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Evaluating Recommendation System Effectiveness on Customer Experience in Sri Lankan E-commerce: The Moderating Role of Shopping Goal

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ABSTRACTS

This study evaluates the effectiveness of recommendation systems specifically through four dimensions: accuracy, diversity, serendipity, and system response time and their influence on customer experience within Sri Lankan e-commerce marketplaces. Drawing on the Technology Acceptance Model (TAM) and the Online Customer Experience (OCE) framework, the study further examines the moderating role of shopping goals in shaping these effects. Based on a survey of 335 e-commerce users in the Western Province of Sri Lanka revealed that diversity, serendipity, and response time significantly contribute to a positive customer experience, while the effect of recommendation accuracy was comparatively weaker. The moderating role of shopping goals showed a limited but directionally positive influence. The theoretical and practical implications of the study are discussed.

Keywords: Customer Experience, E-commerce, Recommendation System Effectiveness, Shopping Goal, Sri Lanka

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1 INTRODUCTION

E-commerce has become an integral component of contemporary business activity, transforming how organizations interact with consumers and conduct transactions across borders. Its rapid rise is driven by the convenience, accessibility, and efficiency it offers to both buyers and sellers (Jain, Malviya, & Arya, 2021). The evolution of digital technologies particularly mobile commerce, social commerce, and diverse payment innovations such as buy-now-pay-later (BNPL), cash-on-delivery (COD), and digital wallets has further accelerated the expansion of online retail ecosystems (Ousman, 2024).

However, this exponential growth has also created a new challenge: the abundance of information available on e-commerce platforms often overwhelms consumers, complicating their decision making process. To address this issue, recommendation systems (RS) have emerged as essential tools that help users navigate product choices by providing personalized suggestions derived from behavioral and contextual data (Alyari & Navimipour, 2018).

Over time, the design of recommendation systems has evolved beyond the pursuit of algorithmic accuracy. Modern systems increasingly emphasize multidimensional aspects such as diversity, serendipity, and system responsiveness factors that collectively shape the user's overall experience and satisfaction (He, Liu, & Jung, 2024; Kotkov, Wang, & Veijalainen, 2016). Consequently, RS are now viewed not merely as technical enablers but as strategic instruments for enriching customer experience (CX), which encompasses cognitive, emotional, and behavioral responses that arise during digital interactions (McLean, 2017; Bleier, Palmatier, & Harmeling, 2019).

In Sri Lanka, e-commerce is experiencing notable growth, with projected revenues reaching approximately USD 2.4 billion in 2024, largely driven by rising internet penetration and consumer engagement in urban centers such as the Western Province (International Trade Administration, 2024; APIDM & DMM, 2024). Despite this progress, empirical studies exploring how the effectiveness of recommendation systems contributes to customer experience remain limited. Existing local research predominantly examines adoption barriers or basic artificial intelligence applications, overlooking the customer-centric dimensions of RS performance.

Against this backdrop, the present study examines how four key dimensions of recommendation system effectiveness accuracy, diversity, serendipity, and response time influence customer experience in Sri Lankan e-commerce platforms, with specific empirical focus on active users in the Western Province. Furthermore, the study investigates whether the shopper's underlying motivation hedonic or utilitarian moderates these relationships. Anchored in the Technology Acceptance Model (TAM) (Davis, 1989) and the Online Customer Experience (OCE) framework (Bleier et al., 2019), this research adopts a quantitative explanatory design to test theoretically grounded hypotheses and to provide context-specific insights for practitioners seeking to enhance engagement and competitiveness in the country's digital retail sector.

1.1 Research Problem

Although recommendation systems (RS) have become central to digital retailing, much of the existing literature remains heavily technical, emphasizing algorithmic accuracy, data sparsity, and cold-start issues, while paying limited attention to customer experience (CX) particularly at the pre-purchase stage. For instance, Jim et al. (2024) examined user satisfaction outcomes but treated accuracy and diversity as separate dimensions, overlooking hybrid indicators such as novelty and response time. Similarly, while Alamdari et al. (2020) proposed an extended RS evaluation model encompassing accuracy, diversity, serendipity, and response time, their work was primarily conceptual and lacked empirical validation. This reflects a broader gap where personalization mechanisms are discussed extensively, yet their tangible influence on CX remains underexplored in quantitative research.

Moreover, the CX construct itself is often operationalized narrowly through satisfaction or loyalty measures, overlooking comprehensive frameworks such as the Online Customer Experience (OCE) model, which integrates cognitive, emotional, and behavioral dimensions (Bleier, Harmeling, & Palmatier, 2019). In parallel, while shopping goals hedonic versus utilitarian are recognized as key behavioral determinants, their moderating influence on the RS & CX relationship has received limited empirical investigation.

