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PREDICTIVE ANALYSIS THROUGH AI AND CUSTOMER BUYING BEHAVIOR: AN EMPIRICAL STUDY OF ONLINE SHOPPERS FROM CHENNAI

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ABSTRACT
Increasing application of Artificial Intelligence (AI) technology in online retail has brought a paradigm shift in the way companies comprehend customer preferences and affect their purchase decisions. With the help of predictive analytics supported by AI, online shopping websites can analyze customer behavior, detect buying patterns, and give personalized product recommendations. In the current study, the impact of predictive analytics based on AI on purchase decision making of online customers in Chennai is studied. Special emphasis is laid on five dimensions that include Predictive Accuracy, Personalization Capability, Recommendation Relevance, Real-time Data Analysis and Data-Driven Insight. The study is conducted using the descriptive research method, and is based on the proposed sample size of 147 online customers in Chennai. As per the information provided, primary data are collected from respondents with the help of a structured questionnaire, using convenience sampling technique for selecting respondents. Statistical techniques that are proposed to be used in the study include percentage analysis, Cronbach's alpha, multiple regression analysis and one-way ANOVA. The findings indicate the existence of statistically significant regression equation ($R^2 = 0.562$) with Recommendation Relevance being the strongest predictor.

Keywords: Artificial Intelligence, Predictive Analytics, Machine Learning, Online Shopping, Customer Purchase Decision-Making, Personalisation, Strategic Management.

I. INTRODUCTION

The advancement in digital technology has led to changes in how customers search, compare and make decisions when purchasing products. Online shopping websites have taken the conventional approach of product display and promotion through AI and ML techniques to learn about customer preferences and predict future consumer behavior. This is achieved through analyzing customers' data, determining behavioral trends and offering recommendations that better match individual customers' preferences (Sharma Dixit et al., 2025; Hassan et al., 2025). AI has become a critical part of modern-day business strategy especially in digital marketing, customer relationship management and online shopping. By predictive analysis of previous purchases, browsing, product searches and customer engagements, companies can predict the possibility of future purchases. This enables businesses to shift from generic promotions to more personalized and informed marketing strategies (Chen, 2025; Bharathi & Elakkiyan, 2026).
Several factors influence customer purchase decision-making such as product attributes, price, convenience, product reviews, brand name and personal preferences. However, in online

shopping, customers are faced with many options and hence making decisions becomes difficult. This issue has been handled by the use of AI in recommending products that match the customer's interest and shopping history (Sasikala et al., 2026; Tiwari & Namdeo, 2026). Predictive accuracy is one of the significant components of AI-based analytics because customers would be able to benefit more from recommendations that meet their real needs. Personalization ability will enhance the shopping experience through providing personalized products recommendations. Likewise, recommendation relevancy, real-time analysis, and data-driven insights are some of the factors that determine the quality of information received by consumers during the purchasing process (Tiwari & Namdeo, 2026).

In terms of strategic management, predictive analytics offers numerous benefits for companies in understanding shifting consumer expectations, improving marketing performance, and managing company's resources efficiently. On the other hand, the usefulness of AI-based recommendations will be determined by the precision and significance of the response of technology to customers' needs. Customers may also have reservations about the reliability of recommendations, usage of their personal information, and lack of transparency in automation decisions (Hassan et al., 2025; Bharathi & Elakkiyan, 2026). In the light of the above, the current research aims to investigate the impact of AI-based predictive analytics on customer purchase decision-making among online shoppers in Chennai. Specifically, the paper analyzes five selected aspects of predictive analytics and its role in consumer purchasing decisions.

II. AI-POWERED PREDICTIVE ANALYTICS

Predictive analytics through artificial intelligence entails the use of artificial intelligence technology to analyze available data in order to forecast the likelihood of a future event or customer behavior. The technique is employed in online shopping through analysis of customer browsing habits, purchasing behaviors, searches and digital engagement. While regular marketing techniques mostly rely on customer segments, predictive analytics using artificial intelligence helps organizations identify more specific consumer behaviors. Artificial intelligence technology allows processing of customer information to make product recommendations based on consumer behavior. This makes it easier for organizations to make better customer targeting and design more relevant marketing strategy. Predictive analytics also aids strategic management in decision making based on information about customers. Businesses can discover consumer demands and preferences, know customer expectations and do more effective promotion of their products and services. Therefore, predictive analytics through artificial intelligence is one of the tools used by organizations to enhance consumer experience.

