The Impact of AI-Powered Recommendation Systems on Consumer Retention in Online Marketplaces: The Mediating Roles of Perceived Relevance and Customer Satisfaction

The Impact of AI-Powered Recommendation Systems on Consumer Retention in Online Marketplaces: The Mediating Roles of Perceived Relevance and Customer Satisfaction

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LETTER OF TRANSMITTAL

22 July 2026

Mr. Ahmed Imran Kabir
Assistant Professor
School of Business and Economics
United International University

Subject: Submission of Project Report on "The Impact of AI-Powered Recommendation Systems on Consumer Retention in Online Marketplaces: The Mediating Roles of Perceived Relevance and Customer Satisfaction"

Dear Sir,

With great pleasure, I present for publication my undergraduate **"The Impact of AI-Powered Recommendation Systems on Consumer Retention in Online Marketplaces: The Mediating Roles of Perceived Relevance and Customer Satisfaction"** to be a part of the requirements for the degree Bachelor of Business Administration (BBA) in Business Analytics of United International University.

This research focuses on exploring the factors affecting consumer retention in AI-powered online marketplaces. It focuses on the impact of Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization and Context-Aware Suggestions on Consumer Retention Rate. The study also explores the mediating role of Perceived Relevance and Customer Satisfaction in bridging the gap between these AI-driven recommendation features and consumers' willingness to use online marketplaces. In the process of this research, I have taken care in order to be sincere, have shown academic honesty and have followed methodological rigor throughout the research. I have also attempted to study the collected data thoroughly and presented it in a clear and systematic way.

Thank you to you for all of your guidance, constructive feedback, encouragement and helpfulness in the research process. This project was very successful thanks to your supervision and suggestions.

This is a project report which I would like to submit for your consideration and acceptance.

Sincerely yours,



Sayma Islam
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DECLARATION OF THE STUDENT

I, Sayma Islam herewith certify that the above-mentioned thesis entitled The Impact of AI-Powered Recommendation Systems on Consumer Retention in Online Marketplaces: The Mediating Roles of Perceived Relevance and Customer Satisfaction" is a true and accurate copy of the thesis submitted by me in partial fulfillment of the requirements for the Degree of Bachelor of Business Administration (BBA) Major in Business Analytics at United International University under the supervision of Mr. Ahmed Imran Kabir (Assistant Professor), United International University (UIU).

I also certify that this research is my own work and has not been submitted, either in full or in part, to any other university or college for the purpose of obtaining any degree, diploma or other academic award. The sources of information in this study have been adequately referenced and attributed.



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First and foremost, I would like to thank Almighty Allah for giving me the strength, patience

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Throughout my schooling, I have been patient and persevering.

ABSTRACT

As AI recommendation systems gain traction, the way customers navigate online marketplaces has fundamentally changed. The effect of the four factors, Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, and Context-Aware Suggestions on the Consumer Retention Rate is discussed in this study. It also examines the role of Perceived Relevance and Customer Satisfaction in the drivers of consumers' continued use of online marketplace platforms, when it comes to the role of AI-powered recommendation features.

A quantitative research method was used and a cross-sectional survey design was employed. The sample size of the respondents was 200 individuals who experienced the use of online marketplaces featuring personalized recommendation feature in the past. The seven constructs in the conceptual framework were measured using a structured questionnaire, which was based on a Likert scale ranging from 1 to 5. The collected data were analyzed with SPSS and PLS-SEM with SmartPLS version 3.2.8. Indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity were all used to evaluate the measurement model. Path coefficients, bootstrapping, coefficient of determination, effect size, and predictive relevance and collinearity statistics were used to evaluate the structural model.

The results show that Recommendation Accuracy and Recommendation Diversity have a positive impact on Perceived Relevance and Consumer Retention Rate. Other metrics that have a positive impact on Customer Satisfaction and Consumer Retention Rate are Real-Time Personalization and Context-Aware Suggestions. Moreover, Perceived Relevance and Customer Satisfaction are both positive factors affecting consumer retention. The findings also indicate that the three relationships between AI-powered recommendation features and retention can be explained by Perceived Relevance and Customer Satisfaction. Of all the factors that were studied, Recommendation Accuracy had a particular impact on Perceived Relevance, and Real-Time Personalization had a significant impact on Customer Satisfaction.

The study finds that online marketplaces can enhance consumer retention by offering accurate, diverse, responsive and appropriate recommendations to consumers' current contexts. The results provide valuable theoretical and practical guidance for designing an effective and responsible AI-based recommendation strategy for online platforms.

AI-powered recommendation systems, recommendation accuracy, recommendation diversity, real-time personalization, context-aware suggestions, perceived relevance, customer satisfaction, consumer retention.

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LIST OF ACRONYMS AND ABBREVIATIONS

Acronym/Abbreviation	**Full Form**
AI	Artificial Intelligence
AVE	Average Variance Extracted
CA	Context-Aware Suggestions
CR	Composite Reliability
CRR	Consumer Retention Rate
CS	Customer Satisfaction
f^2	Effect Size
HTMT	Heterotrait-Monotrait Ratio
NFI	Normed Fit Index
PLS-SEM	Partial Least Squares Structural Equation Modeling
PR	Perceived Relevance
Q^2	Predictive Relevance
RA	Recommendation Accuracy
RD	Recommendation Diversity
R^2	Coefficient of Determination

RTP	Real-Time Personalization
SoBE	School of Business and Economics
SPSS	Statistical Package for the Social Sciences
SRMR	Standardized Root Mean Square Residual
UIU	United International University
VIF	Variance Inflation Factor

CHAPTER I: INTRODUCTION

I.1 Background of the Study

The ecommerce sector has undergone a dramatic transformation in the digital age thanks to the swift progress of the internet, digital platforms, data analytics and Artificial Intelligence. Online retail sales have changed the nature of the relationship between consumers and businesses, by enabling consumers to search, compare and buy products from online markets irrespective of geographical boundaries. It has made online shopping more accessible and convenient, but also made it more complicated for consumers to make decisions.(Taiwo, 2024)

Today, there are thousands, or even millions, of products available in a wide range of categories, brands, prices and quality in an online marketplace. While this option provides consumers with choice, it can also prove challenging to determine which is the best product for their specific needs. Consumers can be inundated with amounts of product descriptions, reviews, advertisements and alternatives (Marchand & Marx, 2020). If the users can't process all the information they receive efficiently, they may get confused, postpone their decision, drop out of shopping, or switch to another platform.

This is where Artificial Intelligence (AI) comes into the picture. To overcome this challenge, online retailers are adopting more and more AI on their websites. According to (Agila, 2025) AI can help businesses mine and analyze vast amounts of behavioral and transactional data to generate personalized shopping experiences .These systems, which include analysis of browsing history, search activities, previous purchases, product ratings, clicks and time spent on particular items, can analyze the information. This information is used to make predictions about consumer preferences and product recommendations, which are likely to be more aligned with individual needs, using AI-powered systems. The adoption of AI-driven recommendation systems has significantly transformed the way consumers shop, making them a key element of the modern e-commerce experience as they offer personalized content and minimize (Blut, Ghiassaleh, & Wang, 2023; Chatterjee & Banerjee, 2025)the need to sift through extensive product lists. They are most useful as “virtual sales assistants” that steer consumers in the direction of appropriate products. These systems can work around the clock, unlike sales reps, and can give suggestions to many users simultaneously. Typical methods for recommending system are collaborative filtering, deep learning, etc. The common methods for recommending system are collaborative filtering, deep learning, etc. Deep-learning algorithms can process more complex patterns of customer behavior, while collaborative filtering can detect similarities between customers or products. These methods (Minhaj & Khan, 2025)can help recommendation systems deal with real-time interactions, minimizing the cognitive load for consumers during product search and evaluation . If recommendations are applicable and appropriate, consumers are better able to make choices effectively and with greater confidence.

There (Mohamed, 2024)has also been a shift in the objective of the strategic role of the recommendation systems. Many companies have been primarily leveraging these systems to drive more product views, clicks and sales right away. Their trajectory, however, has slowly turned towards doing long-term deals with consumers. As emphasized in (Ononiwu, Azonuche, Okoh, &

Enyejo, 2023), the main goal of implementing AI-powered recommendation agents is increasingly connected to consumer retention rather than only short-term transactions.

In the e-commerce realm, where other platforms are easily available, consumer retention is crucial. If the quality of the shopping experience is not up to the consumers' expectations, they can easily move to another marketplace with only a slight effort. As a result, eCommerce companies need to offer ongoing value, convenience, relevance, and satisfaction in order to elicit repeat business. AI recommendation systems(Behara) can help achieve this by providing personalized experiences, ensuring that consumers feel understood by the platform they're using.

(Zac & Gal, 2025) says, many online marketplaces around the world now consider personalized recommendations a key competitive differentiator. These systems can contribute almost 35% of the total sales and also allow the companies to reduce the customer acquisition cost .By providing regular and helpful recommendations, consumers might choose to stay with the same platform for future purchases(Upadhyay, 2025) as it saves them time and makes their shopping decisions easier.

But the performance of the recommendation systems is not only critical. However, as mentioned by (Mubdir, Hashim, & Rosli, 2025), they are highly dependent on their relevance and appropriateness to the user's needs and psychology. A technically correct suggestion might be irrelevant if it does not match the consumer's current use, budget, location or situation.

For instance, one customer might be searching for a product on behalf of another customer, but the system could continue to suggest similar products based on that single activity. If this is the case, historical data may not reflect the present interest of the consumer. As such,(Mohamed, 2024) the recommendations that a recommendation system provides must go beyond the past actions and take into account the present situation.