From a practical perspective, Sri Lanka’s e-commerce sector now exceeding six million active users (APIDM & DMM, 2024) is expanding rapidly, yet recommendation systems often fail to deliver contextually relevant experiences. Many platforms rely on algorithmic precision that leads to repetitive product suggestions, neglecting user intent or situational needs. Balancing competing design priorities such as accuracy and diversity requires localized insights into user behavior, which remain scarce in developing markets.

Accordingly, this study addresses both empirical and practical gaps by examining how four dimensions of RS namely accuracy, diversity, serendipity, and response time influence online customer experience in Sri Lankan e-commerce marketplaces. Additionally, it explores the moderating role of shopping goals (hedonic vs. utilitarian) to provide a nuanced understanding of personalized recommendation outcomes.

1.2 Research Objectives

1. To examine the impact of recommendation system effectiveness on customer experience in Sri Lankan e-commerce marketplaces.
2. To examine the moderating effect of shopping goal on the relationship between recommendation system effectiveness and customer experience.
3. To provide empirical insights for e-commerce developers to enhance recommendation strategies and align them with local consumer preferences.

2 LITERATURE REVIEW

2.1 Evolution and Mechanisms of Recommendation Systems

Recommendation systems (RS) have evolved substantially since their conceptual origins in the early 1980s, when Gerard Salton introduced vector-space algorithms for textual information retrieval. These early models laid the groundwork for filtering vast datasets according to user relevance, later expanding to multimedia and e-commerce contexts (He, Liu, & Jung, 2024). In the digital marketplace, RS now function as strategic tools that help consumers navigate information overload, improve personalization, and enhance decision efficiency (Adomavicius & Tuzhilin, 2005).

At their core, RS are predictive systems designed to identify user preferences and recommend relevant items accordingly. They achieve this through three primary mechanisms content-based filtering, collaborative filtering, and hybrid filtering models.

Content-based filtering analyzes product attributes and prior user interactions to generate tailored suggestions. Although it offers personalization, it often limits novelty and diversity (Suyeon, Park, & Lee, 2021). Collaborative filtering, by contrast, leverages behavioral patterns among similar users but faces challenges such as data sparsity and cold-start issues (He et al., 2024). Hybrid models integrate these approaches to enhance adaptability and overcome individual limitations, providing a balance between accuracy and diversity (Bodduluri, 2023).

While algorithmic innovations have improved recommendation precision, the literature remains largely focused on technical performance metrics such as precision, recall, and computational efficiency, with limited emphasis on the user experience dimension (Alyari & Navimipour, 2018). This study shifts attention toward customer-perceived RS effectiveness how users cognitively and emotionally evaluate system outputs during online shopping (Rajapakse & Dabare, 2024).

Recommendation System Effectiveness in E-commerce

Recommendation System Effectiveness (RSE) refers to the degree to which a system successfully delivers relevant, engaging, and personalized recommendations to users (Alamdari, Jahani, & Ghapanchi, 2020). In e-commerce environments, RS enhance pre-purchase experiences by simplifying product discovery and fostering satisfaction and engagement (Fonseka & Jaharadak, 2022). However, most research isolates single performance dimensions rather than adopting an integrated view. The present study focuses on four interrelated dimensions namely accuracy, diversity, serendipity, and response time which collectively shape customer experience.

Accuracy

Accuracy represents the extent to which an RS correctly predicts user preferences (Chen, Wang, & Xu, 2021). It has long been the benchmark of system quality, often assessed using quantitative measures such as Root Mean Square Error (RMSE) (McNee, Riedl, & Konstan, 2006). However, scholars increasingly caution that excessive focus on statistical precision may not equate to higher user satisfaction (Gunawardana & Shani, 2015). Overly accurate systems can lead to "filter bubbles," where users are repeatedly exposed to similar products, reducing discovery and long-term engagement (He et al., 2024). Thus, while accuracy remains fundamental, it must be balanced with novelty and diversity.

Diversity

Diversity refers to the variety of recommendations presented to users, ensuring that suggestions are not overly homogeneous (Kunaver & Pozrl, 2017). It supports exploration and prevents decision fatigue, offering cross-category exposure that sustains engagement (Vargas & Castells, 2011). Although diversity sometimes conflicts with accuracy, it enriches customer experience by broadening user horizons and enhancing the perceived value of recommendations (Chen et al., 2021). A well calibrated RS should therefore maintain an optimal balance between relevance and variety.

Serendipity

Serendipity introduces an element of pleasant surprise by suggesting unexpected yet relevant products. Unlike random novelty, serendipitous recommendations deliver experiential value, enhancing emotional engagement and satisfaction (Kotkov, Wang, & Veijalainen, 2016). Zhou, Hui, and Chen (2012) emphasize that effective serendipity combines relevance with novelty helping users discover items they did not initially seek but still appreciate. This quality is particularly valuable in hedonic shopping contexts, where discovery and enjoyment drive purchasing behavior.

