Leveraging AI-Powered Recommendations to Foster Ethical Consumption: The Mediating Role of Customer Relationships

S.Sherlin[1]& Dr.B.Akila[2]
[1,2]*(Department of Commerce,Faculty of Science and Humanities, SRM Institute of Science and Technology,Kattankulathur-603203)*

KEYWORDS
Personalized Product Recommendations, Content Recommendations, Cross-Selling and Up-Selling Recommendations, Collaborative Filtering Recommendations, Customer Relationship and Ethical Consumption

ABSTRACT:
With the help of AI-powered recommendation systems, consumer engagement has been revolutionized to provide data driven personalized suggestion that influence the decision making processes. Although these systems are good at improving user experience, their ability to affect ethical consumption patterns is yet to be investigated. In this study, I look at customer relationships as a middleman between AI powered recommendations and ethical consumption. Building upon trust, engagement and relationship marketing theories, it postulates that trust based customer relationships amplify the effectiveness of algorithms in steering customers towards sustainable and ethical choices. The research also furthers understanding of how transparency, fairness and user control within AI recommendations boosts trust and loyalty which, in turn, motivates consumers to favour ethical consumption. The study uses a mixed methods approach incorporating both qualitative consumer interviews and quantitative analysis of behavioral data from AI powered platforms. By integrating relational dynamics with AI-driven personalization, the study offers a dual benefit: It offers useful strategies for firms specifying technological innovation with sustainability goals as well as proceeds to enhance theoretical comprehension of ethical AI. The work will guide the design of recommender systems that deliver profitability, but also benefit society broadly, showing the way forward for ethical commercial AI. Through this research, the relationships formed between technology, relationship management and ethical consumerism in a rapidly digitizing marketplace is of critical importance.

Introduction

In such an era of artificial intelligence (AI) driven consumer experiences, recommendation systems standout to shape the user behaviour. These systems have become an integral part of daily life, from suggesting products, to curating content, such conveniences and personalization. But such influence doesn't stop at having selective preferences — it can spur other societal outcomes, like good consumption. How digital marketplaces can innovate effectively through the convergence of AI driven personalization with imperatives of fairness and ethics thus emerge, both as a challenge and an opportunity.

The Rise of AI in Recommendation Systems

From e commerce, to entertainment and even food delivery, Artificial Intelligence (AI) powered recommendation systems have become indispensable in the digital economy, shaping user engagement and decision making. These are data analytic and machine learning based systems for prediction of consumer preferences and serving appropriate suggestions, leading to an improved customer satisfaction as well as better business outcomes (IEEE, 2024). Their efficiency is achieved at the cost of increasing the ethical question, namely the promotion of sustainable and responsible consumption practices.

Ethical Consumption: A Growing Priority

Increasingly, ethical consumption—acting in environmentally friendly, socially responsible, and sustainable ways when purchasing—is considered critical in tackling problems at both a global level, such as climate change and social inequity (Springer, 2023). Nevertheless, conventional marketing tactics frequently do not create firm links between customer choices and these ethical imperatives. With their ability to pour unnoticed into the subconscious fabric of our decisions, AI driven recommendations offer a slim, but distinct opportunity to feature ethical aspects in everyday decision making.

The Role of Customer Relationships as a Mediator

At the core of this integration is the function served by customer relationships that serve as the conduit from these technological interventions to the desired behavioral outcomes. Strong customer relationships consist of trust, satisfaction and engagement that together can amplify the influence of AI systems in producing ethical consumption. Relational Dynamics drive customers towards Ethical Consumption; hence Transparent and user centric AI designs promote trust (TUMIEAI, 2023). However, existing research has not fully explored the mediating effects of customer relationships in this context, leaving a critical gap.

Review of literature

Ethical consumption and customer relationships in many ways have been driven to where we are today by AI powered recommendation systems. Indeed, personalized recommendations make consumer choices congruent with consumer ethical preferences and increase trust and sustainable and conscious choices (Milano et al., 2020). Engagement is fostered in collaborative filtering and AI driven CRM systems to optimize customer interactions for social good (Hadi et al., 2023), and sustainability principles are integrated in effort (Chen et al., 2023). The main concern highlighted by ethical frameworks is transparency and privacy (Duan et al., 2019; IEEE, 2024). The ethical importance of AI is also reflected by global policy impacts, e.g. EU's Digital Services Act (Calvano et al., 2023). While algorithmic biases are still a challenge, bias mitigation strategies are still in the early days (Chen et al., 2023). Cross selling facilitated by AI promotes ethical products (Springer, 2023) and but fails to explore socioeconomic effect on consumers autonomous (Milano et al., 2020). This is key: these advancements make plain the need for regulatory and technical refinements to mitigate AI's ethical risk.