This is relevant since consumers tend to browse online without any professional guidance. Customers may not be aware of the alternative that is best suited for them to satisfy their needs without the expert advice about products and services (Agila, 2025). Hence, so-called intelligent software is required to act on behalf of consumers and assist these consumers in their buying choices (Mohamed, 2024)

Some properties of recommendation systems(Ononiwu et al., 2023) are crucial to its effective support. One of these is recommendation accuracy, which measures the degree of alignment between the recommendations and the user's preferences and/or past actions. Properly formed recommendations can boost the probability of consumer consideration of the recommended products. But you might need more than accuracy, (Vashishth, Sharma, Kumar, Chaudhary, & Panwar, 2024)as repeat product suggestions will limit the shopping experience.

Thus, diversity in recommendations is also key. Diversity enables the system to offer a wider variety of products, some of which the consumer might not even be aware of or think about. An optimized accuracy-diversity ratio can enable consumers to find new alternatives without losing relevance.(Potla & Pottla, 2024)

(Vashishth et al., 2024) ,One of the key features is its real-time personalization feature. Consumer interests may change rapidly during an active shopping session. A user might start searching for something general and then get interested in a particular category, brand or price. A real-time system will be able to identify these changes and adjust their recommendations accordingly.(Potla & Pottla, 2024; Sharma, Patel, & Gupta, 2021)

In the same way, context-aware suggestions enhance recommendations by taking also into consideration situational variables like time, location, occasion and task. (Hasan, 2025)A useful product in one context may be not so useful in another. Thus,(Ono, 2025) context-aware systems try to make recommendations that are more representative of the consumer's current situation.

These technological elements (Adomavicius & Tuzhilin, 2005)have the potential to affect two relevant psychological characteristics: relevance and satisfaction. Perceived relevance indicates whether or not users consider that the recommendations are useful and appropriate for their own decisions. (Kim, Choi, & Li, 2021)Customer satisfaction is the general perception of the experience of using the AI platform.

In this context, (Blut et al., 2023)this study looks at how the accuracy of recommendations, the diversity of them, the ability to do the recommendations in real-time, and the related capability of suggesting the items contextually affect the retention of consumers in a global online marketplace. It also takes into account the role of perceived relevance and customer satisfaction as mediators. The study aims to understand how AI-based recommendation systems can facilitate consumer–e-commerce platform relationships in the long term by encapsulating these variables in a single model. The study's goal is to offer insights into the capability of AI-based recommendation systems to assist long-term consumer–e-commerce platform relationships by incorporating these variables into a single model.

I.2 Statement of the Problem

While AI is widely adopted in eCommerce, online platforms still struggle with retaining customers.(B. Zhou & Zou, 2023)Online marketplaces are struggling with maintaining high customer retention rates, even as they make use of AI within their eCommerce. The digital world is a fiercely competitive marketplace, and users are not reluctant to switch to another platform when they're not satisfied. Compeers often just a click away, as mentioned in (Marchand & Marx, 2020). So, it has become a big challenge for e-commerce companies to keep their customers.

While many companies try to make recommendations more technically accurate, there is a shortage of work investigating how accuracy can translate to satisfaction. As in (Pathak, Garfinkel, Gopal, Venkatesan, & Yin, 2010) consumers may find the “accuracy-diversity dilemma.” A system can successfully suggest products that are alike to those that were previously viewed or bought by the user, however if the user continues to see similar products he/she will become bored with the suggestions.

This situation can lead to a so called 'filter bubble', by which consumers only see products that are limited to their choice. As time goes on, these restricted recommendations can diminish product discovery and result in disengagement or churn (Adomavicius, Sankaranarayanan, Sen, &

Tuzhilin, 2005). Thus, recommendation systems need to strike a balance between their recommendations being accurate and they being varied.

Another problem is related to how consumers perceive personalized recommendations. The AI systems gather extensive data regarding behavior, which they use to create personalized recommendations. This can make things easier for consumers, but can also make them feel uncomfortable if the recommendations seem intrusive or manipulative. As mentioned in (Li, Chen, & Raghunathan, 2020), these perceptions can diminish trust and have a negative impact on the perceived relevance of the platform.

It can also be difficult to overcome the situation of asymmetric information between the AI agent and the consumer. It can be a system with a lot of knowledge about user behavior, or it can be consumers who don't realize that they are being recommended products or that their data is being used. This imbalance can lead the user to feel like he or she has lost control over his or her buying decision, as described in (Abumalloh, Ibrahim, & Nilashi, 2020).

More than the algorithm, the effectiveness of a recommendation agent relies on other factors as well. finds that users judge recommendations on the variety and context (Huseynov, Huseynov, & Özkan, 2016)of the recommendations. Recommendations that are similar to past behaviors, but do not reflect the current situation may still be inappropriate.

Sometimes the recommendations do not adapt in real-time, and can still show outdated or irrelevant content (Pu, Chen, & Hu, 2011). For instance, a customer can switch up their interest rate while they are still in a shopping session, but the system may not offer accordingly. This means that personalization becomes less effective and can lead to frustration.

This can also be due to incomplete or inadequate information in the recommendations. As stated in (Herlocker, Konstan, Terveen, & Riedl, 2004), false suggestions could hurt the business's reputation and result in losing customers. When recommendations are made repeatedly more than once, a consumer might see this as proof of a lack of understanding.

To develop sustainable consumer relationships, customer satisfaction should be integrated with technical performance, as discussed in (Schafer, Konstan, & Riedl, 2001). Algorithmic improvements are not enough to guarantee retention in and of themselves; the algorithm has to be useful and satisfying to the consumer.

This study poses the central problem as the inadequate explanation of how the recommendation accuracy, recommendation diversity, personalization capability in real-time and the context-aware suggestions interact to affect the consumer retention rate. (Wu, He, Wang, Zhang, & Wang, 2022)It is also important to know if there is an intermediate between perceived relevance and customer satisfaction and if there is, the nature of that link.

Therefore, in this study, the authors ask themselves whether accurate and diverse suggestions make suggestions more relevant in the eyes of the user, whether real-time and context-aware suggestions lead to higher satisfaction, and whether these psychological aspects have an impact on customer retention.

I.3 Research Gap

The previous literature has made a significant contribution to the development of the AI-powered recommendation systems. Numerous works have been conducted on technical performance measures like prediction accuracy, coverage, click-through rates and computational efficiency. Much has been discussed about the first use of AI technology and the enhancement of technical improvements like click-through rates as mentioned in (Herlocker et al., 2004).

Thus, there is a significant research gap in how accuracy, diversity, real-time capability and a combination of such factors jointly affect the retention behavior over the long term (Schafer et al., 2001). Other important design features have been overlooked, while the accuracy measurement is often assumed to be the primary criterion of the quality of the recommendation.

Many studies focus on accuracy and coverage, and yet neglect to explore other design issues, as identified in (Wu et al., 2022). Technical indicators can tell us the extent to which an algorithm works, but not whether the recommendations are useful, different, timely, or appropriate in the context.

Although the mediating effects of perceived relevance and customer satisfaction in the multidimensional context of recommendation features are not well understood, as pointed out by (T. Zhou et al., 2010). Often, previous research simply focuses on direct personalization-consumer behavior links, but does not explain why these links exist.

Limited evidence of long-term impact of personalization also exists. Short-term gains have been observed as described in (Raza et al., 2026)but how long-term exposure to customization affects consumer retention is still not known. Often the short-term benefits of platform use, like clicks, buying or initial satisfaction, are measured, but not long-term platform use.

This study fills these gaps by creating a holistic framework linking the accuracy of recommendations with their diversity, the ability of making recommendations in real-time and taking into account the context, and the impact of these (Resnick & Varian, 1997)recommendations on consumer retention via perceived relevance and customer satisfaction.

This study discusses these variables in conjunction to give a more complete picture of the effectiveness of a recommendation system. It goes beyond technical correctness and accounts for the possibility of varying, responsive, contextually appropriate, relevant and satisfying recommendations.

The primary research gap in this study is the lack of an integrated framework that shows how the different characteristics of AI-powered recommendation affect the retention rate via perceived relevance and customer satisfaction.

I.4 Objectives of the Study

This research's primary goal is analyzing the effects of the features of the AI-powered recommendation systems on consumer retention in the international online marketplaces.

Specific objectives are:

1. To test the effect of recommendation accuracy and diversity on perceived relevance and consumer retention rate.
2. To explore the role of real-time personalization capability and context-aware suggestions on customers' satisfaction in online marketplaces.
3. To evaluate the mediations of perceived relevance and customer satisfaction between AI recommendation features and consumer retention.
4. To give strategic advice to ecommerce companies on how to leverage AI in their retention strategy and ensure it is optimized.

I.5 Research Questions

In order to meet the aims of the study, the following research questions are put forward:

1. What is the relationship between the accuracy and diversity of recommendations and the perceived relevance of the recommendations and the overall intention to stay with the recommendation provider?
2. How much does real-time personalization and context-aware suggestions increase customer satisfaction?
3. Are the relationships between AI recommendation system characteristic and customer satisfaction and between customer satisfaction and the consumer retention rate significant?

I.6 Scope and Limitation of the Study

Scope of the Study

The emphasis of this research is on users with active experience with the AI-based recommendation feature of a global online marketplace (Ansari, Essegaier, & Kohli, 2000). It focuses on those consumers who are provided with personalized recommendations during their browsing, searching, comparing and buying activity on the Web.

Presently, the study focuses on B2C-marketplaces, where consumers' interactions result in high velocity behavioral data that is required for real-time personalization (N. Kumar & Benbasat, 2006). It explores the following four key characteristics of recommendations: recommendation accuracy, recommendation diversity, real-time personalization capabilities, and context-aware suggestions.

The study also explores perceived relevance, customer satisfaction as intermediate variables and the consumer retention rate as the main outcome variable. It is not about the internal workings of AI algorithms themselves, but rather on the consumer's perception.

