

Original Research Article

Impact of AI-Based Personalized Recommendations on Consumer Purchase Behaviour: A Study Using the Amazon Consumer Behaviour Dataset

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Abstract

Artificial Intelligence (AI) has transformed digital marketing by enabling e-commerce platforms to analyse consumer behaviour and provide personalized product recommendations. Recommendation systems can reduce information overload, improve product relevance and support customer decision-making. Their effectiveness, however, depends on factors such as recommendation frequency, perceived helpfulness and perceived accuracy.

This study examines consumer purchase behaviour using the publicly available Amazon Consumer Behaviour Dataset hosted on Kaggle. The dataset contains 602 observations and 23 variables covering demographics, purchase frequency, browsing behaviour, personalized recommendations, recommendation helpfulness, rating accuracy, reviews, Save-for-Later activity and shopping satisfaction. The study follows a quantitative, explanatory secondary-data design.

Reported statistical analyses of the same dataset show significant positive associations between purchase frequency and browsing frequency, Save-for-Later frequency and review helpfulness. A K-means analysis also identifies two distinct behavioural segments. Recommendation-specific analysis reports a positive association between personalized recommendation frequency and rating accuracy. Because the dataset contains

Purchase_Frequency rather than a direct Purchase_Intention measure, the findings are interpreted as evidence of consumer purchase behaviour.

Keywords: Artificial Intelligence, Personalized Recommendations, Recommendation Systems, Consumer Behaviour, Purchase Frequency, E-commerce, Amazon, Digital Marketing.

1.0 Introduction

1.1 AI in Business and Marketing

Artificial Intelligence has become an important capability in modern business because it can process large volumes of customer and transaction data and convert them into actionable insights. In digital commerce, AI is used for customer segmentation, demand prediction, search, automated communication, content personalization and recommendation systems. These applications allow businesses to improve customer experience while making marketing decisions more data-driven.

1.2 Personalization and Recommendation Systems

A recommendation system attempts to identify products or services that a customer may find relevant. Personalization goes further by tailoring recommendations to an individual using behavioural signals such as browsing history, purchase history, searches, ratings and interactions. For an online marketplace, this can reduce the effort required to find products and can help customers navigate a large product catalogue.

1.3 Consumer Purchase Behaviour

Consumer purchase behaviour is an observable outcome of consumer activity. In the selected dataset, Purchase_Frequency captures how frequently respondents purchase from Amazon. The present research therefore uses purchase frequency as the measurable behavioural outcome. This distinction is important because purchase behaviour and purchase intention are related but are not identical constructs.

1.4 Importance of Recommendation Quality

Personalization is useful only when recommendations are sufficiently relevant and helpful. Very frequent or poorly matched recommendations may create repetition or reduce user confidence.

Therefore, the study considers personalized recommendation frequency together with recommendation helpfulness and rating accuracy.

2.0 Problem Statement and Need for the Study

Online marketplaces contain very large product catalogues, which can create information overload. Recommendation systems are designed to reduce this problem by presenting products that appear relevant to individual customers. However, the business value of recommendations depends on how customers interact with the platform and whether recommendations are perceived as useful and accurate.

Businesses therefore need evidence about the behavioural factors associated with purchase activity and about the role of recommendation-related experiences. A secondary dataset with both recommendation variables and purchase behaviour provides a practical basis for this analysis.

3.0 Literature Review

The literature reviewed for this study includes Indian and international research on recommender systems, AI personalization, consumer behaviour, trust, relevance and privacy. The evidence generally supports the importance of recommendation quality, but studies differ by platform, country, sample and method.