III. FACTORS INFLUENCING AI-POWERED PREDICTIVE ANALYTICS ON CUSTOMER PURCHASE DECISION-MAKING

Predictive Accuracy

Predictive accuracy implies how effectively AI-based tools are able to recognize the preferences of consumers and predict their purchasing needs. During the process of online shopping, consumers expect that product suggestions would correspond with their needs. When product suggestions match the preferences of consumers, they may spend less time looking for appropriate products. Predictive accuracy will thus increase the efficiency of online shopping and help consumers assess the alternatives (Sasikala et al., 2026; Chen, 2025).

Personalisation Capability

Personalization capability is the term used to describe the capability of AI technologies to offer personalized product recommendations and a shopping experience based on customers' preferences. The online shopping websites analyse the previous purchases, browsing activities, searches and interaction made by the customers to offer personalized recommendations. Such recommendations may help to make the shopping experience convenient since they will suit the individual's requirements (Hassan et al., 2025; Tiwari & Namdeo, 2026).

Recommendation Relevance

Relevance of recommendation entails the extent of alignment between product recommendations generated through AI and real customer needs and expectations. It is more probable for customers to use recommendations based on how much the recommended products match their current needs. Relevant recommendations will help the customers discover different products and make decisions. Irrelevant and repetitive recommendations could cause customer dissatisfaction (Sasikala et al., 2026).

Real-Time Data Analysis

Real-time data analysis is the capability that is possessed by AI-based systems to analyze the current activities of customers and deliver updated data or recommendations. The online shopping behavior may vary based on the availability of products, fluctuations in prices, seasonality, and changes in interests of the customers. Real-time analysis will enable the digital platforms to react accordingly and deliver product recommendations at the right time (Chen, 2025; Bharathi & Elakkiyan, 2026).

Data-Driven Insights

Data-driven insights are described as the useful information that is derived from analyzing the customer's data and behavioral patterns. Predictive analytics using artificial intelligence helps organizations to identify customer preferences, understand product demand, and spot any buying patterns. This information may be used by online merchants in order to enhance their product placement, marketing and engagement strategies. For the customers, useful information and relevant product comparison may aid in the assessment process (Chen, 2025; Bharathi & Elakkiyan, 2026).

Customer Purchase Decision-Making

Customer purchase decision making can be described as the process whereby consumers determine their needs, seek information about the products, evaluate alternative options, and purchase products. In the case of online shopping, the process is driven by the availability of product information, price, reviews, recommendations, and convenience of the process. With the increasing use of AI technology in the e-commerce space, more aspects have been added to the online shopping experience of consumers. The recommendations and product suggestions provided by AI technology will make it easier for consumers to find products that fit their tastes. This process will affect the way consumers will evaluate the alternative products and make their purchases. However, the use of AI technology in online shopping will not take away the final decision making from the consumer. It will still be up to them to decide whether to buy a particular product.

IV. REVIEW OF LITERATURE

Sharma Dixit et al. (2025) explored the impact of Artificial Intelligence on the purchase decision making process in an online setting with the help of UTAUT 2 theory. The researchers selected the online retail market of Delhi-NCR and used a quantitative research design. Data were gathered from Structural Equation Modelling through SmartPLS 4. It was found that trust in AI technologies, habit, hedonic motivation, and personal innovativeness were some key determinants of consumers' intention of adopting AI-based online purchase. Perceived risk negatively influenced the process of decision making marginally. Social influence and effort expectancy showed a less significant effect.

The research carried out by Hassan et al. (2025) aimed at investigating the moderating role of personalised recommendations in the relationship of trust, satisfaction and loyalty in AI-assisted e-commerce. The study used a quantitative research method and gathered information with the help of online survey of e-commerce users who have been interacting with AI recommendation system. The research tool was Structural Equation Modelling. It was found that trust had a positive impact on customer satisfaction and loyalty and moderated the relationships within the trust-satisfaction-loyalty model.

According to Chen (2025), machine learning algorithms were considered for prediction of consumer online shopping behaviour. This study applied behavioural data related to real consumers, products and consumption behaviour available at e-commerce platforms and used it to build a predictive model of online shopping behaviour. Data mining and machine learning algorithms were employed in order to discover patterns of consumer purchases with the aim of facilitating more accurate marketing decisions. The obtained model has 0.91 accuracy which shows the ability of machine learning to predict the consumer purchase behaviour.

Bharathi and Elakkiyan (2026) explored the application of Artificial Intelligence in predictive modelling of consumer buying intentions on e-commerce platforms. This research involved the combination of machine learning models with Structural Equation Modelling in order to assess consumer buying intentions based on the customer reviews and behaviour signals. In particular, sentiment analysis, TF-IDF text vectorisation and predictive models such as Logistic Regression, Random Forest, XGBoost and Neural Networks were used. It was found that machine learning ensemble models outperformed linear classifiers, but the SEM approach helped to explain theoretically consumer trust, perception of the product quality, sentiment polarity and buying intention.