System Response Time

System response time captures the speed and smoothness with which an RS generates outputs after user interaction. A responsive system contributes to perceptions of efficiency and technological reliability key drivers of satisfaction and continued usage (Ricci, 2015). Slow or inconsistent performance can erode trust and interrupt the flow of online interaction (Zhang, 2012). Consequently, response time represents not only a functional attribute but also a psychological determinant of perceived service quality in digital shopping.

2.2 Theoretical Framework: Integrating TAM and OCE

This study is anchored in two complementary theoretical models—the Technology Acceptance Model (TAM) (Davis, 1989) and the Online Customer Experience (OCE) framework (Bleier, Harmeling, & Palmatier, 2019).

TAM posits that Perceived Usefulness and Perceived Ease of Use shape users' attitudes and behavioral intentions toward technology. Applied to RS, this model explains how users cognitively evaluate system attributes such as accuracy or responsiveness in forming acceptance decisions. OCE, in contrast, emphasizes experiential aspects, capturing cognitive, emotional, and behavioral reactions to online interactions (Rose, Clark, Samouel, & Hair, 2012). Integrating TAM and OCE allows this study to link technological performance with experiential outcomes offering a dual lens through which RS effectiveness and customer experience can be jointly analyzed.

To strengthen the theoretical linkage, the four dimensions of recommendation system effectiveness were grounded in TAM where accuracy and system response time reflect perceived usefulness and perceived ease of use, respectively. Meanwhile, diversity and serendipity contribute to affective and cognitive elements of the Online Customer Experience (OCE) framework. Customer experience was modeled as an outcome of perceived usefulness and emotional responses, consistent with TAM and OCE assumptions. Shopping goals function as a motivational moderator shaping the degree to which TAM-related evaluations translate into OCE outcomes. Thus, the conceptual model integrates TAM as the cognitive basis and OCE as the experiential outcome.

2.3 Customer Experience in Recommendation Systems

Customer Experience (CX) is the cumulative outcome of a customer's cognitive and emotional interactions with a digital platform (Carbone & Haeckel, 1994). In e-commerce, RS directly shape CX by influencing satisfaction, engagement, and perceived personalization (Pu, Chen, & Hu, 2011). Kim, Park, and Oh (2015) conceptualize CX as multidimensional, encompassing both functional and affective components of the shopping journey.

Drawing on the OCE framework, this study focuses on four facets of CX relevant to RS-driven environments:

1. Satisfaction with recommendations, reflecting perceived value and relevance
2. Engagement level, indicating emotional and cognitive involvement
3. Ease of navigation, relating to the clarity and intuitiveness of the platform and
4. Usability, reflecting the efficiency and fluidity of interactions.

These dimensions collectively determine how users interpret and respond to recommendation quality, shaping both immediate satisfaction and long-term loyalty (Rose et al., 2012).

2.4 Shopping Goal as a Moderating Variable

Shopping goals represent the underlying motivations driving consumer behavior and can be broadly categorized as utilitarian (task-oriented) and hedonic (experience-oriented) (Babin, Darden, & Griffin, 1994). These goals significantly influence how users interact with e-commerce platforms and respond to recommendation systems (Zhang et al., 2024).

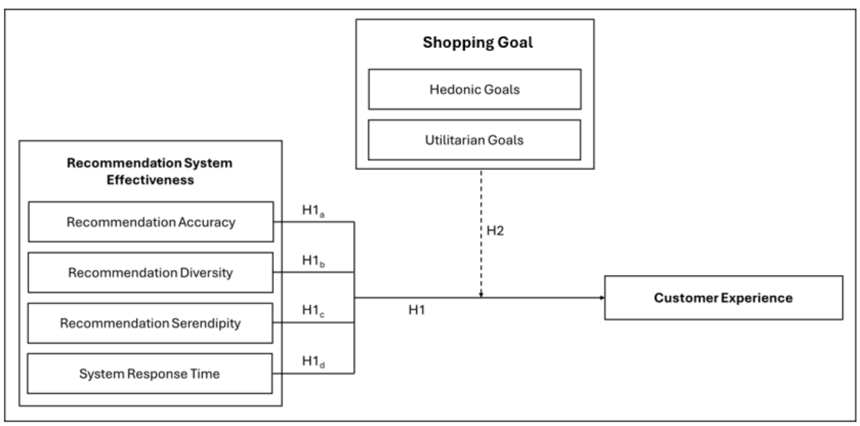
Utilitarian shoppers prioritize efficiency, accuracy, and relevance, seeking straightforward, goal-directed outcomes. Conversely, hedonic shoppers seek enjoyment, variety, and surprise factors often linked with emotional satisfaction and exploratory behavior (Childers et al., 2001). As such, recommendation systems must align with these shopping goals to optimize user experience.