The research focuses specifically on digital interactions, so while brick and mortar retail is excluded, you can find it in other research reports from the same series. Platforms that don't have AI recommendation agents built in are also not included (Senecal & Nantel, 2004).

Limitations of the Study

One limitation is the use of cross-sectional data. As stated in(Dias, Locher, Li, El-Deredy, & Lisboa, 2008), cross sectional studies take a snapshot of perceptions and intentions at a single time and may not reflect over a span of years.

The results also may be affected by the profile of the respondents(Tam & Ho, 2006) selected and the marketplaces. Different people from different countries, different cultures or technology backgrounds may assess the recommendations of AI differently.

Another limitation is the use of self-reported data. The authors' definitions of the concept of recommendation accuracy, relevance, diversity, satisfaction and retention may not be the same as those of the respondents.

In addition, there may be datasets that are not representative of all real-world complexities (Tam & Ho, 2006). However, customer satisfaction and brand reputation, the price, delivery, website design, customer service, and promotional activities those are not the main focus of this study which is also could play a role in consumer retention.

Yet, the research offers a narrow understanding of the impact of AI-driven recommendation functionalities and psychological mediators on consumer retention.

I.7 Definition of Key Terms

Consumer Retention Rate

The consumer retention rate relates to an online platform's ability to sustain the relationship with its consumers and encourage their repeat purchase over time (Aksoy, 2013). In this study, it represents the probability of consumers' continuing to use the platform.

Recommendation Accuracy

The accuracy of recommendations made by the system is measured by the extent to which system-provided suggestions are aligned with users' interests, requirements and past preferences (Bleier & Eisenbeiss, 2015).

Recommendation Diversity

This is called the recommendation diversity, in which the AI system can offer a diverse set of recommendations, such as those that have not been recommended or purchased by the consumer (Arora et al., 2008).

Real-Time Personalization Capability

Real-time personalization capability is the technical capacity of a system to adapt recommendations in real time, according to the user's behavior during a current shopping session (Zhang et al., 2010).

Context-Aware Suggestions

Context-aware suggestions are suggestions that are based on context (time, place, task etc. that is being performed by the user) (Kwon & Kim, 2012)

Perceived Relevance

Perceived relevance indicates whether the information the AI agent provides is relevant and suitable for the situation in which the consumer is making a decision (Jannach & Adomavicius, 2016).

Customer Satisfaction

Customer satisfaction is the overall perception and emotion derived from their interactions with an AI powered online platform (Pappas, Kourouthanassis, Giannakos, & Lekakos, 2017).

I.8 Organization of the Remaining Chapters

This thesis will be divided into four other chapters. The literature review in Chapter II covers various aspects of AI-recommended systems, including recommendation accuracy, diversity, real-time personalized recommendations, context-aware recommendations, perceived relevance, customer satisfaction, and customer retention. It also presents the theoretical basis for the phenomenon, such as Expectation-Confirmation Theory, and a theoretical model development (Mobasher, Cooley, & Srivastava, 2000).The methodology used in the research is presented in Chapter III. It outlines the quantitative survey design, population, sampling methods, designing questionnaire, data collection and analysis. The empirical results are presented in Chapter IV, along with the results of the PLS-SEM analysis. It involves the demographic profile of the respondents, the assessment of the measurement models, the reliability and validity of the instruments, evaluation of the structural models, mediation analysis, and hypothesis testing. Lastly, Chapter V examines the key findings and offers theoretical and practical implications from research conducted. It also includes strategic recommendations, a summary of research findings, an explanation of the limitations and research directions.

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CHAPTER II: LITERATURE REVIEW

II.1 Relevant Theory

To grasp the behavior of consumers in AI-powered online marketplaces, it is necessary to understand a few theories that examine the effect of the technological characteristics on the continued use of the platform. (Mobasher et al., 2000)states that consumers' intention to continue using automated tools is mainly based on their evaluation of system performance. According to (Knijnenburg, Willemsen, Gantner, Soncu, & Newell, 2012), satisfaction and continued usage is affected by whether the actual performance of the recommendation system is in line with consumers' initial expectations or not. If the system works as expected, consumers will have a higher level of satisfaction and more likely to continue using the system.

The other important model that is relevant to this study is the Technology Acceptance Model (TAM). Perceived usefulness and ease of use affect users' acceptance of technology, as cited in (64), which is why TAM is often used in research on recommendation agents. AI-driven marketplaces have a higher success rate of persuading consumers of the value of recommendation systems if they are perceived as useful and convenient. Furthermore, (Xiao & Benbasat, 2007) shows that the direct factor of trust on the adoption and subsequent use in personalized environments.

This work's basic theory is the Stimulus-Organism-Response (SOR) framework. (Xiao & Benbasat, 2007) describes the framework as providing a way to understand how external technological stimuli impact consumers' internal cognitive and emotional processes that ultimately drive behaviors. The external stimuli for this study are recommendation accuracy, recommendation diversity, real-time personalization and context-aware suggestions. These features affect the internal responses of the consumer: his or her sense of relevance, and his or her satisfaction. The ultimate behavioral result is the retention of consumers.

The framework is also supported by the Information Processing Theory, which provides an understanding of how AI systems can facilitate the processing of large volumes of information with minimal effort. AI recommendation systems assist consumers by curtailing information overload and filtering relevant information, according to (Widjaja, 2023). Likewise, (Avdić, 2025) states that AI helps to make decisions quicker and easier by reducing consumers' search effort. (Vashishth et al., 2024) also notes that lowering the effort is important to the effectiveness of the system and satisfaction of the user in electronic commerce.

II.2 Literature Survey

The fast-paced evolution of the AI-driven recommendation engines has transformed online marketplaces from mere transactional platforms into customer-focused ecosystems that foster enduring relationships. (Sivasankari, Kasireddy, Shrivastava, Patra, & Patil, 2025)highlights the need for personalized retention strategies, backed by intelligent systems, for maintaining digital competitiveness. They are becoming more commonplace in order to gain insight into consumer tastes, enhance the shopping experience and to get consumers to return to the platform.

One important aspect is Recommendation Accuracy, as defined by (Behara): the degree of similarity between the item recommended to the consumer and his or her true preference. The recommendations help consumers to identify appropriate products, and decrease the time needed to explore the numerous alternatives. But, as (V. Kumar, Rajan, Venkatesan, & Lecinski, 2019) notes, simply being correct doesn't necessarily lead to sustained engagement if recommendations are repetitive or there's not enough variety.

This is why it's also a great feature to have Recommendation Diversity. (Prentice, Dominique Lopes, & Wang, 2020) defined diversity as the ability of a recommendation system to recommend products which a consumer may not have been aware of. Diverse recommendations increase the possibility of discovering new and interesting products. Diversity has been shown to enhance customer satisfaction by providing more options and mitigating constraint due to link sparsity (Wang et al., 2023). However, there is a 'accuracy-diversity dilemma' here, as the platforms have to weigh the content, they are familiar with against the new content available if they want to avoid boredom and customer churn.

Another key aspect is Real-Time Personalization, which allows systems to tailor recommendations based on the consumer's real-time activities. Platforms can use technology like Recurrent Neural Networks to quickly react to shifts in consumer preferences within a session, as explained by (Krishnan, Gupta, Gupta, & Singh, 2022). This real-time feature also helps companies anticipate behavior and act before dissatisfaction and disengagement can happen, (Zac & Gal, 2025) said.

Context-Aware Suggestions are very similar to real-time personalization. These suggestions take into account situational data, like location and time, and suggest more appropriate recommendations. (Minhaj & Khan, 2025)describes how the accuracy and meaningfulness of multidimensional recommendations are enhanced with contextual information. Likewise, (Biswas & Patra, 2023)argues that context-aware systems can recommend products based on user's context, and that it can result in higher Perceived Relevance.

Perceived Relevance is the degree of consumer's belief that recommendations are relevant and useful for them. Personalized strategies impact on consumers' perceptions of relevance of suggestions, as shown in (NOUZRI & Ejjami, 2024). (Upadhyay, 2025) also explains that appropriate recommendations help to make a purchase decision and save consumers' search efforts.

Customer Satisfaction is also a crucial aspect of consumer behavior. Based on the results of (B. Zhou & Zou, 2023), satisfaction is a linkage that increases the relationship between trust and loyalty, and personalization is one of the variables. Based on the results of (Marchand & Marx, 2020), satisfaction is the linkage that makes the relationship between trust and loyalty stronger and personalization is one variable. Consumers are more likely to have a positive evaluation of a platform when they are given recommendations that are timely, appropriate, and useful.

These psychological and technological factors finally lead to Consumer Retention Rate. Consumer retention is highlighted as an important future study field by (Pathak et al., 2010), which indicates that it denotes the consumers' willingness to keep using a platform. Enhancing retention management is a core goal for online marketplaces aiming to be a sustainable business in today's data-rich world, as per (Adomavicius et al., 2005).

II.3 Hypotheses Development

II.3.1 Recommendation Accuracy, Recommendation Diversity and Perceived Relevance

The primary goal of an AI-powered recommendation system is to deliver useful and meaningful suggestions that the consumers can value. Recommendation Accuracy is related to whether a consumer feels that the system grasps their preferences, as per (31). Consumer-perceived relevance of recommendations depends on the extent to which the recommended products are congruent with the consumer's interest (33).

Recommendation Diversity also helps to ensure relevance in the end user's perception, since it avoids repetition in recommendations. According to (46), diversity offers customers a larger array of options; according to (32), the recommendations are new ones that may correspond to the changing interests of customers. Based on the relationships presented in the research model (824), the following hypotheses are proposed:

H1: The relationship between Recommendation Accuracy and Perceived Relevance is significantly positive and strong.

H2: The effect of Recommendation Diversity on Perceived Relevance is significantly positive.