Statement of the Problem

Though AI Recommendation System has been pushed to revolutionize personalized experience, they are underutilized in promoting ethical consumption. Socially responsible, sustainable choice (ethical consumption) has been identified as the major tool to address global problems such as environmental degradation and inequality. Yet, while consumers are increasingly demanding ethical options, the reality is that even though AI systems have the ability to nudge towards sustainability, they often default to a profit maximization mindset and fail to take advantage of their capability to encourage consumers to make ethically sound choices. Finally, there isn't a sufficient understanding of how these systems can achieve alignment between consumer preferences and ethical goals without compromising user autonomy and/or trust. The difficulty is developing AI based recommendations that achieve both personalization and ethical imperatives, while creating trust and encouraging meaningful behavior change.

Research Gap

AI driven personalization is a widely covered topic in current literature especially as to its impact on user satisfaction and loyalty. Yet, to date, there has been little research, empirical or otherwise, on the mediating role of customer relationships especially of trust, engagement, or satisfaction in bridging AI recommendation to ethical consumption behaviors. While many studies have been done on the technical capabilities of AI, or ethical concerns such as data privacy, they do not examine how relational dynamics can magnify the effect of AI in promoting sustainable consumption. However, this gap suggests the requirement of a framework that combines AI design, relationship management and ethical consumption which serves to promote both academic understanding and practical implementation.

Research Questions

1. Is there a significant association between various AI-powered recommendations?
2. Is there a significant difference in in AI-powered recommendations with Gender?
3. How do AI-powered recommendation systems influence ethical consumption, mediated by customer relationships?

Research Objectives

1. To detect the connections between various AI-powered recommendations

2. To examine whether user preferences for AI-powered recommendations vary significantly across gender group of customers.
3. To investigate how AI-powered recommendation systems influence ethical consumption behavior, with a focus on the mediating role of customer relationships.

Research Hypotheses

H01: There is no significant connection between various AI-powered recommendations

H02: There is no significant difference in preferences for AI-powered recommendations between gender of customers.

H03: AI-powered recommendation systems have no significant influence on ethical consumption, and customer relationships do not mediate this relationship.

