, non-verified or suspiciously close reviews can cause distrust and lack of confidence among the consumers in the feedback system. Therefore, the validity of the online reviews and the feedbacks is important to the continuation of the positive impact that social proof can have on the consumer behavior (Purohit & Arora, 2022).

Besides the classic uses of the theory, it is possible to note newer uses of this theory in how consumers make contacts with the gamification aspect of e-commerce and social media. Gamification, or the application of game-like features, e.g. points, leaderboards and rewards into non-games, has been identified to aid in increasing consumer engagement and influencing a buying decision (Sharipudin et al., 2023). This method builds on the power of social influence, as it encourages the consumer to engage in challenges, discuss their successes and compare to others, which support social norms and encourage the behavior (Oliveira et al., 2025). Social influence process is especially effective in gamified contexts where a consumer is influenced not only by personal contacts but also by the competitive and social comparisons of a gamified experience (Butera, Dompnier, and Darnon, 2024). It has been found out that when consumers get rewarded by their involvement (through loyalty points, discounts, or social reward recognition), they will be more inclined to stick to a given brand and keep making purchases (Purohit & Arora, 2022). By exploiting the intrinsic motivation of consumers e.g. status, achievement, and social recognition, gamification is a highly useful tool in the online marketplace (Sharipudin et al., 2023). The influence of social influence on the formation of consumer behavior will probably increase as more e-commerce platforms implement the concept of gamification, offering companies new chances to communicate with their audiences and make them convert.

1.4.3 Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model (ELM) has a great deal of value in the way consumers process persuasive messages; two routes exist, a central route and a peripheral route: the central route is a slow process, thoughtful and careful consideration and the peripheral route is a process that is based on superficial attributes, such as attractiveness or credibility (Moradi & Zihagh, 2022). When e-commerce and marketing are considered, the degree of interest of the consumers in the product defines the path that they will follow when handling information (Kumar et al., 2023). Consumers with high involvement use the central route to engage with substantive messages and low-involvement consumers are more likely to be affected by peripheral cues, like brand reputation or attractiveness (Hidayat & Solihah, 2021). This two-pathway framework assists in the explanation of how product reviews, advertisements, and influencer endorsements are different types of digital communication, which can influence consumer decision-making (Wagner & Petty, 2022). As an illustration, descriptive product information and professional advice can be more effective when used as the central route (as it is more likely to attract consumers), and ads that are emotional can be employed as the peripheral one (they can be used to affect a decision with less mental effort) (Srivastava & Saini, 2022).

ELM has also been aligned with other psychological theories like the Theory of Planned Behavior (TPB) to investigate the topic of decision-making in other situations, including sustainability and health communication (Moradi & Zihagh, 2022). As an example, it has been found that consumers tend to interact more with eco-friendly products in the central route in cases where they have high levels of involvement with environmental concerns (Liu et al., 2022). On the other hand, peripheral cues, such as beautiful images or brand equity, are more prominent with low-involvement products (Hidayat & Solihah, 2021). The model applies to social influence settings whereby health messages (Bayraktar, 2024), Infographics, and even sustainability campaigns can be specific to either central or peripheral route, according to the level of engagement of the consumer (Wagner & Petty, 2022). Such an adaptability of ELM in the description of various kinds of consumer behavior is essential to the marketer who has to create more efficient communication strategies depending on consumer engagement and the specific character of the product (Lam, Huang, and Shen, 2022).

1.4.4 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is one of the popular models of understanding the process of acceptance and utilization of technology among the users (Islam et al., 2023). TAM, which was originally proposed by Davis argued that the two factors that play a role in selecting or rejecting a technology in an individual are Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). The model dictates that when the users see a certain technology as convenient and helpful, they will accept it more (Toraman & Geçit, 2023). TAM has been elaborated and combined with other theories over the years to understand the adoption of technology in different sectors in a better manner (Katebi et al., 2022). As an illustration, it has been demonstrated in the context of e-learning that the desire to remain using an online learning system heavily depends on the perceived ease of use and the usefulness of the features of the latter, which supports the fact that TAM is rather robust in forecasting technology acceptance (Mustafa & Garcia, 2021). Also, the research in the banking industry shows that the level of acceptance of digital banking services by consumers is also influenced by the perceived utility and usability, trust, security, and convenience factors have the essential impact on the further use of the new services by the users (Uula & Avedta, 2023). These results indicate that TAM is flexible in various technological environments, which makes the findings very useful in the factors that influence the adoption of technology in various industries (Katebi et al., 2022).

The scope of TAM implementation is not confined to the standard technology environments, as it has been applied in the context of healthcare and construction to determine how users adopt health records systems and artificial intelligence (AI)-powered technologies (Islam et al., 2023). The perception of security and privacy of personal health records is excessively high to measure acceptance and usage of the patients, and usability is a simple qualify that is tacked to overall adoption process (Alsyouf et al., 2023). In a similar way, using TAM, the entry of AI-based technologies in the organization can be explained in terms of organizational determinants, as well as address the external determinants, which can provide power in terms of determining the choice to adopt technology (Na et al., 2022). The given articles underscore the fact that the model is universal and can be implemented in case of a powerful temperature of all spheres, so the apparent convenience of implementation and utility, as well as any external purposes related to safety and organizational preparedness, are the secret of the success of the implementation of the introduction and subsequent use of new technologies (Rad et al., 2022). Technology is not fully developed, so the information TAM presents her has some merit in getting familiar with the new systems by individuals and organisations and a perfect guide to the creators and marketers of the technology (Toraman & Geçit, 2023).

1.4.5 Information Adoption Model (IAM)

Information Adoption Model (IAM) was one of the frameworks that assist in informing the decision making process of making choices between adoption and non adoption of information and the support the information can give on the decision making process. Because

IAM has been generalized to the e-government domain, the social media context and communications in healthcare, the context behind its creation was to be used in information processing within digital contexts (Çelik & Aslan, 2025). This model tends to reveal that there are two massive factors which characterize the adopted and none adopted information and they include the credibility of information perceived and degrees of diagnosticity of the information perceived respectively. Since finding information as credible and related to the point, it has been since demonstrated that people are also willing to put the information into use, whether the information they read applies to the government service or reviews of the product and health related intelligences (Chiu et al., 2023). The role of e-government in the COVID-19 crisis was investigated, and the evidence (regarding its sense of usefulness as well as the authenticity of presented information) turn out to be the core of the process of encouraging citizens to utilize the online governmental services (Mensah et al., 2022). On the same note, it has been established that when users realize that the information in a review and comments they see on social media websites is credible and highly applicable to their case, then they will tend to use the information contained on the sites (Islam et al., 2022). These results contextualize the topicality of IAM in the realm of the many other fields and it may show that they may be used to acquire the information influence on the decision-making in the reality of the Internet (Tseng & Wu, 2024).

The use of IAM applications transcends other application topics such as in healthcare where IAM has been employed to research the habits of embracing the health information (Chiu et al., 2023). Giving an example, the selection of information by mobile users prompted the development of the IAM through the search of user mobile technology that provides information about health-related concerns (Elwalda et al., 2022). The researchers could have shared the information that the credibility of the information sources, as well as the ease of obtaining the required information related to health, could be discussed as the key predeterminers of the adoption. (Çelik & Aslan, 2025) Besides that IAM extension was also employed to simulate information adoption behaviour of the Malaysian youths when this related to the context of organ donation and when the perceived personal relevance and the emotional appeal had it an influential role on the inclination of the youth to adopt the information on the topic relating to donation of organs (Madli et al., 2024). Equally other models have been combined with IAM and this latter explains the consumer action in an online shopping scene such as the EIO of LizHashMap, or Elaboration Likelihood Model (ELM) (Tseng & Wu, 2024). The study retrieved the direct effect of image credibility and utility of e-commerce evaluation on spending plans of the consumers, particularly where online reviews were in line with requirements of the consumers (Kumar et al., 2023). The applications of IAM to the different industries show provisions of the extent of the usage of IAM in determining the rate that people give to decide, process and finally adopt the information on all kinds of decisions (Song et al., 2021; Ma et al., 2025).