II.3.2 Recommendation Accuracy, Recommendation Diversity and Consumer Retention

The accuracy of recommendations can also directly impact consumers' desire to keep using an online marketplace. As per (Blut et al., 2023), the utility is provided by consistently accurate recommendations and this can induce consumers to return to the platform. Correct recommendations also lower cognitive load of looking for products or going onto another platform (Kim et al., 2021).

Likewise, recommendation diversity can aid in Consumer Retention by maintaining the shopping experience interesting. (Adomavicius & Tuzhilin, 2005) says that different suggestions make the experience more interesting and unexpected. Also, as described in (Potla & Pottla, 2024), it is possible to avoid filter bubbles and boredom with a diverse set of recommendations. Based on the framework, the following hypotheses are proposed:

H3: Recommendation Accuracy has a significant positive effect on the Consumer Retention Rate.

H4: Recommendation Diversity positively affects the Consumer Retention Rate.

II.3.3 Real-Time Personalization, Context-Aware Suggestions and Customer Satisfaction

An AI recommendation system's responsiveness can significantly impact consumers' satisfaction. (Ononiwu et al., 2023)notes that Real-Time Personalization establishes an instant feedback loop, making consumers feel that the platform is meeting their needs as they are using it. This responsiveness can make Customer Satisfaction more responsive by offering immediate and individual value (Okeke, Alabi, Igwe, Ofodile, & Ewim, 2024).

Context-Aware Suggestions also enhance the consumers' satisfaction by taking into account their current context. Recommendations based on time, place and situational needs offer more “in-the-moment” value, according to (Hassan, Abdelraouf, & El-Shihy, 2025). If suggestions are appropriate to the current context, they can be beyond the consumer's expectations and lead to a higher satisfaction (Chatterjee & Banerjee, 2025). The following hypotheses are proposed, based on the model:

H5: Real-Time Personalization has a significant positive effect on Customer Satisfaction.

H6: Context-Aware Suggestions have a significant positive effect on Customer Satisfaction.

II.3.4 Real-Time Personalization, Context-Aware Suggestions and Consumer Retention

Real-time personalization can affect retention as the system can react to the consumer behavior changes. (Agila, 2025) states that systems that observe the interaction of consumers can detect imminent consumer departure and act before it happens. This responsiveness can have a direct impact on the Consumer Retention Rate. Context-aware suggestions can also help improve retention by making shopping more convenient and useful. As mentioned in (Mubdir et al., 2025), context-aware features can help bring a platform closer to people's daily lives. The platform can also deliver timely and contextually relevant suggestions, which can help to foster loyalty and advocacy for long-term retention (Upadhyay, 2025). Based on this, the following hypotheses are put forward:

H7: Real-Time Personalization has a significant positive effect on the **Consumer Retention Rate**.

H8: Context-Aware Suggestions have a significant positive effect on the **Consumer Retention Rate** (Minhaj & Khan, 2025).

II.3.5 Perceived Relevance, Customer Satisfaction and Consumer Retention

The final relationships in the framework relate to the internal evaluations that impact on retention. Perceived Relevance (Mubdir et al., 2025) is an important link between system performance and continued use. Consumers are more inclined to stick around when they feel contented that the recommendations are personally relevant. According to the same way, the study also shows that ((Upadhyay, 2025) says that Customer Satisfaction is a significant factor in predicting repeat purchase behavior. Happy consumers are less inclined to seek a different marketplace (24). These internal states help to explain the impact that AI-powered features have on consumer retention rate (NOUZRI & Ejjami, 2024; Upadhyay, 2025). The following hypotheses are proposed, based on the framework (Upadhyay, 2025)

II.4 Conceptual Framework

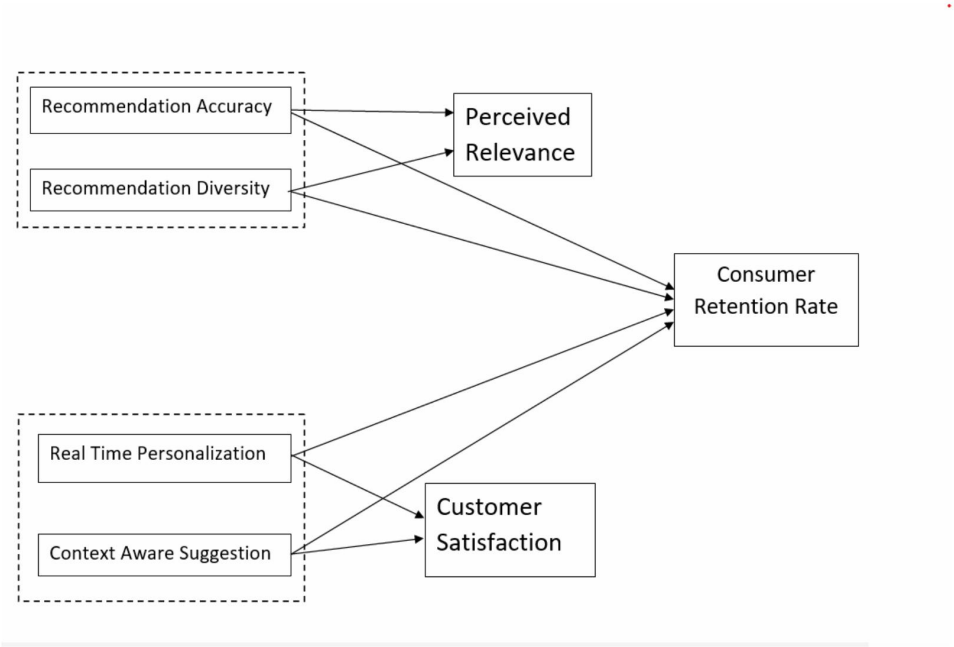


Figure 1 Framework of the Study

CHAPTER III: METHODOLOGY OF THE STUDY

III.1 Study Context

AI-driven recommendation systems have transformed the way consumers search for products, compare options, and make purchases in online marketplaces.AI-driven recommendation systems have altered the way consumers conduct product searches, compare options, and make the purchasing choice in online marketplaces. Recommendation technologies are becoming a common feature on online platforms to analyze consumer preferences and offer tailored product suggestions. These systems can enhance the shopping experience by showing relevant, contextually appropriate, accurate and timely recommendations. But, how well these systems are able to hold on to users relies on the user's assessment of the relevance of the recommendations and the level of satisfaction they experience with the system.

The main purpose of this study is to investigate the factors affecting the Consumer Retention Rate in AI-driven online marketplaces. In particular, study focuses on the correlations of Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, and Context-Aware Suggestions with the Consumer Retention Rate. Moreover, this study examines the roles of Perceived Relevance and Customer Satisfaction in these relationships. The Recommendation Accuracy and Recommendation Diversity are explored in terms of Perceived Relevance, whereas Real-Time Personalization and Context-Aware Suggestions are explored in terms of Customer Satisfaction. In addition, the study assesses the direct impact of all four of the recommendation system features on the Consumer Retention Rate, as well as the impact of Perceived Relevance and Customer Satisfaction on retention.

It is an investigation to know about the technological and psychological aspects that might make the consumers continue using online marketplaces. It also sheds light on the ways in which the quality and effectiveness of AI-powered recommendation systems can enhance consumers' perceptions, satisfaction, and actual relationship with online platforms.

III.2 Research Design

This study was a quantitative research method, which was cross sectional survey. The quantitative method was appropriate for the study because the study was intended to measure certain relations between several variables, and statistically test the hypothesis. The questionnaires were used to gather primary data from the respondents.

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data. The analysis was conducted by the software packages SmartPLS version (3.2.8). PLS-SEM was selected due to the presence of several latent constructs and multiple direct relationships in the proposed conceptual framework that needed to be considered simultaneously. The method is also suitable for research aimed at explaining and predicting the variation of the dependent variable, in this case, the Consumer Retention Rate (Sarstedt et al., 2021).

Four exogenous constructs (Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, and Context-Aware Suggestions) were included in the study. In order to bring in these constructs that would be measured from the consumer's perspective, Perceived Relevance

and Customer Satisfaction were added as internal constructs of consumer evaluation, and the Consumer Retention Rate was used as the final endogenous construct. The structural model tested 10 proposed relationships between these constructs.

A pilot study with 30 respondents was conducted prior to the main survey, to check the clarity of the questions and reliability of the instrument. Internal consistency was determined by Cronbach's alpha, which was computed using SPSS. There were four measurement items on each construct. After the pilot study, the questionnaire was checked and was ready for the main data-collection process.

III.3 Questionnaire Design

A two-part questionnaire was used for this study. The first section gathered the demographic data of the respondents such as gender and age group. The second section was used to assess the constructs in the conceptual framework.

The questionnaire consisted of seven constructs: Recommendation Accuracy (RA), Recommendation Diversity (RD), Real-Time Personalization (RTP), Context-Aware Suggestions (CA), Perceived Relevance (PR), Customer Satisfaction (CS), and Consumer Retention Rate (CRR). Four indicators were used to measure each construct.

The measurement of recommendation accuracy was done by RA1 to RA4, and recommendation diversity was done by RD1 to RD4. Real-Time Personalization was tracked using RTP1 – RTP4 and Context-Aware Suggestions were tracked using CA1 – CA4. The measures of Perceived Relevance were PR1, PR2, PR3, and PR4; the measures of Customer Satisfaction were CS1, CS2, CS3, and CS4; and the measures of Consumer Retention Rate were CRR1, CRR2, CRR3, and CRR4.

All the measurement items were rated on a 5-point Likert scale, from Strongly Disagree (1) to Strongly Agree (5). The Likert scale enabled the respondents to rate their agreement or disagreement with the statements relating to their experiences with AI-driven recommendation systems in online marketplaces.