Arora, Sivakumar, and Lall (2020) argue that RS can dynamically shape shopping behavior by tailoring outputs to evolving consumer goals. When aligned effectively, RS improve satisfaction, reduce cognitive effort, and increase emotional engagement (Rose et al., 2012). Recent work also indicates that shopping goals can change the strength and direction of technology–experience relationships, suggesting a moderating rather than purely direct effect (Zhang et al., 2024; He et al., 2024).

This study extends that line of inquiry by examining how shopping goals moderate the relationship between the four RS dimensions accuracy, diversity, serendipity, and response time and customer experience. It fills a significant gap in the Sri Lankan e-commerce literature, offering novel insights into how goal alignment with RS outputs enhances the personalization and strategic targeting capabilities of local platforms.

2.5 Conceptual Framework

Based on the reviewed literature and theoretical foundations, the present study proposes a conceptual framework that examine the impact of recommendation system effectiveness (RSE) on customer experience (CX) in Sri Lankan e-commerce marketplaces. The framework also considers the moderating role of shopping goals (hedonic vs. utilitarian) in shaping this relationship.



3 RESEARCH METHODOLOGY

3.1 Methodological Approach and Design

This study adopts a quantitative, explanatory research design under a deductive approach, guided by the Technology Acceptance Model (TAM) and the Online Customer Experience (OCE) framework. The objective is to examine the impact of Recommendation System Effectiveness (comprising accuracy, diversity, serendipity, and response time) on Customer Experience, with Shopping Goal (hedonic/utilitarian) as a moderating variable. Data were collected using a structured, self-administered online questionnaire, enabling the testing of hypotheses derived from prior theory and literature.

3.2 Population, Sample, and Sampling Technique

The target population included active e-commerce users in Sri Lanka, estimated at 6.3 million (43% of 14.68 million internet users), with a focus on the Western Province representing 50% of total e-commerce activity. Based on this, the estimated population size was approximately 3.15 million users. Using Krejcie & Morgan's sample size table, a sample of 384 was deemed appropriate. The study successfully collected 355 responses, out of which 335 valid responses were retained for analysis. A non-probability convenience sampling technique was used due to accessibility constraints and time limitations. Participants were selected based on their experience with online shopping and interaction with recommendation systems.

3.3 Data Collection and Instrumentation

Primary data were collected via a self-administered online questionnaire distributed through platforms such as WhatsApp and email using Google Forms. The instrument was structured in seven sections, covering:

- Demographics (age, gender, income, etc.)
- Recommendation System Effectiveness (4 dimensions: accuracy, diversity, serendipity, system response time)
- Customer Experience (satisfaction, engagement, usability, ease of navigation)
- Shopping Goals (hedonic and utilitarian)

All constructs were measured using previously validated multi-item Likert scales (5-point scale: 1 = strongly disagree to 5 = strongly agree). Items for accuracy, diversity, serendipity, and system response time were adapted from prior recommender system evaluation studies (e.g., Pu et al., 2011; Chen et al., 2021; Kunaver & Pozrl, 2017; Kotkov et al., 2016), with minor wording adjustments to fit the Sri Lankan e-commerce context. Customer experience was operationalized using items reflecting satisfaction, engagement, ease of navigation, and usability, drawing from the Online Customer Experience framework (Rose et al., 2012; Bleier et al., 2019). Shopping goals (hedonic and utilitarian) were measured using items adapted from Babin et al. (1994) and Childers et al. (2001).

3.4 Data Analysis Techniques

The collected data were analyzed using SPSS (v30). Descriptive statistics were used to profile the sample and summarize key variables. Reliability and validity of constructs were assessed using Cronbach's Alpha. To test the hypothesized relationships, regression analysis was employed, while moderation effects of shopping goals were examined using interaction terms. The results were interpreted through significance levels and model fit indicators, aligning with the study's explanatory objectives.

To test the hypothesized direct effect (H1), simple linear regression analysis was employed, consistent with prior studies examining the impact of system-related variables on customer experience (e.g., McLean, 2017). To examine the moderating effect of shopping goals (H2), Hayes' PROCESS macro (Model 1) was used, which enables estimation of interaction effects and conditional relationships within an ordinary least squares (OLS) regression framework (Hayes, 2018). Significance levels, confidence intervals, and effect sizes were reported in line with recommended guidelines for behavioral research (Cohen, 1988; Wasserstein & Lazar, 2016).

4 DATA ANALYSIS AND RESULTS

The Cronbach's alpha was calculated to evaluate the internal reliability of the assumptions derived from the study's factors. Exploratory factor analysis determined whether each research statement aligned with the predicted factors. The validity and reliability of the research model were examined through confirmatory factor analysis. Additionally, the study’s hypotheses were tested using the simple linear regression. To assess the moderating effects of shopping goal PROCESS Model was utilized. The analysis was conducted using SPSS (Statistical Package for the Social Sciences) 25.0 software.

Before hypothesis testing, correlation statistics were inspected to confirm the expected direction of relationships among key constructs. Subsequently, the direct and moderating effects were tested using the following regression models.