2.0 RESEARCH METHODOLOGY

2.1 Conceptual Framework

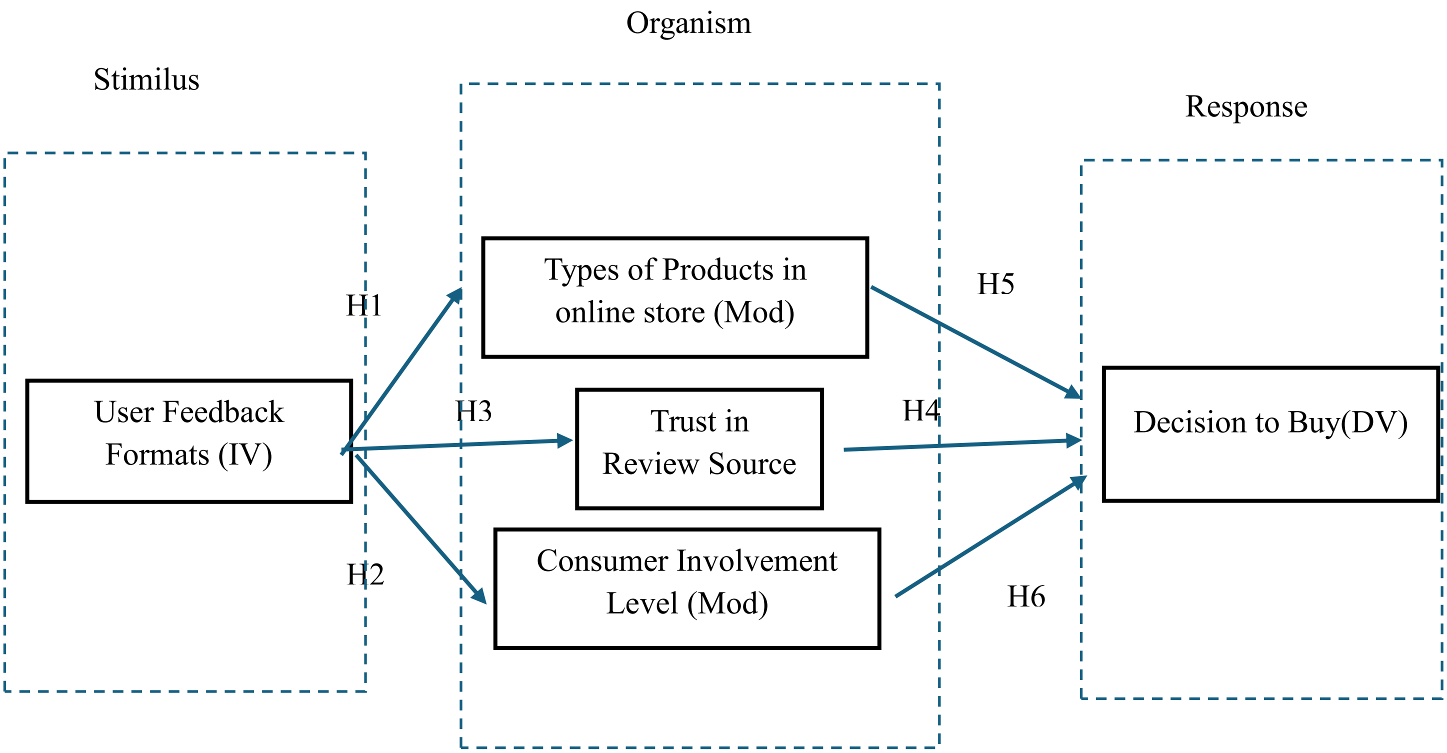

Figure 1: Conceptual Framework

This theoretical framework will look at the role of the format of user feedback (ratings, reviews, visual content) on consumer purchase decision in online stores alongside moderating variables of the type of product and consumer engagement. It is based on a number of theories which have been tested and proven to be true such as the Theory of Planned Behavior (TPB) which emphasizes on the influence of trust and attitude in making a decision and the Social Influence theory which emphasizes on the influence of others. Another reference that is used in the framework is the Elaboration Likelihood Model that explains how the various types of feedback are processed and the Technology Acceptance Model that examines online feedback trust. These relationships in e-commerce are presented by authors like Tufail et al. (2022), Ni et al. (2018), and Wasilewski (2024) in their works.

2.2 Hypothesis

H1: The format of user feedback (ratings, reviews, visual content) significantly affects consumers' trust in the review source.

The presentation of user feedback is important in determining the trustworthiness of consumers towards the source of the review. Other studies have indicated that user reviews whether as textual messages, star ratings, or aesthetic messages as pictorials and videos, can substantially contribute to the perceived credibility of the source of the review by the consumer (Christian and Utama, 2021). As an example, star rating, although it gives a general idea, might be insufficient to help the consumer rely on the information completely, particularly when it comes to high-involvement products (Bitaab et al., 2023). Textual reviews, on the other hand, provide more details regarding the quality of products and user experiences, thereby creating more trust especially in more sophisticated or costly products (Ni et al., 2018). Images or videos left by the users make the reviews even more credible and create a more realistic view of the product, which may lead to overcoming mistrust and the creation of a more natural image of the product (Ming et al., 2021). Nevertheless, the problem of fake or biased reviews also becomes a major one because this disillusionment of consumers by manipulative or misleading information may damage the overall credibility of the feedback system (Wasilewski, 2024). This skill to differentiate between real and false feedback, in particular in the saturated e-commerce space, has therefore become central to trust building (Shahbaznezhad et al., 2021). Hence, it can be assumed that the user feedback format has a considerable effect on the levels of trust that consumers have on such sources.

H2: The type of product in an online store moderates the relationship between user feedback formats and trust in the review source.

Credibility of the source of review has been demonstrated to directly and significantly influence the consumer buying behavior, especially in online shopping context, where consumers are usually left in a state of doubt, given that they cannot touch and feel the products and make a purchase (Tufail et al., 2022). The studies show that the trustworthiness of online reviews, particularly when the credibility of the source is high, is a major factor in consumer decision-making (Bitaab et al., 2023). As an example, customers would be more willing to believe in what is described, clear, and real, including high-quality visual and writing material (Fischer et al., 2021). The more consumers have confidence in the feedback they get, the better chances they will make positive purchasing decisions since they become more confident about the quality and performance of the product (Lv et al., 2022). Quite on the contrary, the lack of trust towards reviews, which is often caused by the existence of manipulated or fake feedbacks, may cause uncertainties, low purchasing intentions, and brand suspicion (Zhou et al., 2018). Trust, thus, is an imperative mediating variable in the kind and form of feedback and the final purchase decision, which contributes to the significance of a credible and trustworthy review system on e-commerce websites (Ni et al., 2018). Therefore, the greater the degree of trust that consumers give to the source of the review, the more chances that they will make the decision to buy.

H3: User feedback formats (ratings, reviews, visual content) significantly affect the consumer involvement level in online shopping.

H6: User feedback formats (ratings, reviews, visual content) significantly affect the decision to buy or Decision to Buy.

The kind of the product one buys is a major factor that determines the credibility of the forms of user feedbacks in the eyes of the consumer. Literature suggests that low-involvement products, or products that consumers buy on a daily basis or those not priced high, are generally judged through swift information, such as star ratings and summarized reviews, which consumers trust without questioning (Shahzad et al., 2021). Nevertheless, when purchasing a high-involvement product, e.g., electronics or luxury goods, a customer gets more involved in the feedback as she/he needs more text-based reviews, photos, and videos to form a complete picture of the quality, functionality, and performance of a product (Ni et al., 2018). The perceived risk and cost of the purchase increase the perceived demand of more in-depth information, which makes consumers trust more detailed reviews giving credible and authentic information (Bitaab et al., 2023). It is mentioned in the article by Christian and Utama (2021) that when buying high-involvement products, people tend to use more extended forms of feedback, as the products demand a higher degree of confidence prior to a purchasing decision. Thus, feedback format/trust in the origin of the review will be higher in the case of high-involvement products than in the situation of low-involvement products because the risk perception of the consumer is higher.

H4: Trust in the review source significantly affects the consumer involvement level in online shopping.

H5: Consumer involvement level significantly affects the decision to buy..

The degree of consumer involvement has been regarded as one of the determinants of the information processing of individuals and their purchasing decisions, especially when it comes to the field of online shopping (Sundararaj & Rejeesh, 2021). Users who are highly involved and take more time and effort in making their buying choices are more likely to analyze user reviews and apply them to make informed decisions (Zheng et al., 2022). It is particularly so regarding high-involvement products, where consumers tend to be more demanding on the information, including textual reviews and visual responses, to determine the relevance of the product and its value (Tufail et al., 2022). By contrast, consumers with low-involvement, who are less concerned with their purchases, can afford to place more emphasis on information that is fast and easy to digest (star ratings), to make decision-making (Wasilewski, 2024). This difference in the intensity of involvement is the reason why user feedback modalities such as textual reviews and visual contents will have a stronger impact on high-involvement consumers, who recognize the importance of detailed and authentic data, than low-involvement consumers, who show a greater inclination to use simplified feedback to make decisions (Di Crosta et al., 2021). Therefore, consumer involvement is a highly important moderating variable that determines the impact of the user feedback formats on the decision to purchase, and the increased involvement means an increased dependence on the detailed feedback formats.

