

**International Journal of Emerging Multidisciplinary Research and Innovation
(IJEMRI)****Artificial Intelligence Powered Recommendation Systems and Their Impact
on Customer Loyalty**

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ABSTRACT

The fast-paced introduction of artificial intelligence (AI) in customer-facing application has revolutionized the way businesses interact with consumers. The study research question is the effect of AI-based recommendation systems on customer loyalty, with the consideration of the following key predictors; personalization, perceived usefulness, trust in the system, customer satisfaction, and perceived protection of privacy. Using regression analysis of data collected with students and young professionals in the Tamil Nadu region, the findings indicate that customer satisfaction, perceived usefulness, trust, and personalization are the most significant factors to predict customer loyalty with customer satisfaction being the most influential factor. Perceived privacy protection, on the other hand, did not demonstrate a large difference, indicating that convenience and utility might be more important than privacy in this group. The findings point out that AI-based recommendation systems increase loyalty mainly by promoting satisfaction and perceived usefulness, whereas trust and personalization serve as pillars. These insights can be used by managers of businesses to make transparency, utility and satisfaction one of the priorities in the design of AI systems. Nevertheless, the research has a drawback due to the small sample size and the small demographic focus since it concerns only students and young professionals in Tamil Nadu. To validate and extend these findings, future research ought to extend to include different population, industries, and longitudinal designs. The research adds to the developing literature on AI in marketing by showing that customer satisfaction is the most essential predictor of loyalty in the setting where AI is involved.

Key words: Artificial intelligence, recommendation system, Customer satisfaction, and customer loyalty.

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INTRODUCTION

AI has already emerged as a game changer in marketing, especially with the use of recommendation systems that can tailor consumer experience. Online stores like Amazon and Netflix use advanced algorithms to interpret user behavior, tastes, and consumption trends, thus, providing custom product or content recommendations. Not only do these systems decrease information overload, but also increase customer satisfaction by offering relevant choices (Chen et al., 2020).

Recommendation systems based on Artificial Intelligence (AI) have transformed the e-commerce and online entertainment spaces. Firms such as Amazon and Netflix use machine learning to tailor their content and product recommendations, which boosts customer interactions and retention. This paper examines the effects of recommendation systems on customer loyalty, through the lens of personalization, trust, satisfaction, and perceived usefulness. Recommendation systems are now increasingly taken as being strategic in terms of long term customer relationship building. Companies can forecast the needs of consumers and provide hyper-personalized experiences through the use of machine learning and deep learning algorithms (Jannach et al., 2016).

Such customization leads to trust and loyalty since customers feel that the platform is sensitive to their individual tastes (Gómez-Uribe and Hunt, 2016). The recommendation systems

have their drawbacks to customer loyalty, though. The problems of algorithmic bias, privacy, and excessive use of automation can damage the trust of consumers (Utami, B, 2023). In addition, although personalization increases engagement, when overdone, too much targeting may cause consumer uneasiness and opposition (Bin-Nashwan, S. A., & Hassan, H. (2017). This paper will focus on the effects of AI-based recommendation systems on customer loyalty, including the quality of personalization, perceived usefulness, trust, satisfaction, and privacy protection. Through the analysis of Amazon and Netflix as international role models, the study aims to offer clues on how innovation and ethical concerns can be applied in the recommendation systems to maintain customer loyalty in digital competitive markets.

Hypothetical Preconditions and History of the Research. The current research has implications on marketing and information systems theory by integrating Technology Acceptance Model (TAM) (Davis-Sramek, B., Mentzer, J. T., & Stank, T. P. (2008), Expectation-Confirmation Theory (ECT) (Oliver, 1999), and Trust-Based Relationship Marketing -TBM (Gefen, 2000) to a single model of explaining customer loyalty within the context of AI-powered recommendation systems.