For the direct effect (H1), the following regression equation was applied:

$$\mathbf{CX = \beta_0 + \beta_1 RSE + \varepsilon}$$

Where:

CX = Customer Experience

RSE = Recommendation System Effectiveness

β_0 = Constant term

β_1 = Unstandardized regression coefficient

ε = Error term

For moderation (H2), the PROCESS macro estimates the conditional model:

$$\mathbf{CX = \beta_0 + \beta_1 RSE + \beta_2 SG + \beta_3 (RSE \times SG) + \varepsilon}$$

Where:

SG = Shopping Goal

These models enable examination of whether shopping goal strengthens or weakens the effect of recommendation system effectiveness on customer experience.

4.1 Sample Characteristics

Table 1 depicts respondent demographics, wherein most respondents were Male (204), followed by 131 female respondents. A majority of the respondents were aged between 19 and 24 years old, followed by 147 respondents aged between 16 and 24 years old.

Table 1 Gender Analysis

Gender	Count (%)
Male	60.9%
Female	39.1%

Table 2 Age Analysis

Age	Count (%)
16-24	51.2%
25-34	38.2%
35-44	7.9%
45-54	1.5%
55 Above	1.2%

4.2 Reliability and Validity

The SPSS software was utilized to analyze the reliability of variables. Concerning the scales' reliability, it used Cronbach's alpha Invalid source specified. with a cutoff value of 0.7 Invalid source specified. When considering the independent and dependent variables of the study, recommendation system effectiveness has recorded 0.924 of reliability Cronbach alpha value which is greater than 0.7. consumers experience Sri Lankan E-commerce Marketplaces, the dependent variable of the study states that the reliability Cronbach alpha value is 0.874 which is greater than 0.7. shopping goal has stated that the reliability Cronbach alpha value is 0.869. Hence all the Cronbach alpha values of major variables are greater than 0.7. Summarily, the findings indicated that all indicators were within the acceptable range, thus establishing validity.

Table 3 Reliability results of the research model

Construct	No of Items	Cronbach's Alpha
Recommendation system effectiveness	12	0.924
Consumers experience	3	0.874
Shopping goal	3	0.869

The table 4 shows that the overall KMO value and the Bartlett's Test (sig) value, KMO test variables are greater than 0.5 and Bartlett test of all variables are also significant because the obtained 95% significance P Value 0.000 is less than the benchmark value 0.05. Therefore, it can he said that the operationalization measure of the current study had a standard and an acceptable validity level.

Table 4 Validity results of the research model

Construct	df	KMO	Approx. Chi Square	Significance
Recommendation system effectiveness	12	0.922	2848.283	0.000
Consumers experience	3	0.742	508.868	0.000
Shopping goal	3	0.735	499.516	0.000

4.3 Coefficient

Prior to hypothesis testing, the relationships among the key constructs were examined using correlation analysis to ensure appropriate directions and strengths of association. Subsequently, simple linear regression was conducted to test the direct effect of recommendation system effectiveness on customer experience (H1). This approach is consistent with prior empirical work that models customer experience as an outcome of system-related evaluations in online environments (McLean, 2017).

Simple regression analysis has been used to test the direct hypothesis. This paper hypothesized two hypotheses out of which one hypothesis was direct path hypothesis. According to the results received from SPSS 25 simple regression analysis concluded summarized statistical estimates mentioned in the Table below. According to the results given in the table, there is a positive and significant relationship between Recommendation system effectiveness and consumer experience.

Table 5 Coefficient results of the research model

	Relationship	R Square	P Value	Coefficient	Status
H1	RS ← CX	0.701	0.001	0.837	Accepted
Note. RS: Recommendation System Effectiveness, CX: Consumer Experience					

4.4 Reporting Result of Moderator

The Moderator analysis will be done by using SPSS 25 Process v3.0 Andrew F. Hayes model as the Moderator effect of shopping goal toward Sri Lankan E-commerce investigated with impact of recommendation system effectiveness on customer experience.

Table 6 Moderator results of the research model

Model	R	R^2	F	df_1	df_2	p
1	.840	.706	264.745	3	331	< .001

Predictor	b	SE	t	p	LLCI	ULCI
Constant	.758	.324	2.338	.020	.120	1.396
Recommendation System Effectiveness	.739	.117	6.338	< .001	.510	.968
Shopping Goals	–.123	.138	–.894	.372	-.395	.148
Interaction (RS × SG)	.057	.032	1.763	.079	-.007	.120

A moderation analysis was conducted to test the moderating effect of Shopping Goals on the relationship between Recommendation System Effectiveness and Consumer Experience. Results revealed that recommendation system effectiveness had a significant positive impact on consumer experience ($b = 0.739$, $p < .001$). Although the interaction term was only marginally significant ($b = 0.057$, $p = .079$), the conditional effects showed that the relationship between recommendation system effectiveness and consumer experience strengthened as shopping goals increased. This suggests that Shopping Goals partially moderate the relationship, indicating that consumers with stronger shopping goals experience greater benefits from effective recommendation systems.