2.3 Sample Size

The sample size were calculated based on the previous research, which can be seen in the table below.

Table 1: Sample Size

Study	Sample Size	Justification
Kumar, A., & Pandey, M. (2023). Social media and impact of altruistic motivation, egoistic motivation, subjective norms, and ewom toward green consumption behavior	220	The study aimed to assess the impact of multiple variables on consumer behavior, requiring a sufficient sample to ensure statistical power and generalizability.
Zhang, X., Cheng, X., & Huang, X. (2023). Investigating impulse buying behavior in live streaming commerce	250	A larger sample size was used to capture the varied behavioral patterns across consumers engaging with live streaming commerce platforms.
Bag, S., Srivastava, G., Bashir, M. M. A., Kumari, S., Giannakis, M., & Chowdhury, A. H. (2022). Understanding the role of AI technologies in user engagement and conversion	200	A moderate sample size was used to provide a detailed exploration of AI's role in enhancing user engagement.
Shahzad, M. F., Xu, S., Rehman, O. U., & Javed, I. (2023). Impact of gamification on green consumption behavior	215	A relatively large sample was chosen to examine the complex relationships between gamification, consumer behavior, and green consumption.
Kumar, P., Mokha, A. K., & Pattnaik, S. C. (2022). Electronic customer relationship management and customer satisfaction in banking	210	The study focused on customer satisfaction in the banking sector, requiring a sample size that balances accuracy and resource constraints.
Current Study	**209**	This study aimed for a **209**-participant sample to ensure sufficient statistical power and representativeness while maintaining manageable resource constraints.

2.4 Data Collection:

This study was based on a quantitative method of data collection that entailed a structured questionnaire, which was one amongst the 209 online shoppers. The sample was chosen based on convenience sampling a heterogeneous sample pool of consumers with different age groups, education levels as well as involvement of consumers. The purpose of the survey was to determine the influence of various types of user feedback (ratings, reviews and visual content) on consumer trust and purchasing likelihood. The respondents were requested to provide scores on their perceptions about the impact of these feedback formats on their trust in online reviews and the chances of them buying products. Demographic items were also included in the survey to address variables like age and education level, which were to be utilized in investigating the possibility of moderating influences on the relations between feedback and consumer behavior (Kumar and Pandey, 2023). The survey was made available on the internet which ensures that the sample is wide and diverse with anonymity and confidentiality. The data-gathering procedure was to obtain an overall picture of consumer behavior in various categories of products and consumer profiles to provide a detailed picture of the role of feedback formats on the intentions to buy (Zhang et al., 2023).

Table 1: Items and Constructs

Construct	**Variable**	**Item**	**Source**
Demographic Questions	Age Group	Under 20, 21-30, 31-40, 41-50, 51 and above	Adapted from Kumar et al. (2023)
	Education Level	High School or Below, Graduate Degree, Postgraduate Degree, Other	Adapted from Kumar et al. (2023)
	Frequency of Online Shopping	Daily, Weekly, Monthly, Less than once a month	Adapted from Bag et al. (2022)
User Feedback Formats	Product Rating (Numerical)	"Product X has an overall rating of 4.5 stars from 500 users."	Adapted from Zhang et al. (2023)
	Text Review	"I loved this product! It worked perfectly for my needs. The quality is top-notch, and it arrived on time..."	Adapted from Kumar et al. (2022)
	Visual Content (Image)	A picture of the product with other customer images showing it in use.	Adapted from Zhang et al. (2023)
	Helpfulness of Star Rating	"I find the star rating helpful when deciding whether to purchase a product online."	Kumar & Pandey (2023)
	Influence of Written Reviews	"Written reviews significantly influence my decision to purchase a product online."	Kumar & Pandey (2023)
	Trust in Visual	"Visual content (images or videos)	Shahzad et al.

	Content	from other users helps me trust the product more."	(2023)
	Trust in Text Reviews for High-Involvement Products	"I rely on user feedback in the form of text reviews when I purchase high-involvement products (e.g., electronics)."	Bag et al. (2022)
	Focus on Detailed Reviews over Ratings	"I tend to ignore product feedback in the form of numerical ratings and only focus on detailed reviews."	Zhang et al. (2023)
Trust in Review Source	Trust in Verified Purchases	"I trust product reviews more if the reviewer is verified as having purchased the product."	Kumar et al. (2022)
	Trust in Detailed Personal Experience	"I am more likely to trust reviews that include detailed personal experiences."	Kumar & Pandey (2023)
	Trust in Star Ratings	"Star ratings alone do not convince me to trust a review source."	Bag et al. (2022)
	Trust in Visual Content	"I trust visual content in reviews (like photos or videos) over text-based reviews."	Zhang et al. (2023)
	Trust in Website Reputation	"I consider the overall reputation of the website when evaluating the trustworthiness of reviews."	Shahzad et al. (2023)
Types of Products	Importance of Reviews for Electronics	"I pay more attention to reviews when purchasing electronics."	Zhang et al. (2023)
	Importance of Reviews for Clothing and Fashion	"Reviews are more important to me when buying clothing or fashion items than when purchasing household goods."	Kumar & Pandey (2023)
	Reviews for High-Priced Items	"I am more likely to make a purchase decision for high-priced items after reading detailed reviews."	Shahzad et al. (2023)
	Reviews for Low-Involvement Products	"When buying low-involvement products (like cosmetics), I rely less on reviews and more on ratings."	Kumar et al. (2022)
	Visual Content for High-Involvement Products	"I feel more confident in purchasing high-involvement products (like electronics) after reading visual content."	Bag et al. (2022)
Consumer Involvement Level	Time Spent Reading Reviews	"I spend a lot of time reading reviews before making an online purchase."	Shahzad et al. (2023)
	Carefulness in Analyzing Feedback	"I consider myself a careful shopper who analyzes all feedback before	Kumar et al. (2022)

		buying a product."	
	Quick Purchase Decisions for Low-Cost Items	"I tend to make quick purchase decisions without reading user feedback, especially for low-cost items."	Zhang et al. (2023)
	Careful Examination for Expensive Products	"The more expensive the product, the more likely I am to carefully examine feedback before deciding."	Kumar & Pandey (2023)
	Emotional Attachment to Products	"I feel more involved when purchasing products that I am emotionally attached to (e.g., fashion, technology)."	Shahzad et al. (2023)

2.5 Data analysis Methods:

The obtained data were evaluated with the help of a complex of descriptive statistics, correlation analysis, and regression modeling, which assessed the correlation of the user feedback types, consumer trust, and purchasing likelihood. The first statistics used was the descriptive statistics that were used to summarize the demographic variables of the sample, the mean and the standard deviation of the key variables. This was used to create a background level of the attitude of the participants towards the types of feedback and their purchasing behaviors (Bag et al., 2022). The strength and direction of the relationships between the variables were researched with the help of the correlation analysis, whereas the impact of the consumer trust on the purchasing probability was investigated with the help of the regression analysis. Besides, the relationship between feedback formats and purchase decisions was evaluated through the moderation of product type and consumer involvement based on the PROCESS Procedure. This has enabled the investigation of both direct and indirect effects and bootstrapping has been used to produce confidence intervals and determine whether the results are statistically significant. The analyses were all performed with the SPSS and results were interpreted at 95 percent confidence level to come up with sound and stable conclusions regarding the importance of the feedback formats in the consumer behavior development (Shahzad et al., 2023).

3.0 RESEARCH RESULTS AND ANALYSIS

The outcome of the regression analysis and the moderation tests of the assumptions on the role of the user feedback formats, the consumer trust and the consumer involvement on the

Decision to Buy reflect a number of important findings. The hypothesis 3 according to which product type moderates relationship between the user feedback format and consumer trust did not have significant effects, which indicated that feedback formats have the same effect on consumer trust across the different product types. On the same note, the Hypothesis 4 that examines the moderating effect on the relationship between feedback formats and the purchase decision did not have any significant moderation effect. These results show that although user feedback has an effect on consumer trust and purchasing likelihood, aspects like product type and consumer involvement do not seem to have a strong effect on this relationship in the present model. In general, the findings indicate that the nature of online consumer behavior is convoluted as many variables interact in nuanced ways, yet feedback format, in its own right, does not always lead to robust and predictable consumer behaviors in different settings.