III.4 Sampling and Data Collection

A non-probability convenience-sampling technique was used in this study. The survey targeted individuals with prior experience in online platforms with AI-powered recommendations. The study was convenience sampled due to the need for respondents who were easily accessible and familiar with online, personalized product recommendations.

The data was gathered by an online questionnaire from April 2026 to May 2026. Initially, 230 responses were collected. When the data cleaning and screening process was completed, 200 responses were kept for the final analysis. Responses that were incomplete or inconsistent or unknown were not included in the data.

The respondents were users from various demographic groups with experience of using the recommendations system in online marketplaces. Their answers gave insights into the accuracy of their recommendations, recommendation diversity, real time personalization, context-aware

recommendations, perceived relevance, customer satisfaction and their intentions to remain with the platform.

The number of N = 200 was deemed adequate for the PLS-SEM analysis. PLS-SEM can be used to analyze complex models with multiple constructs and relationships, even in relatively moderate sample size (Ramayah et al., 2016).

III.5 Data Analysis Plan.

The data collected were analyzed with SPSS and SmartPLS version 3.2.8. A demographic analysis, data screening, and pilot reliability test were performed using SPSS software and PLS-SEM analysis was conducted using the SmartPLS software.

The analysis procedures were based on the following: Demographic analysis, reliability analysis, measurement-model assessment, discriminant-validity assessment, collinearity assessment, and structural-model analysis. Indicator loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted were used to assess indicator reliability, internal consistency, and convergent validity.

The analysis results that were uploaded had Cronbach's alpha ranging from 0.959 to 0.966, composite reliability ranging from 0.970 to 0.975 and average variance extracted ranging from 0.891 to 0.908. The measures were employed to assess the constructs' reliability and convergent validity. Discriminant validity was assessed by means of the Fornell-Larcker criterion, the Heterotrait-Monotrait ratio and the cross-loadings.

Path coefficients, bootstrapping, coefficient of determination (R2), effect size (f2), predictive relevance (Q2), and Variance Inflation Factor (VIF) were used to evaluate the structural model. The statistical significance of the proposed relationships was tested using a bootstrapping approach with 5,000 subsamples.

CHAPTER IV: RESEARCH FINDINGS AND ANALYSIS

IV.1 Profile of Survey Respondents

A total of 200 respondents were included in the sample. There were slightly more males than females, with 56.0% being males and 44.0% being females. As to age, the largest group of respondents was between 41-50 years (25.5%) followed by the respondents aged between 31-40 years (24.5%). The demographic 21-30 years was represented by 22.5%, and those over 50 years of age with 18.5%. The age group less than 20 years was the smallest age group at 9.0% of respondents. The majority of the respondents were students (34.0%), with employed respondents coming in next at 29.5%. The business owners accounted for 13.5%, homemakers for 10.5%, self-employed respondents for 7.5% and others accounted for 5.0%. When it comes to purchasing online, 35.5% said they did so weekly and 29.0% said they did so on a monthly basis. 18.0% of the daily shoppers, while 14.0% shopped rarely, only 3.5% reported never shopping online. This suggests the majority of respondents used online marketplaces regularly, which is appropriate for assessing AI recommendation systems and customer loyalty.

Table 1Demographic Profiles of Respondents

Characteristics	**Frequency**	**Percentage (%)**
Gender		
Male	112	56
Female	88	44
Age Group		
Below 20 years	18	9
21–30 years	45	22.5
31–40 years	49	24.5

41–50 years	51	25.5
Above 50 years	37	18.5
Occupation		
Student	68	34
Employed	59	29.5
Business Owner	27	13.5
Homemaker	21	10.5
Self-Employed	15	7.5
Others	10	5
Online Shopping Frequency		
Daily	36	18
Weekly	71	35.5
Monthly	58	29
Rarely	28	14
Never	7	3.5
Most Used Online Marketplace		
Shopee	79	39.5

Lazada	56	28
Daraz	38	19
Amazon	17	8.5
Others	10	5
Total	**200**	

IV.2 Measurement, Validity, and Reliability of Data

The outcomes of the Partial Least Squares Structural Equation Modeling (PLS-SEM) measurement model testing are presented in table 2. Indicators loadings, Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), R2, adjusted R2 and NFI and SRMR were used to assess the quality of the measurement model.

Table 2: Measurement Model Assessment

Table 2Measurement Model Assessment

Constructs	**Items**	**Loading**	**Alpha**	**AVE**	**CR**	**R^2**	**Adj. R^2**	**NFI**	**SRMR**
Consumer Retention Rate	CRR1	0.942	0.959	0.891	0.97	0.894	0.892	0.916	0.052
	CRR2	0.94							
	CRR3	0.944							
	CRR4	0.949							
	CA1	0.951	0.962	0.897	0.972				

Context-Aware Suggestions	CA2	0.947							
	CA3	0.939							
	CA4	0.95							
Customer Satisfaction	CS1	0.949	0.96	0.894	0.971	0.749	0.746		
	CS2	0.941							
	CS3	0.953							
	CS4	0.939							
Perceived Relevance	PR1	0.943	0.96	0.894	0.971	0.655	0.652		
	PR2	0.945							
	PR3	0.948							
	PR4	0.946							
Real-Time Personalization	RTP1	0.957	0.966	0.908	0.975				
	RTP2	0.955							
	RTP3	0.942							
	RTP4	0.957							
Recommendation Accuracy	RA1	0.945	0.962	0.897	0.972				
	RA2	0.947							

	RA3	0.946							
	RA4	0.951							
Recommendation Diversity	RD1	0.953	0.963	0.901	0.973				
	RD2	0.95							
	RD3	0.946							
	RD4	0.946							

Indicator Loadings

The loadings of all indicators were greater than the criterion of 0.70. The loading values were between 0.939 and 0.957. The minimum loading among every item was 0.939 (CA3 and CS4) and the maximum loading was 0.957 (RTP1 and RTP4). Thus, all of the measurement items sufficiently covered their respective constructs with no item deleted from the measurement model.

Reliability

The Cronbach's Alpha of each construct was greater than the acceptable level of 0.70 which ranged from 0.959 to 0.966. Consumer Retention Rate and Real-Time Personalization had the lowest Cronbach's Alpha of 0.959 and 0.966, respectively. The results show that the items in the measuring instrument were highly consistent with each other. The Composite Reliability values were between 0.970 and 0.975 and all were higher than the recommended value. Consumer Retention Rate was the lowest value with Composite Reliability of 0.970 and the highest value was 0.975 for Real-Time Personalization. Thus, all seven constructs had acceptable internal consistency reliability.

Convergent Validity

Average Variance Extracted values were from 0.891 to more than half of the variance in the measurement indicators for each construct. R^2 0.908. The lowest AVE value was found for Consumer Retention Rate (0.891) and the highest AVE value was found for Real-Time Personalization (0.908). All AVE values are higher than minimum requirement of 0.50, therefore, the results are consistent with satisfactory convergent validity.

R^2 and Model Fit

The R^2 values indicate the amount of variation in the endogenous constructs explained by their predictor variables. The values of R^2 and adjusted R^2 for Consumer Retention Rate were 0.894 and 0.892, respectively. The Consumer Retention Rate was found to be determined by 89.4% of the variance which was accounted for by the following factors: Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, Context-Aware Suggestions, Perceived Relevance, and Customer Satisfaction. The R^2 value of the Customer Satisfaction was 0.749 and the adjusted R^2 value was 0.746. Thus, Real-Time Personalization and Context-Aware Suggestions accounted for 74.9% of the variation in Customer Satisfaction. The R^2 value for Perceived Relevance was 0.655 and adjusted R^2 value was 0.652, meaning that Recommendation Accuracy and Recommendation Diversity accounted for 65.5% of the variation in Perceived Relevance. The estimated model fell within the acceptable range of the SRMR with a value of 0.052 and below the recommended maximum of 0.08, indicating an acceptable model fit. The NFI value was found to be 0.916, which is higher than the recommended NFI value of 0.90. Thus, the overall goodness of fit of the proposed measurement model was found to be satisfactory in both situations, SRMR and NFI.).

4.3 Predictive Relevance and Effect Sizes: Q2 and f2

The Stone-Geisser Q^2 values and the effect size Cohen's f^2 are used to evaluate the predictive relevance and substantive significance of the structural model in PLS-SEM. The Q^2 value is used for determining the predictive relevance of the model for its endogenous constructs and the f^2 value is used to determine the contribution of each predictor to a specific endogenous construct. It is a common practice to report Q^2 and f^2 together with other structural-model results in PLS-SEM analysis. (Akbari et al., 2023)

Table 3: Values of Stone-Geisser Indicator (Q^2) and Cohen's Indicator (f^2)

Table 3Values of Stone-Geisser Indicator (Q^2) and Cohen's Indicator (f^2)

Constructs	**Q^2**	**Consumer Retention Rate (f^2)**	**Customer Satisfaction (f^2)**	**Perceived Relevance (f^2)**
Context-Aware Suggestions		0.195	0.265	
Consumer Retention Rate	0.797			
Customer Satisfaction	0.67			

Perceived Relevance	0.586			
Real-Time Personalization		0.152	0.385	
Recommendation Accuracy		0.12		0.267
Recommendation Diversity		0.09		0.043

Stone-Geisser Q^2: Predictive Relevance

Stone-Geisser Q^2 is a measure of the predictive validity of the structural model for the endogenous constructs. If the Q^2 is greater than 0, then the model has a predictive value. Small, medium and large predictive relevance are in general represented by Q^2 values of 0.02, 0.15 and 0.35, respectively.

The Consumer Retention Rate showed the highest estimated Q2 value of 0.797, which means the structural model is highly relevant in predicting consumer retention. The findings from this result indicate that the Composite Score of the combination of these six measures (Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, Context-Aware Suggestions, Perceived Relevance, and Customer Satisfaction) was sufficiently high to predict the Consumer Retention Rate.