Study	Method / Sample	Main contribution	Limitation
Bokadia, Jain & Singhi (2024)	Systematic review; 908 papers	Recommender systems and purchase intention; identifies important constructs and relationships.	Review evidence; future empirical testing needed.
Kumari & Laheri (2025)	Systematic review / bibliometric; 312 articles	AI recommender systems, decision support, trust/adoption, privacy and web personalization.	Review rather than new consumer-level experiment.
Chandra et al. (2025)	Qualitative Indian study	Consumers evaluate personalization through adaptation, bias, redundancy, information coherence and deals.	Qualitative and context-specific.
Sasikala et al. (2026)	Indian quantitative study; 160 shoppers	Relevance and trust influence purchase intention; customization/transparency influence trust.	Modest sample; broader contexts useful.
Yamuna et al. (2025)	Indian survey; 177 Chennai shoppers	Personalization has an important role in engagement and purchase decisions.	Limited to Chennai and fashion category.
Beniwal et al. (2025)	Indian qualitative study	Convenience and relevance coexist with privacy and data-use concerns.	Qualitative; no direct regression.
Yun & Chun (2024)	Quantitative e-commerce survey	Recommendation method, strength, precision and interactivity can have different effects.	Platform context matters.
Qian et al. (2024)	SEM survey; 703 Taobao consumers	Personalized recommendations positively predicted user stickiness and purchase intention.	China / one platform context.
Yin, Qiu & Wang (2025)	Multi-stage empirical study; 1,097	Relevance, inspiration and insight promoted	Clicking intention differs from purchase

	questionnaires	clicking intention; privacy concerns moderated responses.	behaviour.
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3.1 Research Gap

Existing research establishes that personalization and recommendation quality are important, but evidence is distributed across different platforms and methodological settings. Indian research is growing, yet several studies are recent and context-specific. The present study addresses a practical empirical gap by examining an Amazon consumer-behaviour dataset containing direct recommendation and purchase-behaviour variables.

4.0 Objectives, Variables and Hypotheses

4.1 Objectives of the Study

- To examine the relationship between personalized recommendation experience and consumer purchase frequency.
- To examine whether recommendation helpfulness is associated with purchase frequency.
- To examine whether perceived recommendation accuracy is associated with purchase frequency.
- To identify behavioural differences among customer segments using purchase, browsing and Save-for-Later behaviour.
- To examine recommendation-specific relationships available in the dataset.
- To provide practical recommendations for businesses using AI-based personalization in e-commerce.

4.2 Variables of the Study

Variable Type	Variable	Actual Dataset Field	Measurement / Role
Independent	Personalized Recommendation Experience	Personalized_Recommen dation_Frequency.1	Frequency/intensity of received personalized recommendations; 1–5.
Independent	Recommendation Helpfulness	Recommendation_Help fulness	Perceived helpfulness; No/Sometimes/Yes.
Independent	Recommendation Accuracy	Rating_Accuracy	Perceived relevance/accuracy; 1–5.
Dependent	Purchase Behaviour	Purchase_Frequency	Frequency of Amazon purchases; ordered categories.
Context	Shopping Satisfaction	Shopping_Satisfaction	Overall shopping satisfaction; 1–5.
Context	Browsing Frequency	Browsing_Frequency	Frequency of browsing Amazon.
Context	Age / Gender	age / Gender	Basic respondent characteristics.

The study keeps the dependent outcome clearly defined as Purchase_Frequency. This avoids changing the research question to Purchase_Intention when the selected dataset does not directly contain that measure.

5.0 Conceptual Framework and Hypotheses

5.1 Conceptual Framework

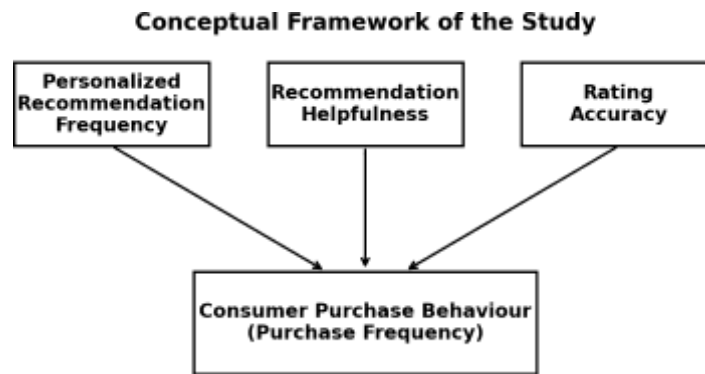


Figure 1. Conceptual framework of the study.

The framework proposes that personalized recommendation frequency, recommendation helpfulness and rating accuracy are relevant recommendation-experience factors, while purchase frequency represents the observable consumer behaviour outcome.