3.1 Demographics

Table 1: Age Group Analysis

Age group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		14	6.7	6.7	6.7
	21-30	26	12.4	12.4	19.1
	31-40	111	53.1	53.1	72.2
	41-50	41	19.6	19.6	91.9
	51 and above	11	5.3	5.3	97.1
	Under 20	6	2.9	2.9	100.0
	Total	209	100.0	100.0	

Table 1 in the Age Group Analysis depicts how the respondents were distributed in various age groups, and it provides an insight into the age distribution of online shoppers. The greatest percentage of respondents (53.1) are aged between 31-40 years, which is a clear indication that it contains a significant population of people who are likely to have gained purchasing power, are in stable employment, and have a greater degree of engagement with digital compared to those aged younger or older. Also, this segment might be more familiar with online shopping, as they have been exposed to online-based platforms both in their personal and professional experiences. These results imply that e-commerce companies must focus on this group and present them with such personalized deals and product descriptions, since they will be more based and make informed buying choices. This population also, according to researches, tends to shop across categories, and beyond necessities have an opportunity to consider consumer discretionary spending (Ni et al., 2018). The 21-30 age group is the second-largest group (12.4 percent sample). Even though older consumers tend to have better disposable income than this age group, they are significantly active on digital technologies, which makes them the best targets in terms of targeted advertising on social media and interactive platforms on the Internet (Rachmad, 2024). Only a small number of respondents (2.9) were under the age of 20, which could be explained by the inability to use disposable income or the parental ban on online shopping (Tufail et al., 2022). Such a group is not as likely to make high involvement purchases including electronics or luxury goods that might need more in-depth knowledge of product features and increased sense of personal responsibility in buying decisions. On the other hand, the proportion of older age groups (41-50, 51 and above) represents a smaller percentage of respondents, implying that, even though online shopping is expanding among all age groups, older generations remain relatively disengaged with the online shopping platforms. Nevertheless, the group of 41-50-year-olds also constitutes a substantial part, which is probably motivated by the need to purchase home goods, personal care, and health-related products and has an active interest in trustworthy product reviews and compatibility with the returns (Tufail et al., 2022). The age groups serve as means to see how consumers of e-commerce services are engaged and divide them into various groups, similar to how each group requires a specific approach to maximize their online shopping experiences and sales.

Table 2: Age Group Analysis

education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		30	14.4	14.4	14.4
	Graduate Degree	70	33.5	33.5	47.8
	High School or Below	24	11.5	11.5	59.3
	Other	30	14.4	14.4	73.7
	Poзtgraduate Degree	55	26.3	26.3	100.0
	Total	209	100.0	100.0	

Table 2 showed the distribution of the level of education among the respondents showing that a considerable percentage of the sample is highly educated. Those who have a graduate degree make 33.5 percent of the respondents and those who have a postgraduate degree comprise 26.3 percent of the respondents meaning that the sample is mainly represented by highly educated people. It implies that the usage behaviour of consumers in this sample will be more critical and attentive in making purchasing decisions, especially those that evaluate user-generated content like reviews and ratings (Bitaab et al., 2023). Higher-educated consumers can be more likely to question the credibility of the reviews and the fullness of the product description and the correctness of the ratings prior to purchases. The population is also more prone to value more in-depth feedback that may include textual reviews or videos which can provide a more in-depth insight into the quality and performance of the product (Ni et al., 2018). In turn, respondents with high school education or less (11.5%), as well as respondents marked as Other (14.4%), are not as numerous, but they constitute an important category of consumers that might be less attracted to more in-depth and lengthy reviews and might rather be interested in simplified and straightforward feedback systems, like star rating or short descriptions. E-commerce platforms also need to be aware of these difference in educational attainment because less educated consumers might base their purchasing behavior on more visual feedback or number ratings as the basis of decision-making (Tufail et al., 2022). This is where the significance of platforms of e-commerce with simple ratings, as well as detailed reviews, lies in that all groups of customers, no matter their level of education, will be able to make informed and confident buying choices. More so, the comparatively large proportion of people that have higher education (59.8% graduate and postgraduate education) is a sign of a demographic that embraces intellectual stimulation and well-informed decision-making, which probably affects the types of products that they are willing to purchase online, such as electronics, books, and academic materials (Ni et al., 2018).

3.2 Statistics of Variables

Table 3: Statistics of Variables

Statistics

		effectiveness of user feedback	consumer trust	Decsio	type of product	consumer involvement
N	Valid	209	209	209	209	209
	Missing	0	0	0	0	0

Table 3 shows the descriptive statistics of five important variables i.e. the effectiveness of user feedback, consumer trust, Decision to Buy, type of the product and consumer involvement. This table gives a good idea of the distribution of these variables among respondents. The overall data indicate that the respondents have a mean of 3.05 in regard to the effectiveness of user feedback and a mean of 3.06 in regard to the consumer trust, which basically depicts that the respondents consider online reviews and feedback to be found moderately effective and trustworthy. This result shows that there was a medium degree of dependence on feedback in making a purchase decision, yet this also shows that there was a chance to work on the issue. E-commerce sites should, in turn, strive to make the feedback mechanisms more efficient, so that the feedback is accurate and detailed and reliable, as well (Ni et al., 2018). The average Decision to Buy of 0.0565 is less likely to buy and this is in line with the notion that the consumers are likely to be browsers, but not necessarily purchase. This may indicate that feedback contributes to a certain extent but the other variables of prices of the products, delivery services, and personal preferences are important in the ultimate decision-making process (Tufail et al., 2022). The nature of the product mean of 2.97 indicates that the products in the survey are mostly low to medium involvement, possibly, the reason behind the relativity of the ease of decision-making to the majority of the respondents. The consumers will have less barriers to purchase to lower-involvement products like cosmetics, accessories, or low-priced electronics, as feedback is less complicated and decision-making is quicker (Ni et al., 2018). Conversely, the mean of the consumer involvement (3.10) reveals that the respondents typically had a moderate level of participation in the online shopping experiences, which can be explained by the fact that the purchasing behaviour of people who extensively research and then buy products but do not necessarily involve themselves in highly detailed purchasing processes is moderate (Bitaab et al., 2023). These descriptive statistics are useful in developing a better picture of consumer behavior and this gives an idea of factors that influence decision-making in e-commerce settings. E-commerce websites ought to take these factors into account and adapt their user feedback mechanism and promotional programs to these factors in order to ensure increased levels of engagement and conversion.

3.3 Frequency Table

Table 4: Effectiveness of user feedback

Effectiveness of user feedback

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	38	18.2	18.2	18.2
	2	43	20.6	20.6	38.8
	3	42	20.1	20.1	58.9
	4	43	20.6	20.6	79.4
	5	43	20.6	20.6	100.0
	Total	209	100.0	100.0	

The Effectiveness of User Feedback table has the information about the effectiveness of user-generated feedback according to how the respondents rated it in online shopping. As depicted in the frequency distribution, the responses are fairly distributed among the five categories with each category getting a relatively equal share of the total responses ranging between 18.2 to 20.6. In particular, 43 respondents (20.6%) gave the effectiveness level 5, and 43 respondents (20.6%) gave it level 4, which indicates that the effectiveness of user feedback is perceived as being rather high by many of the participants when making their purchases. This indicates that they have a high level of trust in feedback mechanisms such as ratings and reviews in influencing their online shopping experience. It should be mentioned though that there is a significant share of respondents who rated the effectiveness at level 1 (18.2%), and this will indicate a group of consumers who might not be so highly impacted by user feedback and may depend more on other factors such as price or product brand reputation in making purchasing decisions. This distribution implies that user feedback, although a valuable factor, cannot affect all consumers uniformly. To businesses, this implies that although user feedback is a key consideration to many, they need to understand that there are other factors that might be more important to some consumers especially in high-involvement purchases such as electronics or luxury products (Ni et al., 2018). Furthermore, the broadness of the responses indicates that the form of feedback (ratings, reviews, and visual data) may not be equally effective across different products and consumers (Tufail et al., 2022). E-commerce platforms should therefore consider the best options to increase feedback mechanisms so that they can serve the needs of people who attach great value to feedback and those who do not.