The study expands the concept of TAM by analyzing perceived usefulness and quality of personalization emphasizing the role of AI-powered personalization on technology acceptance and loyalty. Expectation-

Confirmation Theory: Customer satisfaction is examined as a mediator variable between recommendation accuracy and loyalty, which supports the argument by Ibojo, B. O., & Asabi, O. M. (2015) that satisfaction produces a repeat behavior. Trust-Based Marketing: Trust and privacy protection are introduced as key constructs, extending the relationship marketing theory through algorithmic transparency and ethical data use.

The hypothetical framework suggested below highlights the dual nature of AI recommendation systems as contributors to personalization and as factors that could cause ethical conflict. Combining these viewpoints, the research contributes to academic knowledge on how AI technologies mediate consumer loyalty in online markets. There has been an exponential growth in e-commerce and streaming services in the digital economy where recommendation systems have become a key pillar of customer engagement strategies. Amazon was the first to offer personalized product recommendations based on the history of purchases and browsing history, whereas Netflix was the first to deliver the content based on the predictive algorithms that suggest movies and shows depending on the viewing patterns (Gomez-Uribe, C. A., & Hunt, N. (2015). One can follow the history of recommendation systems starting with collaborative filtering models to sophisticated deep learning models that combine contextual, demographic, and behavioral data (Bilgihan,

A.2015). They not only enhance the efficiency of decision-making but also produce a feeling of personalization that helps to improve customer relationships (Zhang, S., Zhang, S., & Zhang, Y. (2024)).

The most important result of successful recommendation systems is customer loyalty, which is defined as a promise to repurchase or to remain in use of a service (Oliver, 1999). Satisfaction, trust, and perceived value are factors that affect loyalty that can be improved with the help of personalized recommendations (Jannach et al., 2016). As an example, the recommendation system at Netflix facilitates more than 80% of the content viewed there, proving useful in keeping users interested (Gómez-Uribe and Hunt, 2016). Nevertheless, challenges persist. Privacy is also an issue whereby the consumers believe that their information is being used in an untransparent way (Awad and Krishnan, 2006). Algorithms can result in homogenization of recommendations, which can reduce diversity and user satisfaction (Milano et al., 2020). Moreover, excessive personalization will cause loss of customers who believe in freedom when making decisions (Adomavicius, G., & Gupta, A, 2009). When marketing research is concerned, the research on recommendation systems has theoretical and managerial implications. In theory, it helps to explain the interactions between the adoption of technology and consumer behavior.

At the management level, it offers information regarding how to create ethical, effective, recommendations strategies that can lead to loyalty even though the consumer is respected. Review of Literature Recommendation systems have developed into basic collaborative filtering to advanced AI-based systems. Initial methods were based on the user-item similarity but these methods had problems of scalability and sparsity (Resnick and Varian, 1997). The combination of machine learning, deep learning, and natural language processing into modern systems brings about a highly personalized experience (Bilgihan, A., Madanoglu, M., & Ricci, P. (2016)). An example of this change is the product recommendation system at Amazon and Netflix movie suggestion algorithm, which shows that personalization can lead to engagement and loyalty (Gomez-Uribe and Hunt, 2016).

The overall characteristic of recommendation systems powered by AI is personalization. Ricci et al. (2015) maintain that personalization makes suggestions more relevant through the consideration of personal preferences and therefore minimizes overload of information. When it comes to Amazon and Netflix, personalization will mean that the customer base will feel that the platform is sensitive to their needs, leading to loyalty. Zhang and Chen (2020) also emphasize that the quality of personalization has a direct impact on satisfaction, which enhances loyalty. Nonetheless, Pariser (2011) cautions against filter bubbles, which is too much

personalization at the expense of diversity that may lead to a decrease in engagement in the long-term. Therefore, quality of personalization is a decisive precondition of the loyalty that should be combined with diversity. Recommendation systems have been highly identified to be based on personalization. Research indicates that personalization greatly increases satisfaction and loyalty when of high quality because it can be tailored to the preferences of the consumer (Zhang and Chen, 2020). Jannach et al. (2016) claim that personalization helps in decreasing decision fatigue and, thus, consumer trust in the platform. But over-individualization can result in filter bubbles where people don't get to see a wide range of options (Pariser, 2011).