5 DISCUSSION

Overall, the empirical results of this study support the proposed relationships by showing that recommendation system effectiveness has a strong positive impact on customer experience, while shopping goals play a modest but meaningful moderating role in this association. The findings of this study provide valuable insights into how recommendation system effectiveness (RSE) influences customer experience (CX) within the Sri Lankan e-commerce context. The results confirm that RS exerts a strong and positive effect on customer experience, reinforcing prior research that positions recommendation systems as pivotal tools in enhancing user satisfaction, engagement, and decision efficiency (He, Liu, & Jung, 2024; Bleier, Palmatier, & Harmeling, 2019). Specifically, the results indicate that when consumers perceive recommendation systems as accurate, diverse, serendipitous, and responsive, they experience higher levels of enjoyment, trust, and perceived value during their online shopping journey. This finding is consistent with the Technology Acceptance

Model (TAM), which emphasizes that perceived usefulness and ease of interaction significantly determine user satisfaction and continued usage.

Interestingly, while the study confirmed a strong direct relationship between recommendation system effectiveness and customer experience, the moderating effect of shopping goals was only marginally significant. The interaction term ($b = 0.057$, $p = .079$) suggests that shopping goals play a subtle yet meaningful role in shaping how consumers respond to recommendation systems. Specifically, the conditional effect analysis revealed that as shopping goals intensified reflecting a more focused or goal-driven mindset, the positive influence of RSE on CX became stronger. This aligns with findings by Arora, Sivakumar, and Lall (2020), who noted that consumer goals significantly influence digital interaction outcomes by determining how consumers interpret and value system-generated recommendations. In practical terms, this suggests that hedonic shoppers motivated by enjoyment and discovery derive enhanced experiences from systems emphasizing diversity and serendipity, while utilitarian shoppers motivated by task completion respond more favorably to accurate and fast system responses.

Moreover, the results highlight the importance of moving beyond algorithmic accuracy as the sole measure of recommendation system quality. While accuracy remains essential, it does not automatically translate into superior experiences. Dimensions such as diversity and serendipity introduce novelty and emotional engagement, mitigating the risk of “filter bubbles” and promoting exploratory behavior. Similarly, system response time emerged as a critical factor that enhances users’ perception of technological efficiency and trustworthiness, ultimately enriching the overall online experience. This finding aligns with the Online Customer Experience (OCE) framework, which underscores the cognitive and emotional dimensions of digital interactions as essential components of perceived quality and satisfaction (Rose et al., 2012).

In the Sri Lankan context, these findings carry relevance. The country's e-commerce market, though expanding rapidly, remains in a transitional phase where user experience differentiation is key to competitiveness. Many local platforms continue to prioritize algorithmic performance over experiential design. The present study demonstrates that enhancing user experience requires a holistic approach; one that integrates technological functionality with affective engagement and personalization. In essence, consumers are not only looking for "what" a system recommends but also "how" it recommends reflecting the growing importance of interactive, responsive, and emotionally intelligent recommendation systems.

From a managerial perspective, the findings imply that Sri Lankan e-commerce platforms should intentionally design recommendation systems that balance accuracy with diversity, serendipity, and fast response times. Practically, this may involve configuring algorithms to mix highly relevant items with carefully curated cross-category suggestions, investing in backend infrastructure to minimize loading times, and tailoring recommendation strategies to different shopping goals (e.g., inspirational, discovery-oriented feeds for hedonic shoppers and task-focused, efficiency-oriented suggestions for utilitarian shoppers). By aligning recommendation logic with these experiential and motivational insights, local e-commerce firms can enhance customer satisfaction, deepen engagement, and build stronger competitive advantage in an increasingly crowded digital marketplace.

6 LIMITATIONS AND FUTURE RESEARCH

While this study offers meaningful contributions, several limitations must be acknowledged. First, the use of a cross-sectional survey design limits the ability to infer causality between variables. Future studies could employ longitudinal or experimental designs to observe changes in customer experience over time as system features evolve. Second, the sample was restricted to e-commerce users within the Western Province of Sri Lanka, which may limit the generalizability of findings to other regions with different digital literacy levels or purchasing patterns. Third, the self-reported nature of the data may be subject to response bias, as participants might have over- or under-reported their perceptions of system effectiveness. Fourth, the study considered shopping goals as a single moderating construct, but future research could explore its sub-dimensions (e.g., hedonic vs. utilitarian goals) or include additional moderators such as trust, familiarity, or cultural orientation. Lastly, the study focused only on the pre-purchase stage of customer experience; subsequent research could extend the model to include post-purchase behaviors such as retention and advocacy.