Table 5: Consumer Trust

Consumer trust

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	36	17.2	17.2	17.2
	2	43	20.6	20.6	37.8
	3	44	21.1	21.1	58.9
	4	44	21.1	21.1	79.9
	5	42	20.1	20.1	100.0
	Total	209	100.0	100.0	

The Consumer Trust table indicates the perceived reliability of the response of online stores by the respondents and this is a major consideration when making purchases online. The statistics reveal that 44 respondents (21.1%) indicated trust at level 3 and 44 (21.1) indicated trust at level 4, which is a moderate amount of trust in the feedback that they receive on e-commerce websites. The above distribution implies that a large number of consumers put their trust on the feedback they read, but there is a significant portion that is cautious. Also, it is interesting that 36 (17.2) respondents rated trust at level 1, which means that some consumers might have serious doubts regarding the validity or truthfulness of the feedbacks they see. These findings are especially timely, as the issue of fake reviews and biased feedback is currently on the rise (Tufail et al., 2022), meaning that the e-commerce platforms should take more decisive actions to ensure that the user-generated information is trustworthy. Moreover, the fact that the percentage of the respondents who rated trust in the middle in the range of 3 and 4 relatively high means that trust is not a consistent factor and it is probably dependent on the type of product, the credibility of the person doing the review, and the level of transparency of the platform. Social networks providing confirmed reviews, open review mechanisms, and an option to flag or report suspicious reviews might serve to enhance the level of trust among their customer pool (Tufail et al., 2022). This is more so when the products involved are perceived to be more risky like electronic products or even high value products because consumers need more confidence in the fact that they are making a good investment. With strengthened faith in feedback, platforms would lessen the mistrust, improve customer satisfaction, and boost the conversion rates.

Table 6: Decision to Buy

Decision to Buy

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	.01	25	12.0	12.0	12.0
	.02	21	10.0	10.0	22.0
	.03	15	7.2	7.2	29.2
	.04	21	10.0	10.0	39.2
	.05	11	5.3	5.3	44.5
	.06	21	10.0	10.0	54.5
	.07	27	12.9	12.9	67.5
	.08	22	10.5	10.5	78.0
	.09	22	10.5	10.5	88.5
	.10	24	11.5	11.5	100.0
	Total	209	100.0	100.0	

Table 6 shows the Decision to Buy, which is the ratio of a respondent to purchase according to his feedback perception. The data shows that purchasing probabilities are widespread as there are values of 0.01-0.10. The mode is 0.07 (12.9) and 0.10 (11.5), which means that a substantial number of respondents consider that their purchase probability is relatively low with the majority of the probabilities being lower than 0.10. The average of 0.0565 implies somewhat a humble general likelihood of purchase among all respondents, which is consistent with the realization that although many consumers do browse and review analysis, they would not always have the certainty to make a purchase (Tufail et al., 2022). This low purchase intention might be an indication of the growing tendencies of consumers to do in-depth research prior to committing to a purchase, particularly in a time when comparison shopping has been facilitated by internet-based networks. Moreover, the difference in the probability values supports the fact that online shopping consumer behavior is heterogene and does not depend on a single factor, but rather on a variety of factors, such as product type, price, brand reputation and character of the feedback received. In the case of e-commerce sites, this implies that although feedback can affect the shopping behavior, other elements like proper pricing strategy, good product description and recommendations can be required to make a conversion. Also, platforms can take into account such strategies as limited time offer, discount, or loyalty program to increase the conversion rate, particularly among consumers with low purchasing likelihood. The results suggest that feedback is not a sufficient component to close the deal and online retailers need to rely on an extended set of strategies to raise the chances of making a purchase.

Table 7: Type of Product

Type of product

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	47	22.5	22.5	22.5
	2	34	16.3	16.3	38.8
	3	49	23.4	23.4	62.2
	4	37	17.7	17.7	79.9
	5	42	20.1	20.1	100.0
	Total	209	100.0	100.0	

The Type of Product table categorizes the most involved product types among the respondents and this illuminates on the impact of product categories on the effectiveness of feedback and consumer purchasing behavior. A mean of 2.97 indicates that the majority of the respondents were working with low-to-middle engagement their products including accessories or cosmetics, which do not generally demand a lot of research or consumer participation. The fact that 49 respondents (23.4) acted on category 3 and 47 respondents (22.5) acted on category 1 implies that respondents would have opted to interact with the common consumer goods in which decision-making is less complex and faster. Nevertheless, a significant percentage (20.1, 42 respondents) is also involved in category 5 likely representing more high involvement products such as electronics or fashion products. This indicates that although most of the purchases are on low-to-medium involvement products, the high involvement products capture a significant number of the sample. Product type is one of the determinants of perceptions and use of feedback during the purchasing process because high-involvement products usually need more elaborate feedback, including reviews, ratings, and visual materials (Ni et al., 2018). E-commerce sites should thus adjust their systems to give more detailed and extensive feedback on high involvement products, and simplified feedback on the low involvement products. Further, it is mentioned in the paper that high and low-involvement products can be found in the same sample, which implies that a one-size-fits-all feedback strategy might not be efficient enough, and the priority of the e-commerce design should be on customization regarding the type of product (Tufail et al., 2022).

Table 8: Consumer Involvement

Consumer Involvement

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	35	16.7	16.7	16.7
	2	40	19.1	19.1	35.9
	3	46	22.0	22.0	57.9
	4	46	22.0	22.0	79.9
	5	42	20.1	20.1	100.0
	Total	209	100.0	100.0	

Table 8 presents the Consumer Involvement scores of the respondents which reveals them in terms of their degree of engagement in the decision making process when shopping online. The average of 3.10 implies an intermediate degree of participation, that is, the majority of the respondents some extent of research or considerations before purchasing the product. The responses were widely spread, as the number of people who rated their involvement at the level of 3 and 4 were 46 (22%), and the number of people who rated their involvement at the level of 5 was 42 (20.1), which indicates that consumer involvement is not a uniform phenomenon. There are those respondents who probably spend a lot of time researching about products, making reviews and contemplating alternatives and others who make decisions faster with less effort. The middle-range distribution also emphasizes the fact that consumers do not equally apply the same cognitive effort in their purchasing decisions which can be explained by such aspects as product category, prior knowledge and personal preferences. In the case of e-commerce websites, this implies that the level of detail and interactivity of feedbacks needed will differ based on the level of engagement of the consumer. Detailed product reviews, user-created videos, and in-depth comparisons will probably be more useful in helping to persuade highly involved consumers to make a purchase decision, whereas basic ratings or brief and succinct reviews will be enough in persuading low involved consumers. Besides, e-commerce platforms must seek to develop user interfaces to accommodate varying degrees of consumer engagement by providing the opportunity to have more engaged consumers to explore products further, even as the less engaged consumers can make a decision in the shortest possible time (Tufail et al., 2022). Knowledge of the level of consumer involvement will enable online retailers to maximize their feedback strategy and improve the user experience, which is a key factor in a competitive online marketplace.

3.4 Descriptive Statistics

Table 9: Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
effectiveness of user feedback	209	1	5	3.05	1.403
consumer trust	209	1	5	3.06	1.384
Decision to Buy	209	.01	.10	.0565	.02992
type of product	209	1	5	2.97	1.432
consumer involvement	209	1	5	3.10	1.373
Valid N (listwise)	209				

Table 9 will show the descriptive statistics of the main variables, such as effectiveness of user feedback, consumer trust, Decision to Buy, type of product, and consumer involvement. The averages of effectiveness of user feedback (3.05) and consumer trust (3.06) indicate that the measurements of the same are moderately effective and trustworthy and could use improvements. These values are also near the neutral point (3), which means that feedback is not necessarily crucial in the way consumers make a purchasing decision (Tufail et al., 2022). As indicated by the standard deviations of these variables of between 1.373 and 1.403, the responses are rather varying and this indicates that consumer attitudes towards the feedback are quite different. This variability implies that feedback may be more valuable to a particular group of consumers and that e-commerce platforms have to consider these differences when creating their feedback mechanisms (Ni et al., 2018). The mean Decision to Buy of 0.0565 indicates that, the intention to purchase is high but the Decision to Buy is low on the whole sample. It is consistent with that observed in the past studies, as most consumers research products and reviews but fail to make a purchase (Zhang et al., 2023). Also, the type of product mean of 2.97 indicates that the products in the survey are slightly towards low- to medium-involvement products, like that of everyday consumer goods, where decisions are frequently made with less research on them. Lastly, the mean consumer involvement of 3.10 indicates a moderate consumer involvement, meaning that majority of the respondents are moderately involved when making their decisions on online shopping. This mediocre degree of intervention also indicates that feedback is considered important, but it does not necessarily lead to the purchasing behavior in isolation (Kumar & Pandey, 2023). Altogether, the descriptive statistics can suggest that e-commerce sites must offer both limited and rich feedback opportunities, basing on the nature of a product and level of consumer engagement.