5.2 Formulation of Hypotheses

Code	Null Hypothesis (H0)	Alternative Hypothesis (H1)	Statistical Test
H1	Browsing frequency has no significant relationship with purchase frequency.	Browsing frequency has a significant positive relationship with purchase frequency.	Spearman correlation
H2	Save-for-Later frequency has no significant relationship with purchase frequency.	Save-for-Later frequency has a significant positive relationship with purchase frequency.	Spearman correlation
H3	Review helpfulness has no significant relationship with purchase frequency.	Review helpfulness has a significant positive relationship with purchase frequency.	Spearman correlation
H4	The dataset does not show distinct purchase-behaviour segments.	The dataset shows distinct purchase-behaviour segments based on selected behavioural variables.	K-means clustering

Decision rule: $p < 0.05$ indicates statistical significance. For H4, K-means clustering is descriptive/segmentation analysis and does not use a p -value as its decision criterion.

6.0 Methodology

6.1 Research Design

The study uses a quantitative, explanatory and secondary-data research design. A deductive approach is followed by translating the research concepts into measurable variables and testable hypotheses.

6.2 Dataset Source

The selected dataset is the Amazon Consumer Behaviour Dataset, published on Kaggle by Swathi Menon. It is a survey-based public dataset describing Amazon shopping behaviour and consumer experiences.

Dataset link: <https://www.kaggle.com/datasets/swathiunnikrishnan/amazon-consumer-behaviour-dataset>

6.3 Dataset Size and Structure

The dataset contains 602 observations and 23 variables. It includes demographic information and behavioural/service variables such as purchase frequency, browsing frequency, search behaviour, cart behaviour, Save-for-Later frequency, review reliability/helpfulness, personalized recommendation frequency, recommendation helpfulness, rating accuracy and shopping satisfaction.

6.4 Dataset Variables Used in the Analysis

Field	Type	Use in Study
Purchase_Frequency	Ordinal	Dependent variable: consumer purchase behaviour.
Personalized_Recommendation_Frequency.1	Ordinal 1–5	Primary recommendation-experience variable.
Recommendation_Helpfulness	Ordinal categorical	Perceived usefulness of recommendations.
Rating_Accuracy	Ordinal 1–5	Perceived recommendation relevance/accuracy.
Browsing_Frequency	Ordinal categorical	Behavioural predictor/context.
Saveforlater_Frequency	Ordinal categorical	Behavioural predictor/context.
Review_Helpfulness	Ordinal categorical	Behavioural predictor/context.

6.5 Data Quality and Pre-processing

- Check missing values and document treatment.
- Retain ordinal variables in their natural order.
- Apply consistent coding to ordinal categories.
- Check distributions and unusual observations before inferential testing.
- Use Spearman correlation for ordinal relationships rather than assuming interval-scale Pearson conditions.
- Use the complete 602-observation dataset where the published analysis reports results on that basis.

6.6 Statistical Techniques

Descriptive statistics and percentages are used for dataset understanding. Spearman rank correlation is used for ordinal associations, and K-means clustering is used to identify behavioural segments. A significance level of 0.05 is used for correlation-based hypothesis decisions.

7.0 Data Analysis and Findings

The numerical findings below are based on published analyses of the same 602-observation Amazon Consumer Behaviour Dataset. They are presented as secondary-data findings and are not claimed as a new primary survey.

7.1 Dataset Overview

Measure	Value
Observations	602
Variables	23
Dataset type	Survey-based secondary dataset
Source	Kaggle – Amazon Consumer Behaviour Dataset
Main outcome used	Purchase_Frequency
Recommendation fields	Personalized recommendation frequency, helpfulness and rating accuracy

7.2 Descriptive Observations

The published exploratory analysis of the same dataset reports a mixed consumer profile, with demographic and shopping-behaviour variables available for analysis. The dataset is therefore useful not only for recommendation analysis but also for understanding differences in shopping engagement.

7.3 Correlation Results

A published R-based analysis calculated Spearman correlations between selected behavioural variables and Purchase_Frequency. The results are summarized below.