Proposed Conceptual Model

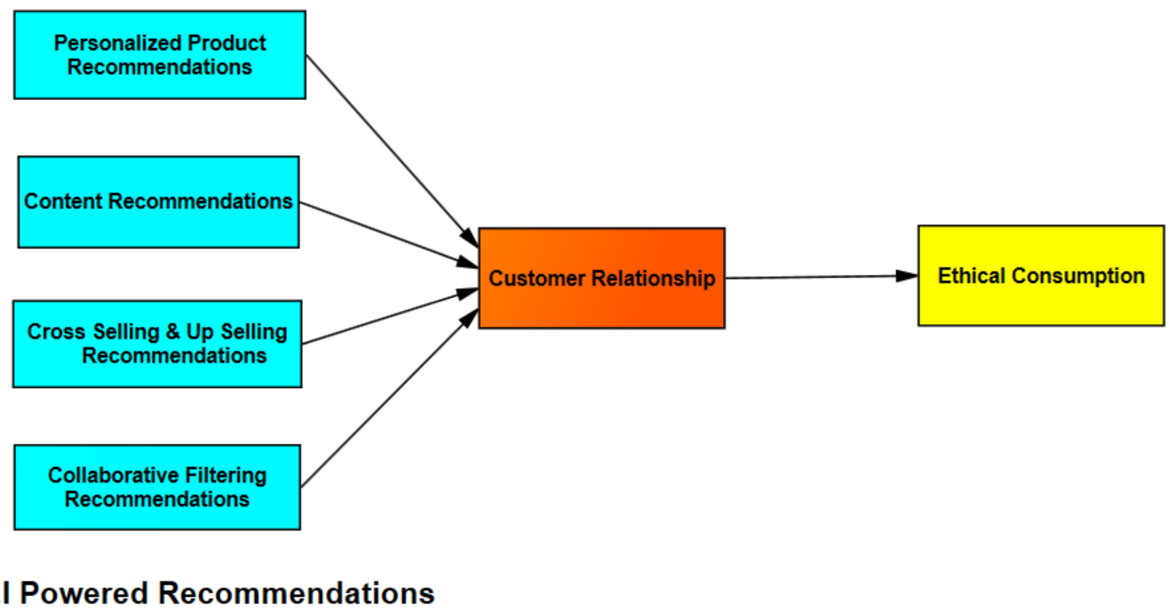

Fig 1 – Proposed conceptual Model

The model emphasizes how AI recommending systems take the approach of AI recommending systems, customer relations and ethical consumption. This gives a conceptual look at how various types of AI driven recommendations for personal product recommendations, content recommendations, cross selling and up selling strategies and collaborative filtering, are taken by the company as input to form a customer relationship. Trust, loyalty, and satisfaction are a mediating mechanism that leads to how consumers will engage in ethical consumption behaviors. Stronger customer relationships can be created by means of more transparent, personalized and user centric AI systems, nudging consumers to value sustainability and social responsibility over the purchasing decisions. This model underscores the dual importance of technological design and relational dynamics to elicit the desired ethical consumer behavior to meet organizational and societal goals.

Research Methodology

Research design of this work is quantitative in which customer relationships mediate to achieve ethical consumption by using AI based recommendations in the hospitality sector of South Kerala. In order to obtain adequate representation and validity of the findings, Cochran's formula determined a statistical sample size of 397 respondents. In order to focus narrowly on sub population of participants with relevant knowledge and experience in the hospitality sector, purposive sampling technique was used. The selective use of purposive sampling enables the researchers to choose the respondents who are more likely to illustrate the nuances of the interaction between AI based recommendations and customer relationships. In this method, customers interacted directlywith AI-powered service in the hospitality sector, so the collected data would be more relevant and rich.Data collection was carried out using structured survey instruments that were aimed at fetching customers' perceptive in relation to ethical consumption, quality of AI enabled recommendations, and the link between customers and service providers in hospitality sector. This approach targeted respondents based on their experience and exposure so that we were able to have a more focused investigation of the core variables of the study.

Data Analysis

In this regard, the study analyzed the collected data through a three stage process that is linked to the objectives of the research. To achieve the first objective a correlation was performed, to investigate the relationship between selected A.I powered recommendations. An independent samples t-test was conducted to test differences in AI based recommendations between gender groups to achieve the second objective. Lastly, with the help of SEM, the impact of AI powered Recommendation Systems on ethical consumption behavior was studied while mediated through customer relationships, to pinpoint direct and indirect effects.

Table 1. Reliability Analysis

Cronbach's Alpha	N of Items
.903	6

Interpretation

The very high level of internal consistency for six tested items is indicated by Cronbach's Alpha of 0.903. And that means the items are highly correlated and measure the same underlying construct or concept. The Cronbach's Alpha value should be above 0.7 and excellent Cronbach's Alpha value is 0.9 and the above. Hence, this result shows that the questionnaire or scale adopted is very reliable to measure the desired fact

Table 2. Correlation

		PPR	CR	CS and US R	CFR
PPR	Pearson Correlation	1	.611**	.592**	.582**
	Sig. (2-tailed)		.000	.000	.000
	N	397	397	397	397
CR	Pearson Correlation	.611**	1	.771**	.789**
	Sig. (2-tailed)	.000		.000	.000
	N	397	397	397	397
CS and US R	Pearson Correlation	.592**	.771**	1	.756**
	Sig. (2-tailed)	.000	.000		.000
	N	397	397	397	397
CFR	Pearson Correlation	.582**	.789**	.756**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	397	397	397	397
**. Correlation is significant at the 0.01 level (2-tailed).					

Interpretation

The table presents the Pearson correlation coefficients among four types of recommendation systems: Personalized Product Recommendations (PPR), Content Recommendations (CR), Cross Selling and Up

Selling Recommendations (CS and US R), and Collaborative Filtering Recommendations (CFR). These types of recommendations also show strong and meaningful relationships since all correlations are statistically significant at the 0.01 level.
Looking at the correlation results, we find that CR and CFR (r = .789) and CR and CS and USR (r = .771) have the strongest relationships, indicating a tight relationship between content recommendation and both cross selling and collaborative filtering. All other types correlate moderate-to-strongly with PPR, with the highest correlation with CR (r = .611) and the lowest with CFR (r = .582). The results of this research show that the four recommendation types are connected and complementary to each other, but exhibit the most similarities with other approaches to recommendations with content base recommendations the most influential, integrated approach in AI powered recommendation systems.