Customer Satisfaction got an estimated Q^2 value of 0.670 and an estimated LR value of 37.045. Therefore, the predictive power of Real-Time Personalization and Context-Aware Suggestions for Customer Satisfaction is strong. An estimated Q^2 value of 0.586 was obtained for Perceived Relevance, indicating a good predictive relevance of Recommendation Accuracy and Recommendation Diversity for this construct. All three of the Q^2 values of the structural model are larger than zero and greater than the large effect threshold, which indicates good predictive relevance for each endogenous construct.

Cohen's f^2: Effect Sizes

The effect size of each individual predictor relationship within the structural model is shown by Cohen's f^2 coefficient. Small, medium and large effects are usually defined as 0.02, 0.15 and 0.35 respectively. The analysis shows different levels of substantive effects among the proposed relationships.

The strongest individual effect was for Context-Aware Suggestions in the Consumer Retention Rate with an $f^2 = 0.195$ or medium effect. Real-Time Personalization also showed a medium effect on the Consumer Retention Rate, $f^2 = 0.152$. The f^2 value for Recommendation Accuracy was 0.120 and thus for Recommendation Diversity 0.090. Both are relatively small effects, suggesting that these two recommendation features contribute to consumer retention in relatively small ways.

Real-Time Personalization had the biggest effect in the structural model in the case of Customer Satisfaction, with an f^2 value of 0.385. This value is higher than the threshold of 0.35, and is therefore indicative of a large effect. The results of Context-Aware Suggestions were recorded at an f^2 value of 0.265, which is a medium effect in regards to Customer Satisfaction. The results indicate that, while both variables significantly impact customer satisfaction, the latter is more strongly related to customer satisfaction than real-time adaptation.

In terms of Perceived Relevance, Recommendation Accuracy had a medium effect of $f^2 = 0.267$. This points to a useful contribution that is made to consumers' perceptions of personally relevant and useful product suggestions, when the recommendations are accurate. In the Recommendation Diversity, however, an f^2 value of 0.043 was found, indicating a small effect on Perceived Relevance. Recommendation Diversity, therefore, has a significantly greater substantive impact on Perceived Relevance than Recommendation Accuracy.

In general, the results of the effect-size analysis show that Real-Time Personalization has the highest influence on Customer Satisfaction, and Recommendation Accuracy has the highest influence on Perceived Relevance. Other factors contributing to the Consumer Retention Rate, such as Context-Aware Suggestions and Real-Time Personalization, play an important role as well. The direct effects of the constructs of Recommendation Accuracy and Recommendation Diversity are smaller, but are relevant constructs in the proposed structural model.

IV.4 Discriminant Validity Assessment

To test the discriminant validity, it was necessary to confirm that each construct measured in the measurement model was empirically distinct from the other constructs. The assessment was done using the Fornell-Larcker criterion, cross-loading analysis and Heterotrait-Monotrait ratio (HTMT). The measurement model was used to generate results with SMARTPLS.

IV.4.1 Fornell-Larcker Criterion

The Fornell-Larcker criterion calls for the square root of the Average Variance Extracted (AVE), as indicated by the diagonal values, to be larger than every correlation of the construct with the other constructs.

Table 4: Fornell-Larcker Criterion

Table 4Fornell-Larcker Criterion

Constructs	CRR	CA	CS	PR	RTP	RA	RD

Consumer Retention Rate (CRR)	**0.944**						
Context-Aware Suggestions (CA)	0.876	**0.947**					
Customer Satisfaction (CS)	0.893	0.808	**0.946**				
Perceived Relevance (PR)	0.821	0.753	0.8	**0.945**			
Real-Time Personalization (RTP)	0.87	0.784	0.826	0.755	**0.953**		
Recommendation Accuracy (RA)	0.902	0.842	0.875	0.8	0.842	**0.947**	
Recommendation Diversity (RD)	0.869	0.797	0.848	0.75	0.803	0.86	**0.949**

The diagonal values were between 0.944 and 0.953 and higher than the inter-construct correlations. For instance, the square root of AVE for Consumer Retention Rate was 0.944, which is higher than its highest correlation with Recommendation Accuracy which is 0.902. In the same way, the square root of AVE for Recommendation Diversity was 0.949 with 0.869 being the maximum correlation value with Consumer Retention Rate. All the seven constructs fulfilled the Fornell-Larcker criterion and helped to validate the measurement model as having a high degree of discriminant validity.

IV.4.2 Heterotrait-Monotrait Ratio Analysis

The Heterotrait-Monotrait ratio was also used to examine discriminant validity. Values of less than 0.85 are considered to be a very strict standard, and less than 0.90 is usually regarded as acceptable. High values (greater than 0.90) suggest that two constructs are not sufficiently separate

Table 5Heterotrait-Monotrait Ratio (HTMT)

Constructs	CRR	CA	CS	PR	RTP	RA	RD
Consumer Retention Rate (CRR)	—						
Context-Aware Suggestions (CA)	0.912	—					
Customer Satisfaction (CS)	0.93	0.84	—				
Perceived Relevance (PR)	0.856	0.784	0.833	—			
Real-Time Personalization (RTP)	0.904	0.813	0.857	0.784	—		
Recommendation Accuracy (RA)	0.94	0.876	0.91	0.832	0.874	—	
Recommendation Diversity (RD)	0.905	0.828	0.882	0.78	0.832	0.893	—

The HTMT values ranged from 0.780 to 0.940. Some construct pairs were also lower than the conservative cut-off score of 0.85, such as Context-Aware Suggestions and Customer Satisfaction (0.840), Context-Aware Suggestions and Perceived Relevance (0.784), and Perceived Relevance and Recommendation Diversity (0.780).

But six relationships went beyond the more generous cut-off of 0.90. The following were the six Consumer Retention Rate related metrics: Consumer Retention Rate and Context-Aware Suggestions (0.912), Consumer Retention Rate and Customer Satisfaction (0.930), Consumer Retention Rate and Real-Time Personalization (0.904), Consumer Retention Rate and Recommendation Accuracy (0.940), Customer Satisfaction and Recommendation Accuracy (0.910), and Consumer Retention Rate and Recommendation Diversity (0.905).

The maximum HTMT value obtained was 0.940, which was between Recommendation Accuracy and Consumer Retention Rate. The results suggest that there are potential discriminant-validity issues between a few closely related constructs, including constructs related to Consumer Retention Rate. Despite the Fornell-Larcker criterion being met, the results of the HTMT indicate that the conceptual differences between some constructs need to be interpreted with caution.

IV.4.3 Cross-Loading Analysis

To check the cross-loading of the measurement items, we applied the cross-loading analysis to see whether each measurement item loaded stronger on its assigned construct than on the remaining constructs. Discriminant validity is supported by the pattern of the indicators' loadings if the loading of an indicator on the intended construct is greater than the loading of the indicator on all other constructs.

Table 6Cross-Loadings of Measurement Items

Items	**CRR**	**CA**	**CS**	**PR**	**RTP**	**RA**	**RD**
CA1	0.839	**0.951**	0.776	0.744	0.755	0.809	0.756
CA2	0.839	**0.947**	0.765	0.71	0.762	0.81	0.761
CA3	0.808	**0.939**	0.754	0.689	0.712	0.775	0.749
CA4	0.832	**0.95**	0.765	0.708	0.74	0.797	0.755
CRR1	**0.942**	0.843	0.865	0.783	0.833	0.862	0.821
CRR2	**0.94**	0.812	0.838	0.773	0.824	0.847	0.828
CRR3	**0.944**	0.807	0.818	0.758	0.82	0.851	0.817
CRR4	**0.949**	0.844	0.849	0.787	0.807	0.846	0.815
CS1	0.855	0.767	**0.949**	0.75	0.789	0.832	0.826
CS2	0.835	0.762	**0.941**	0.756	0.802	0.829	0.796
CS3	0.843	0.766	**0.953**	0.779	0.776	0.825	0.792

CS4	0.844	0.758	**0.939**	0.742	0.756	0.823	0.795
PR1	0.787	0.704	0.776	**0.943**	0.73	0.762	0.724
PR2	0.773	0.716	0.734	**0.945**	0.695	0.733	0.693
PR3	0.777	0.723	0.748	**0.948**	0.728	0.76	0.705
PR4	0.769	0.705	0.767	**0.946**	0.703	0.769	0.716
RA1	0.852	0.806	0.82	0.742	0.81	**0.945**	0.819
RA2	0.862	0.789	0.842	0.754	0.768	**0.947**	0.824
RA3	0.843	0.784	0.809	0.757	0.81	**0.946**	0.803
RA4	0.861	0.812	0.841	0.778	0.804	**0.951**	0.811
RD1	0.83	0.745	0.814	0.681	0.781	0.806	**0.953**
RD2	0.823	0.771	0.789	0.72	0.749	0.802	**0.95**
RD3	0.809	0.742	0.812	0.717	0.759	0.82	**0.946**
RD4	0.838	0.769	0.807	0.73	0.759	0.836	**0.946**
RTP1	0.836	0.744	0.788	0.727	**0.957**	0.784	0.761
RTP2	0.844	0.764	0.799	0.74	**0.955**	0.828	0.766
RTP3	0.815	0.727	0.796	0.708	**0.942**	0.791	0.766
RTP4	0.821	0.751	0.765	0.703	**0.957**	0.806	0.767

The 28 indicators were loaded best on their respective constructs. The primary loadings varied from 0.939 to 0.957 and all the cross loadings were less than the corresponding primary loadings. For instance, the highest cross-loading of the items in the Context-Aware Suggestions scale had values between 0.939 and 0.951 for the primary loadings. Similarly, the Consumer Retention Rate indicators loaded between 0.940 and 0.949 on the intended construct, with the highest cross-loading of up to 0.865 on the other constructs.