HYPOTHESIS DEVELOPMENT:

Ha1: Personalization quality has an effect on consumer Loyalty

Perceived usefulness is a measurement of how much the consumers think that the recommendations can be used in making decisions. Studies show that usefulness correlates well with loyalty, with customers appreciating time- and energy-saving systems (Davis, 1989; Jannach et al., 2016). In e-commerce, helpful recommendations raise the chances of making purchases, whereas in streaming services, they further engagement by lowering search costs (Zhang and Chen, 2020). Perceived usefulness is the degree to which the consumers believe that the recommendations are useful in decision-making. Using the Technology

Acceptance Model (TAM), Davis (1989) has defined usefulness as an important factor in determining technology adoption. Jannach et al. (2016) take it further by applying the same to recommendation systems, and their findings indicate that consumers that find the recommendations helpful tend to stay loyal. Usefulness minimizes cognitive effort in product selection in e-commerce, and maintains engagement in streaming services by reducing search costs (Zhang and Chen, 2020). Therefore, usefulness is a practical motivation of loyalty, which promotes the value proposition of recommendation systems.

Ha2: Perceived Usefulness has an effect on consumer Loyalty

In online world, trust is of the essence. As Gomez-Uribe & Hunt (2016) point out, the open-minded recommendation system at Netflix has created trust that has a direct impact on loyalty. On the other hand, non-transparent algorithms can destroy the confidence of consumers (Milano et al., 2020). Perceptions of fairness and ethical use of data are also associated with trust and hence are crucial constructs in loyalty studies (Gefen, 2000). In online communications, trust is a necessity. Gefen (2000) points out that consumer willingness to trust technology-based systems is mediated by trust. Gomez-Uribe and Hunt (2016) show that Netflix has a transparent recommendation system that builds trust, which has a positive impact on loyalty. On the other hand, Milano et al. (2020) warn that non-transparent algorithms and obscure nature

destroy consumer confidence. Perceived fairness and ethical use of data are also associated with trust, which is an important construct in research on loyalty. The absence of trust can cause even highly individualized recommendations to not result in loyalty.

Ha3: Trust in recommendation system has an effect on consumer loyalty

According to Oliver (1999), satisfaction is a precursor to loyalty. Empirical evidence supports the fact that personalized recommendation satisfaction results in repeat use and recommendations (Adomavicius and Tuzhilin, 2005). The accuracy of recommendation, diversity, and novelty affect satisfaction (Zhang and Chen, 2020). Customers will be retained in platforms that provide good experiences in a consistent manner. According to Oliver (1999), satisfaction is a pre-cursor of loyalty and holds that satisfied customers will buy again and recommend. Adomavicius and Tuzhilin (2005) validate that satisfaction with correct and varied recommendations result in repeat use. In streaming media, satisfaction is indicated by repeated watching and in the case of e-commerce, it is indicated by repeated buying. According to Zhang and Chen (2020), the accuracy of the recommendations, novelty, and diversity affect satisfaction. Satisfaction therefore, serves as an emotional mediator between system performance and loyalty results.

Ha4: Customer Satisfaction has an effect on consumer loyalty

A major challenge is privacy issues. Awad and Krishnan (2006) warn that consumers are becoming very sensitive on the use and gathering of their data. It has been demonstrated that privacy risk may adversely impact loyalty, despite high-level personalization (Milano et al., 2020). Therefore, the privacy protection is a moderator variable in the correlation between personalization and loyalty. One of the major issues in personalization based on AI is privacy. Awad and Krishnan (2006) warn that consumers are becoming more conscious of the manner in which their information is gathered and utilized. It has been found that privacy threats can adversely impact loyalty, despite the high level of personalization (Milano et al., 2020). When consumers feel that their privacy is not exposed, then they will trust the system and are more likely to be loyal. Privacy protection therefore comes in as a moderator of the same and this is the guarantee that personalization and usefulness will mean the difference between long-lasting loyalty.