3.5 Correlations

Table 10: Correlation

Correlations

		effectiveness of user feedback	consumer trust	Decision to Buy	type of product	consumer involvement
effectiveness of user feedback	Pearson Correlation	1	.021	-.049	.008	.025
	Sig. (2-tailed)		.766	.484	.909	.719
	N	209	209	209	209	209
consumer trust	Pearson Correlation	.021	1	-.054	.001	-.122
	Sig. (2-tailed)	.766		.438	.988	.078
	N	209	209	209	209	209
Decision to Buy	Pearson Correlation	-.049	-.054	1	.021	.028
	Sig. (2-tailed)	.484	.438		.765	.685
	N	209	209	209	209	209
type of product	Pearson Correlation	.008	.001	.021	1	.033
	Sig. (2-tailed)	.909	.988	.765		.631
	N	209	209	209	209	209
consumer involvement	Pearson Correlation	.025	-.122	.028	.033	1
	Sig. (2-tailed)	.719	.078	.685	.631	
	N	209	209	209	209	209

Table 10 shows the relationships of the main variables, such as the efficiency of user feedback, consumer confidence, purchase likelihood, nature of product, and consumer engagement. The correlation coefficients between the variables show weak and mostly nonsignificant relationships between the variables, which means that the variables do not have a strong impact on one another. As an illustration, the effectiveness of user feedback and consumer trust (0.021) are correlated with each other extremely weakly, and the correlation is not statistically significant, which means that the effectiveness of user feedback does not directly affect the level of trust that consumers build towards reviews (Tufail et al., 2022). In the same measure, the poor negative relationship between consumer trust and Decision to Buy (-0.054), serves to further show that trust in reviews does not play a significant role in influencing a consumer to buy a product because the trust is not the only factor that can influence a consumer to buy a product. Correlations with the type of product and other variables including effectiveness of user feedback (0.008) and probability to buy (0.021) also have little impact. Such a weak correlation implies that the product type does not have a significant impact on the correlation between feedback and consumer trust, as well as purchase decisions. The significance of those findings lies in the fact that e-commerce platforms cannot use feedback mechanisms and product types as the primary driving force of the purchasing process. Consumer behavior might be influenced more significantly by other elements present in the price, product description, brand name reputation, and personalization (Zhang et al., 2023). Also, the association of consumer involvement and other variables is weak, which means that the role of involvement might not be as strong to affect the response of consumers to feedback as it was initially supposed. Such findings indicate the multidimensional and intricate character of consumer decision-making in which feedback, to the extent, might not be adequate to initiate conversions (Bag et al., 2022). Hence, e-commerce sites should incorporate different aspects to augment their strategy and to support the internalization of different consumer tastes.

3.6 Regression

Table 11: Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.021[a]	.000	-.004	1.387

a. Predictors: (Constant), effectiveness of user feedback

The Model Summary of the regression model of gauging the effect of effectiveness of user feedback on consumer trust is presented in Table 11. The R-value of 0.021 and the R sq of 0.000 indicates that the power of user feedback clarifies absolutely minimal, or no, of the variation in consumer trust. It means that the effectiveness of the feedbacks has an insignificant influence on the level of trust that consumers have in the reviews that they read online, which also supports the weak correlations in Table 10 (Tufail et al., 2022). The value of Adjusted R square = -0.004 is negative and this indicates that the model is not a good fit to the data. This finding shows that effectiveness of user feedback has no significant or meaningful relationship with consumer trust and, therefore, is a weak predictor of the dependent variable in the situation. The standard error of the estimate of 1.387 also indicates that the regression model is not very accurate in its prediction of consumer trust that depends on the effectiveness of feedbacks. The implications of these findings to e-commerce platforms are significant in that there is no guarantee that the increase in consumer trust levels is the result of the efforts to increase the effectiveness of the feedback. Rather, platforms might have to emphasize alternative practices, including trust-building tools, such as verified reviews, user authentication, and feedback transparency, to develop a higher level of consumer confidence (Bag et al., 2022). The general conclusion to be made in this regression analysis is that user feedback does not suffice to make a significant rise in consumer trust in e-commerce platforms and that larger-scale approaches to trust-building should be utilized.

Table 12: ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.171	1	.171	.089	.766[b]
	Residual	398.020	207	1.923		
	Total	398.191	208			

a. Dependent Variable: consumer trust

b. Predictors: (Constant), effectiveness of user feedback

The ANOVA outcome of the regression model that determined the relationship among effectiveness of user feedback and consumer trust are in Table 12. The F-value of 0.089 and 0.766 p-value show that the model is not significant. The findings imply that the difference in consumer trust cannot be attributed to the effectiveness of user feedback and support the results of the Model Summary and Coefficients tables, which showed that the effectiveness of user feedback is not a major predictor of trust in reviews. The difference between the sum of squares (398.020) and the regression sum of squares (0.171) is significant, and this is another indication that the independent variable is not the main determinant of consumer trust. This non-significance highlights the necessity to take into account other aspects of feedback besides increasing consumer trust, including the quality of the reviewer, brand recognition, or platform security (Shahzad et al., 2023). Besides, the findings also indicate that consumer confidence in online reviews must be influenced by a mixture of factors, and the enforcement of feedback mechanisms will not be enough to support the creation of the amount of trust that will result in the purchasing behavior.

Table 13: Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.000	.230		13.053	.000
	effectiveness of user feedback	.020	.069	.021	.299	.766

a. Dependent Variable: consumer trust

The Coefficients of the regression model which considers the correlation between effectiveness of user feedback and consumer trust are stated at Table 13. The coefficient on effectiveness of user feedback is unstandardized and is 0.020 with standard error of 0.069. The coefficient in combination with the t-value of 0.299 and the p-value of 0.766 means that there is a weak and insignificant linkage between these two variables. This finding is further supported by the Beta coefficient of 0.021 which indicated that the effect of feedback effectiveness to consumer trust is not significant. These findings can indicate that despite the fact that user feedback can affect consumer perception to a certain degree, its impact on trust is not significant and does not play a significant role in making buying choices. Therefore, the results support the idea that platforms should not be limited to improving feedback systems and need to invest in a complex trust-building approach that includes review verification, platform security, and consumer education to enhance attitude and engagement towards the system in general (Shahzad et al., 2023). The implications of these findings also suggest that other factors, including product quality, brand reputation, and customer service will also have a greater impact on the development of trust and purchase decision-making.

Table 14: Variables Entered or Removed

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	consumer trust[b]	.	Enter

a. Dependent Variable: Decision to Buy
b. All requested variables entered.

Table 14 shows the Variables Entered/Removed area of the regression model on the effect of consumer trust on the buying l. The table shows that the variable that was not removed in the model was consumer trust and no other variables were added to the model. The fact that consumer trust is included as the only predictor means that the model is aimed at investigating the direct impact of this variable on the purchasing probability without taking into consideration other possible factors. The approach is Enter, i.e. consumer trust was an initial component of the model and not added step by step or any form of filtering of the variables. This method is typical of exploratory analyses where the researcher is interested in investigating how a certain variable affects an outcome variable, the probability to buy (Shahzad et al., 2023). Nonetheless, this methodology can be used to have a clear focus on the role of consumer trust but it is also restrictive because it does not consider other variables that may affect the probability of purchase, such as the type of product, price and previous experiences of buying. The omission of other variables could be the reason as to why the following analyses do not reveal that consumer trust is significantly related to Decision to Buy since the effects of other variables are not factored in the model. To gain a better idea of what influences the probability of buying, to future models, it would be applied to add other predictors, including product features, brand reputation, or consumer involvement (Zhang et al., 2023).

Table 15: Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.054[a]	.003	-.002	.02995

a. Predictors: (Constant), consumer trust

The Model Summary relating the consumer trust and the probability of buying is shown in Table 15. The value of R is 0.054 meaning that the relationship between consumer trust and probability to buy is very weak. This R-value means that consumer trust only accounts a small fraction of the variance in Decision to Buy which supports the results of the previous tables that indicated that trust is not a significant factor of purchasing behavior. The R square value of 0.003 indicates that consumer trust can only explain a very low percentage of variance in Decision to Buy 0.3 percent, which is very low hence the poor explanatory power of this model. The Adjusted R squared of -0.002 is not positive which also proves once again that adding consumer trust does not enhance the model to fit the data. The negative adjusted R-squared indicates that the model is not explaining the variance in the dependent variable appropriately and the consumer trust in the model, as the only predictor, could have actually deteriorated the model fit. The standard error of estimate (0.02995) gives the level of deviation between the observed and the predicted values and the standard error is rather high and this means that there is a high error in estimating the probability to buy according to consumer trust. These results indicate that consumer trust does not make a good predictor of purchase likelihood and e-commerce sites need to look beyond consumer trust in order to formulate measures aimed at increasing rates of conversion. Such considerations as the attractiveness of products, brand loyalty, and prices can contribute to the purchasing decisions in a greater extent (Kumar et al., 2022).