The primary loadings for the Recommendation Accuracy items ranged from 0.945 to 0.951, and the highest cross-loading for the items was 0.862. The Real-Time Personalization indicators also had good primary loadings ranging from 0.942 to 0.957, with a maximum cross-loading of 0.844. Thus, the cross-loading results corroborate for item-level discriminant validity of the measurement model.

Overall, overall discriminant validity is supported by Fornell-Larcker criterion and cross-loading analysis. But the results of the HTMT show that there are high correlations between a few sets of constructs. While the measurement items tend to capture the constructs, they are intended to capture, the relationship between Consumer Retention Rate and some of the measures predicting it should be taken with some care.

IV.5 Assessment of Structural Model

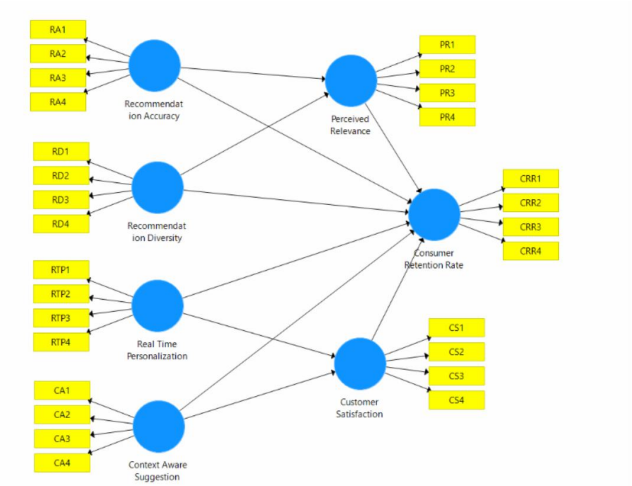


Figure 2 Path Diagram

IV.6 Hypothesis Testing (Direct and Indirect Relationships)

A bootstrapping procedure was used in SmartPLS with a number of subsampling of 5,000 to test the hypotheses. Direction and statistical significance of each relationship were determined by the path coefficient (β), t-statistic and p-value. If the t-value exceeded 1.96 and the p-value was less than 0.05, then the hypothesis was accepted. It is used frequently in PLS-SEM for assessing direct and indirect structural relationships. (Suyudi, 2020)

IV.6.1 Direct Relationship Assessment

The direct-effect analysis was conducted to assess the relationships between Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, Context-Aware Suggestions, Perceived Relevance, Customer Satisfaction and Consumer Retention Rate. The results are presented in Table 4.7.

Table 4.7: Results of Direct Hypothesis Testing

Table 7Results of Direct Hypothesis Testing

Hypothesis	Structural Relationship	β	t-value	p-value	Decision
H1	Recommendation Accuracy → Perceived Relevance	0.594	7.456	0	Supported
H2	Recommendation Diversity → Perceived Relevance	0.239	2.93	0.003	Supported
H3	Recommendation Accuracy → Consumer Retention Rate	0.277	4.332	0	Supported
H4	Recommendation Diversity → Consumer Retention Rate	0.204	3.982	0	Supported
H5	Real-Time Personalization →	0.5	8.559	0	Supported

	Customer Satisfaction				
H6	Context-Aware Suggestions → Customer Satisfaction	0.415	6.987	0	Supported
H7	Real-Time Personalization → Consumer Retention Rate	0.251	5.362	0	Supported
H8	Context-Aware Suggestions → Consumer Retention Rate	0.283	5.938	0	Supported

The results indicate that Perceived Relevance was significantly affected by Recommendation Accuracy, as indicated by the path coefficient of 0.594, t value 7.456, and p value of <0.001. Thus, H1 was upheld. Path coefficient of recommendation Diversity on Perceived Relevance (PR) was also found to be significant (+0.239, 2.930, 0.003). Thus, H2 was supported. Recommendation Accuracy had a stronger impact on Perceived Relevance of these two predictors.

The path coefficient for the recommendation accuracy variable on consumer retention rate was 0.277, t-value 4.332, and p-value was less than 0.001, which shows that the recommendation accuracy significantly and positively affected the consumer retention rate. As such, H3 was supported. The path coefficient of the recommendation diversity was 0.204 with a t value of 3.982 and a p value less than 0.001, which significantly affected the Consumer Retention Rate. So was also supported H4. The findings show that the recommendations are directly correlated with consumers' intent to stay with the online marketplace, provided they are accurate and varied.

Real-Time Personalization showed a positive impact on Customer Satisfaction with a path coefficient of 0.500, a t value of 8.559 and a p value less than 0.001. Therefore, it was decided to support H5. In addition, Context-Aware Suggestions also played a significant positive role on Customer Satisfaction with a path coefficient of 0.415, t-value of 6.987 and p-value less than 0.001. Hence, the support of H6 was given. Compared to Context-Aware Suggestions, Real-Time Personalization had a greater impact on Customer Satisfaction.

Secondly, the direct effect of Real-Time Personalization on Consumer Retention Rate was also positive and significant, with a path coefficient of 0.251, a t-value of 5.362 and a p-value of < 0.001. Thus, H7 was supported. The path coefficient of Context-Aware Suggestions to Consumer Retention Rate was found to be 0.283, t was 5.938 and p was < 0.001, showing that it had a significant positive effect. Therefore, the support was given to H8. Real-Time Personalization had a slightly stronger direct effect on Consumer Retention Rate than Context-Aware Suggestions.

The path coefficient of the perceived Relevance towards Consumer Retention Rate was 0.181 and the t-value was 3.147 with p-value = 0.002

The assessment of an indirect relationship and mediation is detailed in IV.6.2.

An indirect effect of Recommendation Accuracy on Consumer Retention Rate through Perceived Relevance was positive and statistically significant, with an indirect-effect coefficient of 0.108, a t-value of 2.846, and a p-value of 0.004. Perceived Relevance also partially mediated the relationship between Recommendation Accuracy with Consumer Retention Rate, as it was also statistically significant.

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The indirect effect of Real-Time Personalization on Customer Satisfaction on Consumer Retention Rate was positive and statistically significant with the coefficient 0.111, t-value 3.421 and p-value 0.001. Customer Satisfaction also partially mediated the relationship between Real-Time Personalization and Consumer Retention Rate as this was a strong direct relationship. The relationship between Real-Time Personalization and Consumer Retention Rate was also strong and direct, so Customer Satisfaction partially mediated this relationship.

Consumer Retention Rate also had a significant indirect effect through Customer Satisfaction with the coefficient 0.092, t-value 3.105, and p-value 0.002 for Context-Aware Suggestions. Customer Satisfaction partly mediated the relationship between the direct effect of Context-Aware Suggestions on Consumer Retention Rate.

In summary, the indirect-effect results suggest that the four AI-powered recommendation features have both direct and indirect impacts on Consumer Retention Rate. The factors of Recommendation Accuracy and Recommendation Diversity have a partial influence on retention through Perceived Relevance, while Real-Time Personalization and Context-Aware Suggestions have a partial influence on retention through Customer Satisfaction.

CHAPTER V: DISCUSSION

V.1 Conclusion

The study aimed at examining the factors affecting the Consumer Retention Rate in the online marketplace driven by AI. The suggested framework analyzed the following technological characteristics of AI-powered recommendation systems: Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, and Context-Aware Suggestions. Three types of consumer-response variables were included (Perceived Relevance and Customer Satisfaction), and Consumer Retention Rate was treated as the final variable.

The results revealed that Perceived Relevance was significantly affected by Recommendation Accuracy. This suggests that if the suggested products match the consumers' interests and needs, their consideration of the recommendation is more meaningful. Recommendation Diversity also had a significant positive effect on Perceived Relevance, but this effect was less pronounced. Thus, accuracy may be more relevant than variety in determining if recommendations are personally relevant to consumers.

The recommendation accuracy and recommendation diversity also had significant positive effects on the Consumer Retention Rate. Good recommendations can decrease search effort and help an online marketplace be more trustworthy, while diverse recommendations can help keep customers interested by offering them new products and options. The results illustrate that the genuine matching and suitable variety can promote consumers' willingness to keep using an online platform.

Real-Time Personalization was seen to have a very positive impact on Customer Satisfaction and was found to be the most influential on this construct. Context-Aware Suggestions also had a significant impact on Customer Satisfaction. The findings suggest that consumers appreciate recommendations that are quick to provide for the “here and now” and take situational factors into account like location, time, and needs.

Both Real-Time Personalization and Context-Aware Suggestions had notable positive impacts on Consumer Retention Rate. Context-Aware Suggestions had a relatively high direct effect on retention, indicating that customers are likely to stick around longer with a platform when the suggestions are relevant to their situation. Real-time adaptation also helps retain items by keeping them up to date as per the changes in the consumer preferences.

The perceived Relevance and Customer Satisfaction had significant positive relationship with Consumer Retention Rate. If consumers find an online marketplace's recommendations useful to them, and are pleased with the experience, they are more likely to stick with the marketplace. The platform's overall impression to the customers had a comparatively high impact on retention, as expressed by Customer Satisfaction.

The indirect-effect findings also revealed that the indirect paths of Recommendation Accuracy and Recommendation Diversity to Consumer Retention Rate were partially mediated by Perceived Relevance. The relationships between Real-Time Personalization, Context-Aware Suggestions and Consumer Retention Rate were partly mediated by Customer Satisfaction. Thus, the technological

characteristics of the recommendatory system affect the retention in a direct and indirect way, by affecting consumers' cognitive and affective responses.