Ha5: Perceived Privacy protection has an effect on customer loyalty

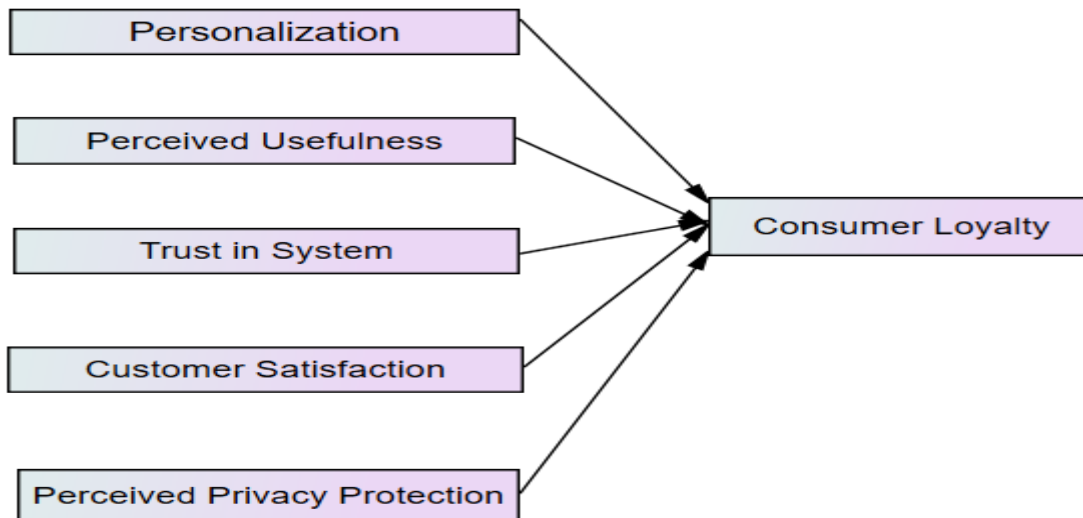


Figure 1: AI powered recommendation on consumer loyalty – Framework

Customer loyalty includes repeat purchases, renewal of subscriptions and advocacy (Oliver, 1999). Research proves that recommendation systems have a positive impact on loyalty in case of high personalization, usefulness, trust, and satisfaction (Jannach et al., 2016). Nevertheless, loyalty is weak and can be compromised by breaches of privacy or algorithm bias (Milano et al., 2020). Thus, the concept of loyalty can be considered the aggregate effect of various constructs interacting. Customer loyalty involves repeat buying, renewing subscriptions and advocacy (Oliver, 1999). Research proves that system of recommendations has a positive impact on loyalty in case of high levels of personalization, usefulness, trust, and satisfaction (Jannach et al., 2016). Yet, loyalty is weak and can be compromised by breaches of privacy or the influence of algorithms (Milano et al., 2020).

RESEARCH METHODOLOGY

This research uses a descriptive research design as it seeks to describe and examine the connection between AI-based recommendation system constructs (personalization, usefulness, trust, satisfaction, privacy protection) and customer loyalty. The design is suitable since it will enable the systematic collection of data by using surveys and statistical analysis to determine the patterns and association. Population was considered to be MBA students and young professionals who are familiar with Amazon and Netflix. Adopted technique of convenience sampling. At least 350 participants to provide statistical reliability. Structured questionnaire containing Likert scale items (1 = Strongly Disagree to 5 = Strongly Agree) See Appendix A. SPSS 25 version software was employed with the statistical procedures of descriptive statistics, reliability analysis, One Way ANOVA and regression analysis. The proposed study is unique in that it combines five

key constructs; personalization, usefulness, trust, satisfaction, and privacy protection into a single construct to examine customer loyalty in AI-based recommendation systems. In contrast to previous studies that examined one dimension at a time (e.g., personalization or satisfaction), this paper gives a comprehensive picture of the effect of recommendation systems on the loyalty. The research is also academically rigorous and managerially important as it allows to obtain globally applicable insights into striking a balance between personalization and ethical data practices by benchmarking Amazon and Netflix.