7 CONCLUSION

In conclusion, this study demonstrates that recommendation system effectiveness plays a crucial role in enhancing customer experience in Sri Lankan e-commerce marketplaces. The findings affirm that when consumers perceive recommendation systems as accurate, diverse, serendipitous, and responsive, their overall experience becomes more satisfying and engaging. Although the moderating effect of shopping goals was modest, it provided valuable evidence that consumer motivation influences how system attributes are perceived and experienced. Theoretically, the integration of TAM and OCE offers a comprehensive understanding of how technology-driven personalization translates into affective and behavioral outcomes. Practically, the study emphasizes the importance of designing adaptive, goal-aligned recommendation systems that balance precision with discovery to enrich online shopping journeys. Ultimately, by prioritizing customer experience over algorithmic perfection, Sri Lankan e-commerce platforms can strengthen consumer trust, differentiation, and long-term loyalty in an increasingly competitive digital economy.

8 REFERENCES

Adomavicius, G. (2005). Toward the next generation of recommender systems: A survey of state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734–749.

Aguirre, A. (2019). *Extending the concept of user satisfaction from customer experience.* Springer Nature Switzerland AG.

Alamdari, P., Navimipour, N. J., & Hosseinzadeh, N. (2020). A systematic study on recommender systems in e-commerce. *IEEE Access, 8*, 140233–140250.

Allen, I. E., & Seaman, C. A. (2007). Likert scales and data analyses. *Quality Progress, 40*(7), 64–65.

Alyari, H., & Navimipour, N. J. (2018). Recommender systems: A systematic review of the state-of-the-art literature and suggestions for future research. *Journal of Information Systems and Telecommunication, 6*(3), 67–81.*

APIDM, & Department of Marketing Management, University of Kelaniya. (2024). *Digital Outlook Sri Lanka 2024 – Annual Market Insight Report.* University of Kelaniya.

Arora, A., Sivakumar, K., & Lall, R. (2020). The role of recommendation systems in enhancing consumer satisfaction and experience. *Journal of Retailing and Consumer Services, 54*, 102034.

Avada.io. (2024, February 20). *Ecommerce growth rate.* https://avada.io/articles/2024-ecommerce-growth-rate/

Babin, B. J., Darden, W. R., & Griffin, M. (1994). Work and/or fun: Measuring hedonic and utilitarian shopping value. *Journal of Consumer Research, 20*(4), 644–656.

Bleier, A., Palmatier, R. W., & Harmeling, C. M. (2019). Creating effective online customer experiences. *Journal of Marketing, 83*(2), 98–119.*

Carbone, L. P., & Stephan, P. (1994). Exploring customer experience in service environments. *Journal of Retailing, 70*(3), 293–315.*

CBR.lk. (2021, September). *Daraz presents the first in-app livestream shopping experience.*https://cbr.lk/markets-and-financial/daraz-presents-the-first-in-app-livestream-shopping-experience/

Chen, M., Wang, Y., & Xu, C. (2021). Values of user exploration in recommender systems. *Proceedings of the 15th ACM Conference on Recommender Systems (RecSys '21),* 11–19.

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing, 77*(4), 511–535.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cohen, J., Cohen, P., & West, S. G. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Lawrence Erlbaum Associates.

Daraz.lk. (2020). *E-commerce index. Ceylon Business Reporter.*

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Echelon.lk. (2023, September). *Thriving in the digital age: How Daraz is transforming retail for top brands in Sri Lanka.* https://www.echelon.lk/thriving-in-the-digital-age-how-daraz-is-transforming-retail-for-top-brands-in-sri-lanka/

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE Publications.

Fonseka, K., & Jaharadak, A. (2022). Impact of e-commerce adoption on business performance of SMEs in Sri Lanka: Moderating role of artificial intelligence. *International Journal of Social Science and Economic Research, 7*(4), 1032–1046.*

FT.lk. (2024, September). *Trends and growth of Sri Lanka's e-commerce industry: An overview of Daraz e-commerce index.* https://www.ft.lk/Business/Trends-and-growth-of-Sri-Lanka-s-e-commerce-industry-An-overview-of-Daraz-e-commerce/

Garson, G. D. (2012). *Testing statistical assumptions.* Statistical Associates Publishing.

Gunawardana, A., & Shani, G. (2015). *Recommender systems handbook.* Springer.

Hair, J. F., Anderson, R. E., & Tatham, R. L. (1995). *Multivariate data analysis with readings.* Prentice Hall.

He, X., Liu, Q., & Jung, S. (2024). The impact of recommendation systems on user satisfaction: A moderated mediation approach. *Journal of Theoretical and Applied Electronic Commerce Research, 19*(3), 112–130.*

International Trade Administration. (2024, September). *Sri Lanka – e-commerce country commercial guide.* https://www.trade.gov/country-commercial-guides/sri-lanka-e-commerce

Jain, V., Malviya, B., & Arya, S. (2021). An overview of electronic commerce. *Journal of Contemporary Issues in Business and Government, 27*(1), 2340–2355.*

Jin, S., & Eastin, M. S. (2023). Matched personality effects of product recommendation chatbots and users. *Computers in Human Behavior, 143,* 107707.