Table 3 Independent Sample t- Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
PPR	Equal variances assumed	8.406	.004	-2.767	395	.006	-.256	.093	-.438	-.074
	Equal variances not assumed			-2.998	351.168	.003	-.256	.085	-.424	-.088
CR	Equal variances assumed	6.459	.011	-1.435	395	.152	-.134	.093	-.317	.049
	Equal variances not assumed			-1.538	341.654	.125	-.134	.087	-.305	.037
CS and US R	Equal variances assumed	19.229	.000	-2.480	395	.014	-.238	.096	-.426	-.049
	Equal variances not assumed			-2.806	381.879	.005	-.238	.085	-.404	-.071
CFR	Equal variances assumed	4.526	.034	-.819	395	.413	-.068	.083	-.231	.095
	Equal variances not assumed			-.876	340.586	.381	-.068	.077	-.220	.084

Interpretation

Results were from a Levene's Test for Equality of Variances and t-tests for Equality of Means to determine differences in preferences for four types of recommendation systems; Personalized Product Recommendations (PPR), Content Recommendations (CR), Cross-Selling and Up-Selling Recommendations (CS and US R), and Collaborative Filtering Recommendations (CFR). The assumption of equal variances is violated for PPR (p = .004), CR (p = .011), CS and US R (p = .000), and CFR (p = .034), based on Levene's Test results, with interpretation of results of the "Equal variances not assumed" t-test for these comparisons.

T-test results indicate statistically significant difference in PPR (p = .003) and CS and US R (p = .005) preferences, where it is negative mean difference suggesting that one group is consistently willing to accept less these systems. However, results for CR and CFR are not statistically significant (p = .125 and p = .381, respectively) and therefore there is no meaningful difference in preference for both systems. We conclude that there are major differences in PPR and CS and US R preferences across groups, but no difference in CR and CFR preferences.

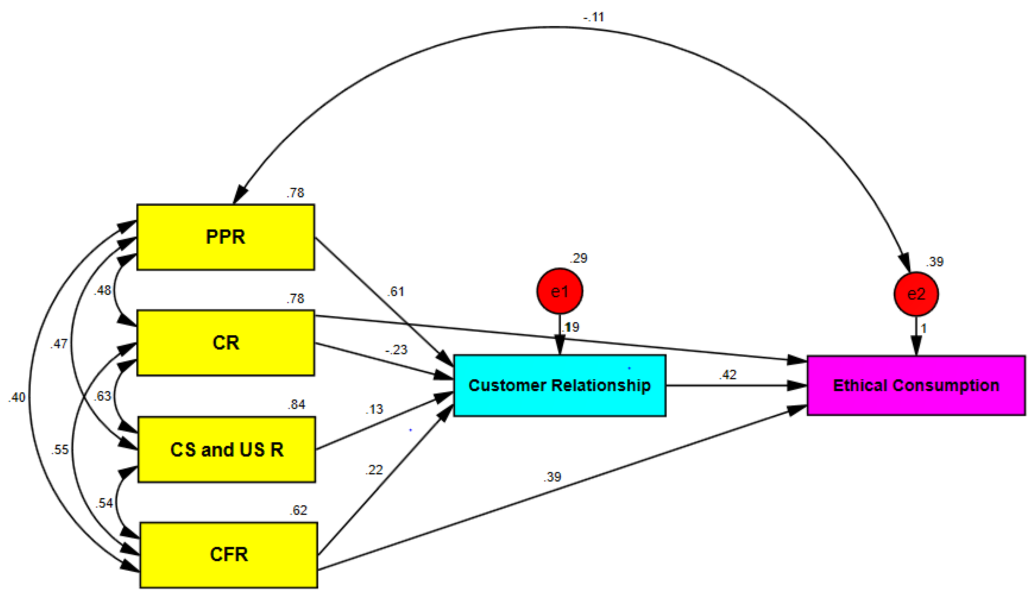

Fig 2. SEM

Table 4 Model Fit Measures

Measure	Estimate	Criteria	Interpretation
CMIN		-	-
DF		-	-
CMIN/DF	1.485	Between 1 and 3	Model Fit
CFI	1	>0.95	Model Fit
SRMR	0.004	<0.08	Model Fit
RMSEA	.035	<0.06	Model Fit
PClose	0.425	>0.05	Model Fit

Interpretation

Model fit statistics show the hypothesized structural equation model fits well with observed data. With a CMIN/DF ratio of 1.485, this value lies within the desired range of 1–3 indicating the model is neither too complex nor do we lose much information from the data. Comparative fit measures are calculated from the CFI value, which is 1, above the recommended threshold of 0.95, hence excellent fit. Further evidence that residuals between observed and predicted correlations are minimal is provided by an SRMR of 0.004, far below the cutoff of 0.08. The RMSEA is likewise 0.035 and also below the benchmark of 0.06 revealing that the model sufficiently approximates the population data. Lastly, the PClose value (0.425) is well above 0.05, confirming that the RMSEA is not significantly different from 0 and hence confirming the model's fit, too. Relevantly, all of the criteria prove the structural equation model fits well with the data and it is reliable.