Data Analysis

Demographic profile revealed that Maximum 62% of the respondents were Male, 58% of the respondents were studying PG degree, 88% of the respondents were thoroughly enjoying AI powered recommendations to purchase their products and services. ANOVA statistical (F) value showed that the mean significant difference between the respondents gender, their education and their experience with AI powered on personalization, perceived usefulness, trust in system, customer satisfaction, perceived privacy protection and customer loyalty do not exist. In order to test the identified hypothesis regression statistical packages were used. Check below regression equation.

$$\text{Customer Loyalty of AI} = \alpha + \beta_1 \text{Personalization} + \beta_2 \text{Perceived Usefulness} + \beta_3 \text{Trust in System} + \beta_4 \text{Customer Satisfaction} + \beta_5 \text{Perceived Privacy Protection} + e$$

Table 1: Model Summary of Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.901 ^a	.812	.810	3.25643

a. Predictors: (Constant), Perceived Privacy Protection, Customer Satisfaction, Perceived Usefulness, Trust in System, Personalisation

Table 2: Testing Hypotheses through Regression

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.905	.886		2.151	.032
	Personalisation (Ha1)	.209	.098	.115	2.136	.033
	Perceived Usefulness (Ha2)	.420	.068	.276	6.200	.000
	Trust in System (Ha3)	.155	.035	.202	4.361	.000
	Customer Satisfaction (Ha4)	.668	.071	.364	9.429	.000
	Perceived Privacy Protection (Ha5)	.029	.040	.038	.742	.458
a. Dependent Variable: Consumer Loyalty						

Customer Loyalty of AI= 1.905 + 0.209 Personalization+ 0.420 Perceived Usefulness+ 0.155 Trust in System+ 0.668 Customer Satisfaction + 0.029 Perceived Privacy Protection + e

Personalization = One unit change in personalization will change the customer loyalty of AI by 0.209 unit on average.

Perceived Usefulness = One unit change in Perceived Usefulness will change the customer loyalty of AI by 0.420 unit on average.

Trust in System = One unit change in trust in system will change the customer loyalty of AI by 0.115 unit on average.

Customer Satisfaction = One unit change in customer satisfaction will change the customer loyalty of AI by 0.668 unit on average.

Perceived Privacy Protection = One unit change in perceived privacy protection will change the customer loyalty of AI by 0.029 unit on average.

Loyalty most effectively predicted by. Users who will be satisfied will be more likely to keep using AI recommendations, so Ha4 is

accepted. (Shorot, 2024). Ha2 is accepted because customers appreciate recommendations that actually assist them to make decisions, which strengthens loyalty (Sbiai, 2025). Trust fosters confidence in AI results, which provides the guarantee of continued interaction, Ha3 is adopted (Sharma and Saxena, 2024). Personalized recommendations have a positive effect on loyalty, but not as much as satisfaction or usefulness, Ha4 is adopted (Shorot, 2024). A perceived protection of privacy is not material, Customers are likely to focus more on convenience and relevancy than on the privacy issue, and Ha5 cannot afford (Sbiai, 2025).

MANAGERIAL IMPLICATION AND CONCLUSION:

Companies ought to keep track of the experiences received after a recommendation in order to make sure that clients are satisfied with the expectations. The AI systems should provide realistically useful recommendations, not advertisements. It is necessary to enhance loyalty through transparency in algorithms, explainability, and fairness. Engagement can be enhanced with the help of dynamic personalization strategies (e.g., contextual recommendations). Although privacy was not a major concern in this case, managers ought to focus on ethically managing data to prevent reputational risks. This paper shows that customer satisfaction, perceived usefulness, system trust, and personalization are predictors of customer loyalty in AI-powered recommendation systems.