In summary, the results show that, effective recommendations with AI must be more than technically accurate. Online marketplaces need to make accurate, and varied, recommendations and need to be able to respond in real time to consumers and take account of their immediate contexts. These technological capabilities have to be used in ways that produce meaningful and meaningful experiences that promote customer retention over time. Prior studies also indicate that when consumers perceive personalization to be useful and trustworthy, personalized recommendations can enhance satisfaction and loyalty. (Hassan e**t al., 2025)**

V.2 Theoretical Contributions

Theoretically, this study contributes to the research on recommendation systems powered by artificial intelligence (AI) and consumer behavior online marketplaces in several ways. Theoretically, this study contributes in multiple ways to the research on AI-powered recommendation systems and consumer behavior in online marketplaces. First, it brings together the technological features, the internal evaluations of the consumers and the behavioral results in one single framework. The study looks at the performance of recommendations beyond accuracy, namely Recommendation Diversity, Real-Time Personalization, and Context-Aware Suggestions. This offers a more comprehensive overview on the impact various AI functions have on consumer retention.

Second, the results justify the use of the Stimulus-Organism-Response model in the context of AI systems to support online marketplaces. Recommendation Accuracy, Recommendation Diversity, Real-Time Personalization, and Context-Aware Suggestions are external technological stimuli. Perceived Relevance and Customer Satisfaction are internal psychological and emotional responses of consumers, and Consumer Retention Rate is the ultimate behavioral response. The key relationship between these constructs indicates that consumers' retention decisions emerge as a result of the system performance and internal evaluation.

Third, the study makes a contribution by differentiating between Perceived Relevance and Customer Satisfaction. The cognitive evaluation of relevance is mostly affected by Recommendation Accuracy and Recommendation Diversity, while the affective evaluation of satisfaction is mostly affected by Real-Time Personalization and Context-Aware Suggestions. This is an example of how consumers can be impacted differently by various technological characteristics.

Fourth, the results are expected to help extend the theoretical knowledge of the effectiveness of a recommendation system, as the independent variables are also found to have direct impacts on Consumer Retention Rate. Therefore, the impact of AI recommendation features cannot be fully understood without considering other factors such as Perceived Relevance and Customer Satisfaction. Technological capabilities can offer direct functional value, such as by reducing search effort, enhancing product discovery, and making online shopping more responsive.

Lastly, the partial mediation results add to the literature as a reflection of the interaction between technological performance and consumer evaluation. The accurate and diverse recommendations

influence the retention rate, partially because of the Perceived Relevance, and real-time and context-aware recommendations influence the retention rate, partially because of the Customer Satisfaction. This facilitates a more holistic consumer retention concept, where technical and psychological effects are not mutually exclusive.

V.3 Implications for AI Ethics and Responsible AI Use in Online Marketplaces

While the results highlight the potential advantages of AI-driven recommendations, they also raise ethical concerns for online marketplaces. Usually, it takes consumers' behavioral and contextual data to achieve Recommendation Accuracy, Real-Time Personalization, and Context-Aware Suggestions. Platforms, in turn, should make sure to not only ensure privacy, fairness, transparency and consumer autonomy, but also ensure that these are not sacrificed in personalization.

First, the internet marketplace should make clear to consumers what data will be gathered and how it will be used. Consumers should be aware if the recommendations are based on their browsing history, purchases, location, search, or other behavioral data. Clear explanations can minimize uncertainty and enable consumers to make informed decisions about sharing of their data. Transparency, privacy protection, and fairness are also highlighted as key considerations for responsible implementation of ethical AI in retail. (Adanyin, 2024)

Second, consumers' consent should not be a formality but meaningful. Consumers have the right to choose the kinds of information that are used for personalization in online marketplaces. Consumers should also be able to change, decrease, or turn off personalized recommendations. This control can help to ensure consumer autonomy and avoid intrusive personalization.

Thirdly, platforms should be vigilant in their algorithms that they do not display unfair bias. Thirdly, platforms should watch their recommendations for unfair bias. It is possible for biased systems to consistently favor specific brands, sellers, products or consumer segments. Routine algorithmic audits, training on a variety of data, and fairness assessments can minimize discriminatory results. Ethical research into e-commerce recommendation systems also suggests that there should be regular audits, diversifying training data and fairness measures to stop biased recommendations. (Jain & Jain, 2024)

Fourth, the aim of Recommendation Diversity is not to manipulate but reduce the filter bubbles. Personalized recommendations can be effective in making recommendations more relevant, but can also lead to exposing consumers to the same narrow product range over and over again if too personalized. Platforms need to provide enough choice, and give users the opportunity to discover something they like that is not what the algorithms have recommended.

Last but not least, a balance between personalization and privacy is needed in the use of AI responsibly. Online marketplaces should gather only information required for making recommendations, safeguard the information with adequate security measures, and not store personal information longer than needed. Consumer trust can be fostered while maintaining privacy-friendly personalization, transparency of consent, secure handling of data, and automated compliance tracking. (Godbole, 2024)

V.4 Practical Recommendations

First, based on the findings, online marketplaces should improve the Recommendation Accuracy by updating the consumer profiles and recommendation models on a regular basis. Recommendations should consider recent consumers' interests instead of only older purchasing/browsing data. There also needs to be easy ways for consumers to let platforms know if a recommendation is helpful or not.

Secondly, it is important to keep a balance between Recommendation Diversity and accuracy. The platform should incrementally introduce new products and categories without introducing alternatives that are not related to the consumer needs. If the recommendation list is well balanced, it can minimize repetition, foster discovery and keep consumers engaged long-term.

Third, the Online Marketplaces should focus more on Real-Time Personalization, as it had the highest impact on Customer Satisfaction. Recommendation systems should be updated based on the latest clicks, search, cart data, and browsing behavior. But, in the real time personalization, it should be aligned with the consent and privacy of consumers.

Fourth, Context-Aware Suggestions need to be useful. If appropriate, and if consumers have consented, information such as time, place, device and shopping situation can be used. Platforms should never gather information that they do not require.

Online marketplaces should pay attention to Perceived Relevance in explaining why specific products have been recommended (fifth). Descriptions like ‘recommended based on your recent searches’ can help consumers relate their interest to the recommendation. Consumer confidence and trust can also be enhanced by explainable recommendations. Transparency around why the recommendation is personalized may help to build trust and acceptance in AI-powered e-commerce. (Hassan et al., 2025)

Last but not least, Customer Satisfaction should be tracked on an on-going basis. Platforms need to use a mix of behavioral, satisfaction survey, complaints, return rates and feedback to uncover shortcomings in the recommendation process. To achieve consumer retention, personalization is just one way, but it must be accompanied by the provision of useful, fair, secure and satisfying interactions.

V.5 Future Research Directions

This research could be continued in a number of ways in the future. First, the present study adopted quantitative cross-sectional design, measuring respondents' perception at one time. Future studies can adopt a longitudinal design to investigate the evolution of consumers' responses to recommendation systems in the medium and long term and whether satisfaction translates into real medium and long-term retention.

Third, other factors like Trust in AI, Privacy Concern, Perceived Risk, Algorithmic Transparency and Consumer Control can be added to future studies. It's likely that these are the reasons some consumers are receptive to personalization while others don't like it or feel it is dangerous.

Third, future research will possibly give a comparison of other online marketplaces, product categories, or countries. The reactions of consumers to AI suggestions could vary significantly based on cultural, digital expertise, platform variety, and the extent of engagement needed to make a purchase. Comparative research, therefore, might enhance the generalizability of the findings.

Fourth, future research can differentiate between intention to retain and actual retention. The repeat visits, purchase frequency, click-through rate and switching activity can be indicative of the effectiveness of the recommendation system and could be considered behavioral data.

Fifthly, experiments can explore various values of Recommendation Accuracy and Recommendation Diversity. This kind of study could help determine the optimum ratio of familiar vs novel suggestions. In addition, researchers can conduct experiments to determine if explanations, privacy controls, and consent mechanisms are associated with enhanced Perceived Relevance, Customer Satisfaction, and retention.

Lastly, future research should explore the ethical implications of personalization via AI in the long term. Special focus should be given to issues of privacy, algorithmic bias, filter bubbles, consumer manipulation, and unequal treatment. The study highlights that, besides being effective, AI personalization must be transparent, fair, private, and give consumers control in order to achieve sustainable engagement. (Nwanna et al., 2025)

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APPENDIX

Independent Variables

Recommendation Accuracy

1. The online marketplace recommends products that match my preferences.
2. The product recommendations are usually accurate.
3. The recommended products are consistent with my shopping interests.
4. The recommendation system correctly predicts the products I may need.

Recommendation Diversity

1. The online marketplace recommends a wide variety of products.
2. The recommendation system introduces me to products that I did not previously know about.
3. The recommended products include different brands and categories.
4. The recommendation system provides enough variety to keep my shopping experience interesting.

Real-Time Personalization

1. The online marketplace updates its recommendations according to my current activities.
2. The recommendations change immediately based on my recent searches and clicks.
3. The platform quickly adjusts its recommendations when my interests change.
4. I receive personalized recommendations during my current shopping session.

Context-Aware Suggestions

1. The online marketplace recommends products that are appropriate to my current situation.
2. The recommendations reflect factors such as time, location, or immediate needs.
3. The platform provides suggestions that are suitable for my present shopping context.
4. The recommendations are delivered when they are most useful to me.

Mediating Variables

Perceived Relevance

1. The recommended products are relevant to my personal needs.
2. The recommendations are useful for my product-selection decisions.
3. The recommended products are closely related to my interests.
4. The recommendations help me find products that are meaningful to me.

Customer Satisfaction

1. I am satisfied with the product recommendations provided by the online marketplace.
2. The recommendation system improves my overall shopping experience.
3. The recommendations meet my expectations.
4. Overall, I am satisfied with the AI-powered recommendation service of the platform.

Dependent Variable

Consumer Retention Rate

1. I intend to continue using this online marketplace in the future.
2. I am likely to revisit this online marketplace for future purchases.
3. I prefer to continue shopping on this platform rather than switch to another marketplace.
4. I intend to maintain a long-term relationship with this online marketplace.