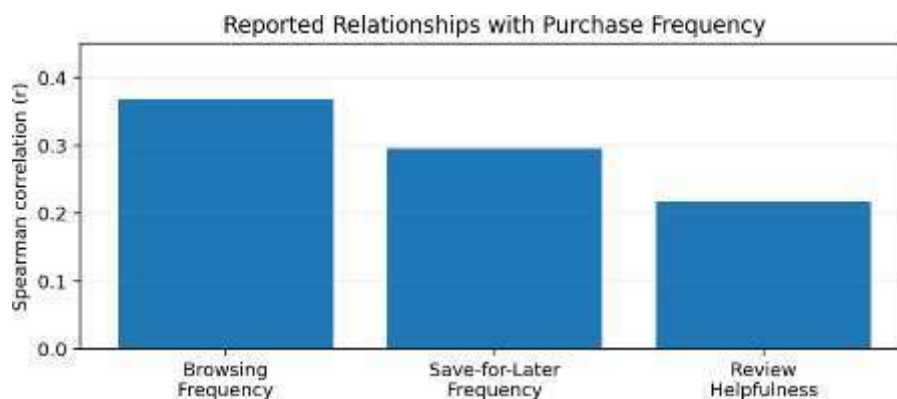


Figure 2. Reported relationships with purchase frequency.

Variable	Spearman r	p-value	Interpretation
Browsing_Frequency	0.3686821	8.068092×10^{-1}	Significant positive association
Saveforlater_Frequency	0.2953307	1.396140×10^{-13}	Significant positive association
Review_Helpfulness	0.2177724	6.776562×10^{-8}	Significant positive association

8.0 Statistical Test Summary and Findings

8.1 Hypothesis Test Summary

Hypothesis	Relationship	Statistic	p-value	Decision
H1	Browsing Frequency → Purchase Frequency	$r = 0.3686821$	8.068092×10^{-21}	Reject H0
H2	Save-for-Later → Purchase Frequency	$r = 0.2953307$	1.396140×10^{-13}	Reject H0
H3	Review Helpfulness → Purchase Frequency	$r = 0.2177724$	6.776562×10^{-8}	Reject H0
H4	Selected behaviour → 2 segments	K-means	Not applicable	Distinct segments identified

All three reported correlation p-values are far below 0.05. Therefore, H1, H2 and H3 are statistically significant in the cited secondary analysis. H4 is evaluated through clustering rather than a conventional p-value test.

8.2 Recommendation-Specific Finding

The dataset directly contains Personalized_Recommendation_Frequency, Recommendation_Helpfulness and Rating_Accuracy. A separate published analysis using the same dataset reported a positive correlation of $r = 0.44$ between personalized recommendation frequency and rating accuracy. This supports the relevance of recommendation experience as a research construct, while not proving that recommendation frequency causes higher purchase activity.

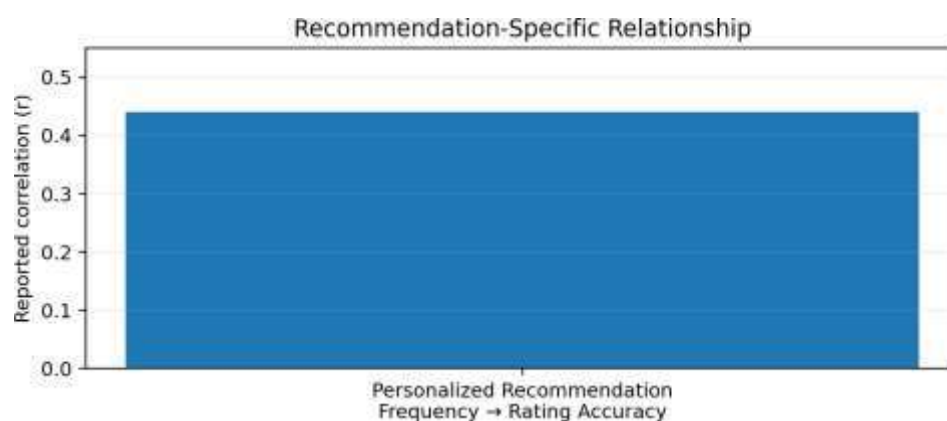


Figure 3. Reported relationship between personalized recommendation frequency and rating accuracy.

8.3 Interpretation

The strongest reported association with purchase frequency is browsing frequency, followed by Save-for-Later frequency and review helpfulness. This indicates that active engagement with the shopping platform is closely connected with purchasing behaviour in the secondary evidence.

9.0 Cluster Analysis and Discussion

9.1 Behavioural Segmentation

The same published analysis used K-means clustering with purchase, browsing and Save-for-Later behaviour. The analysis identified two behavioural segments.