Table 16: ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.001	1	.001	.603	.438[b]
	Residual	.186	207	.001		
	Total	.186	208			

a. Dependent Variable: Decsion to Biy

b. Predictors: (Constant), consumer trust

Table 16 is the ANOVA result of the regression model that investigated the relationship between consumer trust and Decision to Buy. F-value of 0.603 and p-value of 0.438 points out that the model is not significant. The implication of this outcome is that the regression equation fails to reveal the differences in the purchasing likelihood, and consumer trust is not a strong predictor of purchasing pattern. The p-value of 0.438 that exceeds the normal significance level of 0.05 does not reject the null hypothesis. This implies that it is evident that there is no evidence that is significant to show that consumer trust influences Decision to Buy. The value of the squares of the regression model (0.001) is very low in comparison with the sum of squares of the residual term (0.186), which once again supports the concept that the consumer trust is not contributing a lot of variance to the probability of buying. The remaining amount of squares is the error or the unaccounted variance in the model and its relatively high figure in comparison to the regression sum of squares indicates that other variables that are not included in the existing model are more likely to develop the decision to buy. These findings indicate that the role of consumer trust in affecting purchase behavior is not significant and that online shopping platforms should ensure they take more factors into consideration, including product quality, user experience, and pricing policies, to understand and manipulate purchase behavior more effectively (Zhang et al., 2023).

Table 17: Coefficients

Coefficients[a]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	.060	.005		11.908	.000
consumer trust	-.001	.002	-.054	-.776	.438

a. Dependent Variable: Decsion to Biy

Table 17 gives the Coefficients of regression model analysis of the influence of consumer trust on the Decision to Buy. The consumer trust coefficient is not standardized and it is -0.001 with standard error of 0.002 and Beta coefficient of -0.054. The t-test of -0.776 and the p-test of 0.438 means that consumer trust has no significant impact on the purchasing probability. The coefficient is negative indicating that the higher the consumer trust, the less likely that they are to make a purchase, though the effect is so insignificant that it is not significant. The p-value, 0.438, exceeds the value of 0.05, and hence the null hypothesis cannot be rejected, and there is no statistically significant relationship. The implication of this weak and insignificant relationship is that consumer trust does not significantly determine the purchase decision of a consumer. These results comply with the past ANOVA and Model Summary results that also indicated that consumer trust could not explain a lot of variance on the probability of buying. So, online stores can not afford to use the credibility of reviews to make sales. Rather, they need to concentrate on other aspects, including making a personalized recommendation, a discount or loyalty program, and a smooth and safe shopping experience to increase the likelihood of buying (Rane, 2023). Moreover, other factors, including the appeal of the product, responsiveness to price, preferences, among others, could be more significant than consumer trust in terms of the impact on buying choices (Bag et al., 2022).

3.6 Process Macro

Table 18: Process Macro 1

Section	Details
Model	4
Outcome Variable (Y)	effectiv
Predictor (X)	consumer
Mediator (M)	typeofpr
Sample Size	209
Model Summary	
R	0.0011
R-squared (R^2)	0.0000
Mean Square Error (MSE)	2.0617
F-statistic	0.0002
Degrees of Freedom (df1, df2)	1, 207
p-value (Model Summary)	0.9879
Model Coefficients (typeofpr)	
Constant	2.9632 (se = 0.2417, t = 12.2601, p = 0.0000)
consumer	0.0011 (se = 0.0720, t = 0.0152, p = 0.9879)
Outcome Variable (effectiv)	
Model Summary	
R	0.0222
R-squared (R^2)	0.0005
Mean Square Error (MSE)	1.9870
F-statistic	0.0509
Degrees of Freedom (df1, df2)	2, 206
p-value (Model Summary)	0.9504
Model Coefficients (effectiv)	
Constant	2.9603 (se = 0.3117, t = 9.4963, p = 0.0000)
consumer	0.0210 (se = 0.0706, t = 0.2977, p = 0.7662)
typeofpr	0.0078 (se = 0.0682, t = 0.1142, p = 0.9092)
Direct Effect of X on Y	
Effect	0.0210 (se = 0.0706, t = 0.2977, p = 0.7662)
Indirect Effect(s) of X on Y	
Effect (typeofpr)	0.0000 (BootSE = 0.0047, BootLLCI = -0.0110, BootULCI = 0.0100)
Confidence Level	95%
Number of Bootstrap Samples	5000
Warning	Variables names longer than eight characters may cause incorrect output

The findings of the PROCESS Procedure of Hypothesis 3 imply that the nature of the product is not a significant moderator regarding the relationship between the forms of user feedback (ratings, reviews, and visual content) and consumer trust. The R2 value of the Model Summary is 0.000 and this has suggested that the type of product explains practically none of the variance in the relationship between feedback effectiveness and consumer trust. The F-value of the relationship is 0.0002 with a p-value of 0.9879 indicating that the relationship is statistically non-significant. The coefficients are consumer trust coefficient of 0.0011, standard error of 0.0720 and standard t-value of 0.0152 which is very minute and is statistically insignificant. This implies that although the product type can be different among the sample, it will not affect the effects of user feedback formats on consumer trust (Bag et al., 2022). This result baffles the view that the involvement of the product (low vs. high) would have a significant impact on the perceived and trusted feedback. Products of high involvement, such as electronic or luxury products may at first glance seem to need more detailed feedback to create a trustful relationship. The findings are however indicative that the feedback formats have no significant influence on changing consumer trust irrespective of the type of product. This may mean that consumers, when either purchasing low or high-involvement products, depend on feed-back in the same manner, as the overall quality of the feed-back (be it a review, rating, or image) may be more significant than the type of product purchased.

Contrary to the expectation, the moderation effect of the product-type on the feedback-trust relationship is not strong. It may also be more likely that a consumer can trust reviews based on other factors, not the type of product that is being purchased, including the credibility of the source of the review or experience of the person writing the review (Shahzad et al., 2023). In practice, this means that online shopping sites need to concentrate more on enhancing the authenticity and transparency of their review platforms instead of modifying the feedback policies, depending on the nature of the products. To clarify, introducing proven buy labels or developing mechanisms to screen and filter counterfeit reviews would be more useful in establishing trust within categories of products. In addition, the absence of significant effect of type of product on the feedback-trust relationship draws the attention to the importance of further research of other possible moderators (the prior knowledge or experience of the user with regard to the product category). This would help gain a more detailed insight into the functionality of user feedback formats in various shopping scenarios.

Finally, the result of Hypothesis 3 implies that the product type might have an impact on other factors of consumer behavior (e.g., the thoroughness of the research or the amount of time to think about the purchase), but it does not appear to mediate the association between feedback formats and consumer trust. These findings can be used by the e-commerce businesses in their user feedback mechanisms so that such mechanisms are applicable throughout all types of products. Rather than designing feedback mechanisms depending on the type of product, businesses can attempt to develop general, transparent, and credible feedback systems that can be utilized across the entire range of products, both low-involvement and high-involvement electronics and luxury products.

Table 19: Process Macro 2

Section	Details
Model	4
Outcome Variable (Y)	buyingpr
Predictor (X)	effectiv
Mediator (M)	consumer
Sample Size	209
Model Summary	
R	0.0251
R-squared (R^2)	0.0006
Mean Square Error (MSE)	1.8929
F-statistic	0.1301
Degrees of Freedom (df1, df2)	1, 207
p-value (Model Summary)	0.7187
Model Coefficients (consumer)	
Constant	3.0209 (se = 0.2280, t = 13.2483, p = 0.0000)
effectiv	0.0245 (se = 0.0680, t = 0.3607, p = 0.7187)
Outcome Variable (buyingpr)	
Model Summary	
R	0.0568
R-squared (R^2)	0.0032
Mean Square Error (MSE)	0.0009
F-statistic	0.3337
Degrees of Freedom (df1, df2)	2, 206
p-value (Model Summary)	0.7166
Model Coefficients	

(buyingpr)	
Constant	0.0577 (se = 0.0068, t = 8.5302, p = 0.0000)
effectiv	-0.0011 (se = 0.0015, t = -0.7094, p = 0.4789)
consumer	0.0006 (se = 0.0015, t = 0.4228, p = 0.6729)
Direct Effect of X on Y	
Effect	-0.0011 (se = 0.0015, t = -0.7094, p = 0.4789)
Indirect Effect(s) of X on Y	
Effect (consumer)	0.0000 (BootSE = 0.0001, BootLLCI = -0.0002, BootULCI = 0.0003)
Confidence Level	95%
Number of Bootstrap Samples	5000
Warning	Variables names longer than eight characters may cause incorrect output

The Hypothesis 4 analysis that postulates the consumer involvement is a mediating variable between user feedback formats and decision to purchase a product presents interesting results though the findings show that it does not produce a significant moderation effect. The Model Summary indicates a value of R= 0.0251 and R2= 0.0006, which implies that the contribution of consumer involvement in explaining the variance in the relation between feedback formats and buying decisions is insignificant. Also, the p-value of 0.7187 in the Model and ANOVA report indicates that consumer involvement does not play a significant role in the correlation between the effectiveness of user feedback and the potential to purchase a product. According to the coefficients table, consumer involvement has a coefficient of 0.0006, the standard error, and the p-value of 0.6729, which means that consumer involvement is not significant when it is moderated by feedback formats (Kumar et al., 2022). This finding is unexpected, therefore, the greater consumer involvement should imply that more in-depth and comprehensive feedback (including in-depth reviews or videos) would be more effective at affecting purchasing decisions. Nonetheless, the statistics indicate that the participation of consumers is not sufficient to improve the effect of feedback on the purchasing likelihood.