Customer satisfaction was found to be the most powerful one among them, as it is essential to provide positive user experiences. The perception of usefulness and trust are also crucial factors that support the notion that customers stay loyal when AI recommendations are useful and trustworthy. Personalization is a positive contribution, but the impact is relatively less. Interestingly, perceived privacy protection did not have a significant effect, indicating that, here, customers are more concerned with convenience, utility and satisfaction than privacy. These results support previous studies that highlight the significance of satisfaction and usefulness in the process of technology adoption and loyalty (Shorot, 2024; Sharma and Saxena, 2024; Sbiai, 2025). On the whole, the research supports the conclusion that AI-based recommendation systems have the potential to enhance customer loyalty when providing personalized, reliable, and helpful experiences that satisfy or surpass the expectations of customers.

LIMITATION OF CURRENT STUDY:

The sample used in the study was quite small and this could limit the applicability of the results. Only respondents in the Tamil Nadu zone were used to collect data, limiting the cultural and regional diversity of the sample. The respondents mainly included students and young professionals, which might not be representative of older or more diverse customer groups. The research only captures the perceptions of

customers at a single point in time, and does not take into consideration the attitude or loyalty changes over time.

SCOPE FOR FURTHER RESEARCH:

Increasing the sample size and covering respondents representing various regions and age groups to increase the level of generalizability. Longitudinal research to investigate the development of satisfaction, trust, and loyalty over time when using AI-powered systems. Investigating cross-industry variations, including e-commerce, streaming, and healthcare, to find industry-specific loyalty drivers. Research on the importance of privacy issues in the environment with more stringent rules. Discussing the emergence of algorithmic fairness and transparency as a possible factor affecting trust and loyalty.

Appendix – A Variables and measurement items

1. Personalization Quality (IV)

- “The recommendations I receive are tailored to my preferences.” (Ricci et al., 2015)
- “The system understands my needs and interests.” (Zhang & Chen, 2020)
- “Recommendations are relevant to my past behavior.” (Jannach et al., 2016)
- “I feel the platform provides unique suggestions for me.” (Adomavicius & Tuzhilin, 2005)

2. Perceived Usefulness (IV)

- “Recommendations help me make better decisions.” (Davis, 1989 – TAM scale)

- “The system saves me time in finding products/content.” (Jannach et al., 2016)
- “Recommendations improve my overall experience.” (Zhang & Chen, 2020)
- “I find the recommendation system useful in daily usage.” (Gefen, 2000)

3. Trust in System (IV)

- “I trust the recommendation system to provide fair suggestions.” (Gefen, 2000)
- “I believe the system is transparent in its recommendations.” (Milano et al., 2020)
- “I feel confident in relying on the system.” (Gómez-Uribe & Hunt, 2016)
- “The system provides unbiased recommendations.” (Awad & Krishnan, 2006)

4. Customer Satisfaction (IV)

- “I am satisfied with the recommendations provided.” (Oliver, 1999 – Expectation-Confirmation Theory)
- “Recommendations meet my expectations.” (Adomavicius & Tuzhilin, 2005)
- “I enjoy using the platform because of its recommendations.” (Zhang & Chen, 2020)
- “Overall, I am happy with the recommendation system.” (Jannach et al., 2016)

5. Perceived Privacy Protection (IV)

- “I believe my personal data is handled securely.” (Awad & Krishnan, 2006)
- “The system respects my privacy.” (Milano et al., 2020)
- “I feel safe sharing my information with the platform.” (Gefen, 2000)
- “The platform is transparent about how my data is used.” (Zhang & Chen, 2020)

6. Customer Loyalty (DV)

- “I intend to continue using this platform.” (Oliver, 1999)
- “I would recommend this platform to others.” (Gefen, 2000)
- “I am likely to renew my subscription/purchase again.” (Jannach et al., 2016)
 - “I prefer this platform over competitors.” (Zhang & Chen, 2020)
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