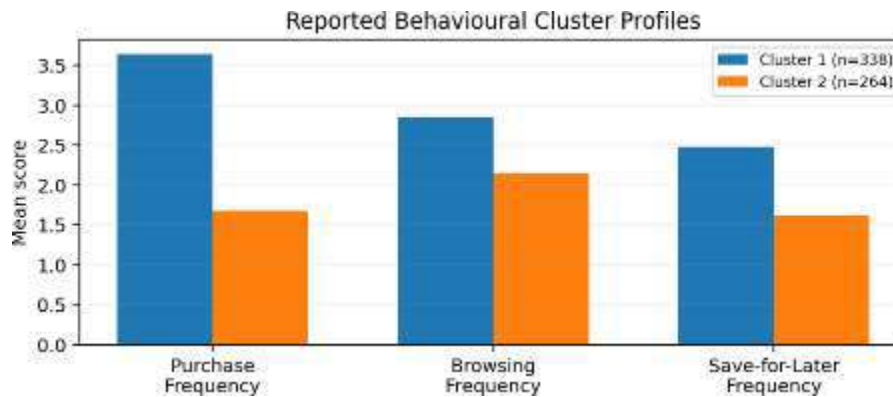


Figure 4. Average purchase frequency by behavioural cluster.

Cluster	n	PurchaseFrequency Mean	Browsing Mean	Save-for-Later Mean
1	338	3.642012	2.849112	2.482249
2	264	1.681818	2.147727	1.625000

9.2 Cluster Profile

Cluster 1 is the higher-engagement group: its average purchase frequency, browsing frequency and Save-for-Later activity are all higher than Cluster 2. Cluster 2 represents comparatively lower shopping engagement. This suggests that recommendation strategies can be differentiated according to customer activity rather than applying one identical approach to every user.

9.3 Overall Discussion

The results support the broader literature showing that consumer response to AI-enabled recommendation environments is multidimensional. Recommendation quality matters, but purchase behaviour is also connected to browsing and other engagement signals. Therefore, businesses should evaluate recommendation systems using multiple behavioural indicators rather than relying only on recommendation exposure.

The findings should be interpreted as associations because the dataset is observational. A significant correlation does not establish that an AI recommendation directly caused a purchase.

10.0 Recommendations

- Improve recommendation relevance and accuracy rather than increasing recommendation volume alone.
- Use customer behaviour signals carefully so personalization remains useful rather than repetitive.
- Monitor recommendation helpfulness and consumer feedback to improve recommendation quality.
- Evaluate recommendation performance alongside purchase behaviour, satisfaction and other engagement indicators.
- Use behavioural segmentation to differentiate recommendation strategies for high- and low-engagement customers.
- Provide transparent explanations where they can improve customer confidence in recommendations.

- Avoid excessive or intrusive personalization that may reduce trust or create a poor user experience.
- Use responsible data practices and appropriate safeguards when processing customer information.

11.0 Conclusion

Artificial Intelligence has become an important tool in digital marketing because it enables businesses to personalize product discovery and recommendation experiences. This study used the Amazon Consumer Behaviour Dataset to examine how recommendation-related and behavioural variables are associated with consumer purchase frequency.

The reported evidence shows significant positive associations between purchase frequency and browsing frequency, Save-for-Later frequency and review helpfulness. The clustering results further identify a higher-engagement and a lower-engagement customer segment. Recommendation-specific analysis also reports a positive relationship between personalized recommendation frequency and rating accuracy.

Overall, the study indicates that effective personalization should focus on relevance, helpfulness, accuracy and customer behaviour rather than recommendation frequency alone. The results provide practical guidance for e-commerce businesses while maintaining an important methodological boundary: the evidence shows relationships, not causation.

12.0 Limitations and Future Scope

- The study is based on secondary data and therefore depends on the quality, coding and variables available in the public dataset.
- The present researcher did not conduct the underlying survey.
- Purchase_Frequency is used as the observable outcome; the dataset does not directly measure Purchase_Intention.
- The numerical correlation and cluster results are based on published analyses of the same public dataset.
- Future work can reproduce the analysis directly from the downloaded CSV and document every preprocessing step.
- Future research can collect primary data with a validated purchase-intention scale and compare it with actual purchase behaviour.
- Additional research can examine privacy, trust, transparency and recommendation fatigue alongside recommendation effectiveness.

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