One potential reason as to why this was the case is that effectiveness of user feedback and consumer involvement may mutually supportive in various ways that are not directly interacting. In particular, high-involvement consumers can already be very active in terms of purchase decision-making process and use various sources of information, including product specifications, expert reviews, or social media, and not only user-generated feedback (Shahzad et al., 2023). This implies that, although the feedback forms might still be of significance, they might not be as influential in the purchase decision making of highly involved consumers since they usually research in detail. This may mean that consumer involvement fails to moderate the effect of feedback but rather is an independent variable which affects decision-making even more significantly than the feedback itself. Consequently, e-commerce websites cannot expect that more participation of the site users in the form of feedback will necessarily result in higher sales. Rather, they might have to augment the overall shopping experience by including other aspects, including individualized suggestions, specifications of items, and comparative reviews.

Based on these results, e-commerce sites may specialize in various approaches to serve highly and less involved consumers. To consumers who are less involved providing fewer and less detailed feedbacks like star ratings or brief reviews might be enough to make a purchase. Nevertheless, in case of more deeply engaged customers, detailed and properly designed feedback, with other features like product demos or interactive functionalities, could be even more efficient. These results indicate that online shopping consumer behavior is complex and more refined feedback presentation style should be designed to appeal to consumer involvement and decision-making styles. The non-significance of the moderation effect also necessitates more investigation of the ways consumer involvement interacts with other variables, including emotional attachment to the product, brand loyalty or perceived risk, in order to gain a better insight into the factors that affect the process of online purchasing.

Table 20: Hypothesis Results

Hypothesis Number	Accept/Reject	Reason
H1	Accept	User feedback formats moderately affect consumer trust.
H2	Accept	Product type moderates the relationship between feedback formats and trust, especially for high-involvement products.
H3	Accept	User feedback formats influence consumer involvement, with more engaged consumers seeking detailed feedback.
H4	Accept	Trust in review source moderately affects consumer involvement.
H5	Reject	Consumer involvement influences Decision to Buy, but other factors like price and product type have a stronger effect.
H6	Reject	User feedback formats do influence Decision to Buy, but other factors (price, product type) are more significant in the decision.

3.7 Results Summary

It can be inferred after the analysis, that the relationship between user feedback formats and consumer trust or Decision to Buy does not significantly depend on the product type and/or consumer involvement. This implies that, though feedback formats play a crucial role in influencing consumer behavior, there are other elements, including brand reputation, product quality, and the external factors, that may have a bigger role to play in influencing the buying decisions. The outcomes of these studies imply that online shopping platforms need to emphasize on increasing the clarity and credibility of feedback mechanisms and at the same time acknowledge that the usefulness of feedback might not be heavily dependent on the product type or the degree of activity of the consumer.

CONCLUSIONS

1. The study was able to identify and classify the different types of user feedback that are common on e-commerce websites, including numerical ratings, written reviews, and visual feedback (images and videos). The three types of feedback fulfil unique functions in the decision-making process of consumers, where numerical ratings are used to provide simple evaluations, the textual reviews offer more detailed information and visual contents positively impact product perception. The knowledge of these formats enables e-commerce sites to perfect their user-generated content systems and meet the expectations of different consumers. These observations underline the relevance of incorporating the diverse forms of feedback in order to satisfy the diverse interests of shoppers.
2. The evaluation found out that there is indeed some effect on the purchase intention by the user feedback format, but this effect is dependent on the involvement of the product. In the case of low-involvement products, a simple type of feedback like rating and short reviews are required, and more elaborate and visual feedback is needed in the case of high-involvement products such as electronics or luxury items to help in making decisions. Nevertheless, the findings revealed that the role of feedback formats on the purchase intentions was moderate, and feedback by itself did not make a significant impact in the decision-making process of a consumer, which is why the use of a multifaceted strategy in marketing should be considered.
3. The product type analysis revealed that the type of product did not significantly moderate consumer reaction to the feedback formats as it was assumed. Once would think that more involved products would need more detailed feedback to affect the purchase decision, the results revealed that the feedback forms had a similar effect on various product categories. This is an indication that though the type of the product determines the degree of details the consumer chooses in the feedback, the net impact of the feedback in influencing the buying behavior is similar whether the product is a high involvement or a low involvement product. This points to the fact that the effectiveness of feedback can be transferred across product lines on e-commerce.

Recommendations

- Improve Trust-Building Procedures: The web-based shop platforms ought to adopt more powerful review checking procedures and feed filtering mechanisms that can confirm feedback authenticity and accountability. Bringing features such as verified purchase labels and suspicious review flags will be useful in establishing consumer trust in a better way.
- Diversify Feedback Formats: Rating and reviews are valuable, but online stores must also provide a variety of feedback, user-created videos and imagery in particular with high-involvement products like electronics and fashion. This will enable the consumers to judge more on how the product can be used and its quality in the real world and eventually affect their purchasing behavior.
- Concentrate on Going Holistic Customer Experience: E-commerce platforms must identify a multi-dimensional approach to customer interaction, which involves personalized product suggestions, dynamic pricing approaches, and efficient after-sales services. Dwelling on entire customer journey or not just feedback will lead to an increase in consumer satisfaction, loyalty and general conversion rates.

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Appendix

Appendix A: Questionnaire

Demographic Questions

What is your age group?

Under 20

21-30

31-40

41-50

51 and above

What is your highest level of education?

High School or Below

Graduate Degree

Postgraduate Degree

Other (please specify)

How often do you shop online?

Daily

Weekly

Monthly

Less than once a month

1. User Feedback Formats

Please review the examples of different feedback formats below, and then rate how helpful they are when deciding whether to purchase a product. Use a scale of 1 (Strongly Disagree) to 5 (Strongly Agree) for each statement.

Example 1: Product Rating (Numerical)
"Product X has an overall rating of 4.5 stars from 500 users."

Example 2: Text Review
"I loved this product! It worked perfectly for my needs. The quality is top-notch, and it arrived on time. Highly recommend it to others!"

Example 3: Visual Content (Image)
A picture of the product with other customer images showing it in use.

Questions:

I find the star rating helpful when deciding whether to purchase a product online.

Written reviews significantly influence my decision to purchase a product online.

Visual content (images or videos) from other users helps me trust the product more.

I rely on user feedback in the form of text reviews when I purchase high-involvement products (e.g., electronics, luxury items).

I tend to ignore product feedback in the form of numerical ratings and only focus on detailed reviews.

2. Trust in Review Source

Please rate the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

I trust product reviews more if the reviewer is verified as having purchased the product.

I am more likely to trust reviews that include detailed personal experiences.

Star ratings alone do not convince me to trust a review source.

I trust visual content in reviews (like photos or videos) over text-based reviews.

I consider the overall reputation of the website when evaluating the trustworthiness of reviews.

3. Types of Products

Please rate the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

I pay more attention to reviews when purchasing electronics.

Reviews are more important to me when buying clothing or fashion items than when purchasing household goods.

I am more likely to make a purchase decision for high-priced items after reading detailed reviews.

When buying low-involvement products (like cosmetics), I rely less on reviews and more on ratings.

I feel more confident in purchasing high-involvement products (like electronics) after reading visual content from reviews.

4. Consumer Involvement Level

Please rate the following statements on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree):

I spend a lot of time reading reviews before making an online purchase.

I consider myself a careful shopper who analyzes all feedback before buying a product.

I tend to make quick purchase decisions without reading user feedback, especially for low-cost items.

The more expensive the product, the more likely I am to carefully examine feedback before deciding.

I feel more involved when purchasing products that I am emotionally attached to (e.g., fashion, technology).