Khalifa, M., & Liu, V. (2007). Online consumer retention: Contingent effects of online shopping habits and online shopping experience. *European Journal of Information Systems, 16*(6), 780–792.*

Kilani, M., & Kobziev, V. (2016). An overview of research methodology in information systems (IS). *Open Access Library Journal, 3*(11), 1–9.*

Kim, Y., Park, H., & Oh, J. (2015). The effects of online customer reviews and product-related information on consumer's decision-making process: A study in the context of mobile apps. *Journal of Business Research, 68*(12), 2559–2567.*

Kotkov, D., Wang, S., & Veijalainen, J. (2016). A survey of serendipity in recommender systems. *Knowledge-Based Systems, 111*, 180–197.*

Kunaver, M., & Pozrl, T. (2017). Diversity in recommender systems: A survey. *Knowledge-Based Systems, 123*, 154–162.*

Kuruwitaarachchi, N., Yajid, M. S. A., & Khatibi, A. (2019). Information technology factors influencing the adoption of e-commerce in small and medium scale organizations in Sri Lanka: A research agenda. *International Journal of e-Education, e-Business, e-Management and e-Learning, 9*(2), 120–128.*

Laudon, K. C., & Traver, C. G. (2022). *E-commerce 2022: Business, technology, and society.* Pearson Education.

Malekpour, A., Navimipour, N. J., & Hosseinzadeh, N. (2020). A systematic study on recommender systems in e-commerce. *IEEE Open Access Journal, 8*, 140233–140250.*

McLean, G. (2017). Investigating the online customer experience: A B2C perspective. *Journal of Marketing Intelligence & Planning, 35*(5), 628–642.*

McNee, S. M., Riedl, J., & Konstan, J. A. (2006). Being accurate is not enough: How accuracy metrics have hurt recommender systems. *Proceedings of the CHI'06 Extended Abstracts on Human Factors in Computing Systems*, 1097–1101. ACM.

Nadia, & Linda, D. (2024, May 16). *Ecommerce trends.* https://www.hostinger.com/tutorials/ecommerce-trends

Ousman, A. (2024, March 28). *E-commerce sector.* https://lmd.lk/ecommerce-sector-3/

Peterson, R. A. (1994). A meta-analysis of Cronbach's coefficient alpha. *Journal of Consumer Research, 21*(2), 381–391.*

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance.* Free Press.

Pu, P., Chen, L., & Hu, R. (2011). Evaluating recommender systems from the user's perspective: Survey of the state of the art. *User Modeling and User-Adapted Interaction, 22*(4–5), 317–355.*

Rajapakse, V., & Dabare, U. (2024). *Emotional Cartwheels: Exploring the online shopping psyche of Sri Lankan consumers.* In Proceedings of the 3rd International Conference on Sustainable & Digital Business (ICSDB 2024).

Ricci, F. (2015). *Recommender systems handbook.* Springer.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: An empirical model of antecedents and outcomes. *Journal of Retailing, 88*(2), 308–322.*

Santora, J. (2024, May 22). *Ecommerce statistics.* https://www.helpscout.com/blog/ecommerce-statistics/

Shopify. (2024, April). *Global e-commerce sales.* https://www.shopify.com/blog/global-ecommerce-sales

Statista. (2024, May 8). *E-commerce worldwide.* https://www.statista.com/topics/871/online-shopping/

Suyeon, L., Ko, H., Park, Y., & Choi, A. (2021). A survey of recommendation systems: Recommendation models, techniques, and application fields. *Electronics, 10*(9), 1120.

Vargas, S., & Castells, P. (2011). Rank and relevance in novelty and diversity metrics for recommender systems. *Proceedings of the Fifth ACM Conference on Recommender Systems*, 109–116.

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2009). From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. *Journal of Retailing, 85*(2), 96–111.*

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA's statement on p-values: Context, process, and purpose. *The American Statistician, 70*(2), 129–133.*

Zhang, P. (2012). Evaluating recommender systems from the user's perspective: Survey of the state of the art. *User Modeling and User-Adapted Interaction, 22*(4–5), 317–355.*

Zhou, T., Lu, Y., & Wang, B. (2012). Integrating TTF and UTAUT to explain mobile internet continuance usage. *Computers in Human Behavior, 28*(3), 858–865.*

Zhang, Y., Shao, W., Quach, S., Thaichon, P., & Li, Q. (2024). Examining the moderating effects of shopping orientation, product knowledge and involvement on the effectiveness of Virtual Reality (VR) retail environment. *Journal of Retailing and Consumer Services, 78*, 103713.