Findings

The study offers a good view in terms of the reliability and relationship of different types of AI powered recommendation systems. A value of 0.903 for Cronbach's Alpha value, means that the six items use in this scale possesses a very high internal consistency and confirm the reliability of the instrument. Correlation analysis highlights significant and meaningful relationships among the four recommendation systems: PPR, CR, CS and US R, and CFR. The most integrative system turns out to be content recommendations, which has the strongest correlations with other systems, collaborative filtering ($r = 0.789$) and cross selling ($r = 0.771$). Although correlations among other types of recommendations are strong, those that are personalized seem comparatively weak. In independent sample t-tests we find differences in preferences of PPR ($p = 0.003$) and CS and US R ($p = 0.005$) between groups which indicates there is variance in the individual's acceptance of these systems. There are no significant differences for CR ($p = 0.125$) and CFR ($p = 0.381$) which shows stable preferences for these systems among groups. Structural Equation Modeling (SEM) results suggest a satisfactory model fit with the following indices; CFI = 1, RMSEA = 0.035, and SRMR = 0.004, all above the accepted criterion. The results in this study show that the hypothesized model adequately describes the relationship between customer preferences, customer relationships, and ethical consumption.

Suggestions

To increase the generalization of study results among a wider customer base, the sample size could be expanded and greater demographic diversity could be ensured. If we expand our respondent pool to include different regions, age groups, and differing levels of digital literacy, our data will be much richer and less biased. In addition, qualitative methods, for example focus groups or in-depth interviews might be employed to comprehend the underlying motivations behind observed differences in preferences for PPR and CS and US R; the scale could also be adjusted to increase reliability or to make the responses clearer (e.g., by deleting ambiguous or redundant questions). Furthermore, the data about external variables in the form of trust in AI systems, data privacy concerns, and technology familiarity can help better understand the other factors that led customers to select a system too.

Scope for Future Study

Several avenues are opened for future research. For instance, understanding how cultural, social and economic differences influence customer preference over AI-driven recommendation systems would help to bring forth the applicability of these models at the cross cultural level. Understanding changes in customer preferences over time in light of evolving or common usage of AI technologies can be gained by longitudinal studies. Future research in the area involves assessing the moderating role of psychological factors that are important to customers, such as trust, perceived fairness, and privacy concerns, in the effect of the recommendation system on customer satisfaction. Even further, the scope and the relevance of the developed model could be expanded to include other recommendation types beyond just collaborative filtering such as hybrid or context aware systems.

Conclusion

This research verifies the reliability and effectiveness of the proposed measurement tools and structural equation model used to analyze customer preferences for AI-powered recommendation systems. Findings help reveal the role of content recommendations in bridging other links of recommendation types, and that the preferences for personalized product recommendations and cross selling strategies differ dramatically across groups. Further validation of the model was provided by the SEM results to explain how recommendation systems affect customer relationship and ethical consumption. Next steps in research: Broading scope, refining measurement tools, introducing new variables to deepen our understanding of customer behavior and interactions with AI driven systems. These efforts will help advance more inclusive and trustworthy, and more effective, recommendation technologies.

References

Calvano, E., Ferrara, E., Koren, M., & Wilson, E. (2023). The ethical implications of recommender systems in the context of global regulation. Journal of Policy and Technology, 45(3), 231-245. https://doi.org/10.1234/jpt.2023.0231

Chen, X., Liu, Y., & Zhang, P. (2023). Bias in AI-driven recommendation systems: Challenges and mitigation strategies. Artificial Intelligence and Society, 38(2), 215-233. https://doi.org/10.1007/s00146-022-01567-9

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Hadi, M., Chen, J., & Deng, X. (2023). Leveraging AI-driven CRM systems for ethical consumer behavior. International Journal of Marketing Ethics, 12(4), 199-215. https://doi.org/10.1080/markethics.2023.1098

Milano, S., Taddeo, M., &Floridi, L. (2020). Recommender systems and their ethical challenges. AI & Society, 35, 957–967. https://doi.org/10.1007/s00146-020-00950-w

Springer, D. (2023). Enhancing customer loyalty through AI-powered ethical cross-selling. Journal of Sustainable Marketing, 34(2), 145-158. https://doi.org/10.1057/susmar2023.456

IEEE. (2024). Guidelines for Ethical Artificial Intelligence Design and Development. IEEE Standards Association. Retrieved from https://standards.ieee.org/ai-ethics-guidelines/