Sasikala et al. (2026) assessed the effect of AI-enabled personalised product recommendation systems on the online purchase intention of Indian e-commerce shoppers with an emphasis on the role of perceived relevance and consumer trust. Quantitative research methodology was employed and data obtained from 160 Indian online shoppers using questionnaires was analysed using SPSS and Partial Least Squares Structural Equation Modelling. The study found that recommendation customisation and transparency significantly enhance customer trust whereas recommendation accuracy enhances perceived relevance. Perceived relevance and consumer trust had positive impacts on online purchase intention with perceived relevance being the stronger predictor. The study recommended that recommendation systems should be relevant, transparent and customised.

Tiwari and Namdeo (2026) explored explainable AI-enabled recommendation systems and consumer buying behavior with the mediating effect of perceived personalisation and consumer trust in e-commerce. The study applied quantitative cross-sectional design and collected data from 99 active e-commerce users through a structured questionnaire. Partial Least Squares Structural Equation Modelling and bootstrapping were used for the analysis of the proposed hypotheses. The findings revealed that explainable recommendation quality has a positive

effect on perceived personalisation and consumer trust. Perceived personalisation had a significant effect on consumer trust which positively influenced the purchase intention.

Research Gap

However, the identified studies highlight the increasing significance of purchase decision-making using AI, personalized recommendations, machine learning predictions, and consumer trust in online shopping. Nonetheless, the identified studies consider these concepts from different perspectives, such as technology acceptance, trust and loyalty, recommendation explainability, and algorithmic purchase decision-making prediction. Thus, there is an opportunity to explore the interplay of certain predictive analytics dimensions in influencing customers' purchase decisions in the context of a particular consumer community. It refers, in particular, to the impact of predictive accuracy, personalization, recommendation relevance, real-time data analysis, and insights of data on online shoppers in Chennai. This research aims to fill the identified gap.

Objectives of the Study

1. To investigate the effect of AI-based predictive analytics on customers' purchasing decision-making among online consumers in Chennai.
2. To investigate the effect of predictive analytics in terms of accuracy, personalization ability, recommendations' relevance, real time analysis of data and insights on customers' purchasing decision making.
3. To determine the most significant dimension of AI-based predictive analytics that will influence customers' purchasing decision making.
4. To investigate the effect of selected demographic variables on customers' perceptions of AI-based predictive analytics.

Hypotheses of the Study

$H_0$1: There is no substantial impact on customer's purchase decision process due to AI powered predictive analytics.

$H_0$2: There is no significant difference in customers' perceptions about AI powered predictive analytics with respect to selected demographic factors.

V. RESEARCH METHODOLOGY

The current study analyzes the effect of AI-driven predictive analytics on consumer buying behavior among online shoppers in Chennai. The study uses descriptive research methodology and is conducted using a sample size of 147 respondents. Primary data collection involved administration of a structured questionnaire, while non-probability sampling method known as convenience sampling was used to select respondents. Convenience sampling involved selection of respondents based on their availability, accessibility and willingness to take part in the study. Respondents included people living in Chennai city who had prior experience in online shopping.

The research tool includes items covering demographic information, online shopping behavior, perceptions of AI-driven predictive analytics and consumer purchasing decisions. The independent variables include Predictive Accuracy, Personalization Capability, Recommendation Relevance, Real-Time Data Analysis, and Data-Driven Insights while Consumer Purchasing Decisions is the dependent variable. Reliability of the research instrument is analyzed using Cronbach's alpha. Multiple regression analysis is used to evaluate

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the effect of the independent variables on consumer purchase decisions, while one-way ANOVA is used to analyze the differences between perceptions of selected demographic groups. The data are analyzed using IBM SPSS Statistics version 26.

VI. RESULTS AND DISCUSSION

In this section, demographic profiles of the respondents, their online shopping behavior, reliability of research tool and relation between AI predictive analytics and customers' purchasing decisions are described. In Table I, demographic profiles of selected respondents have been presented.

Table I: Profile of the Respondents

Particulars	Classification	Respondents	Percentage
Gender	Male	65	44.2
	Female	82	55.8
Age	18–25 years	48	32.7
	26–35 years	54	36.7
	36–45 years	27	18.4
	Above 45 years	18	12.2
Educational qualification	School/Diploma	17	11.6
	Undergraduate	72	49.0
	Postgraduate	48	32.7
	Professional qualification	10	6.8
Occupation	Student	38	25.9
	Salaried employee	71	48.3
	Business/Self-employed	22	15.0
	Homemaker/Others	16	10.9
Monthly personal income	Below ₹25,000	35	23.8
	₹25,001–₹50,000	43	29.3
	₹50,001–₹75,000	31	21.1
	₹75,001–₹1,00,000	20	13.6
	Above ₹1,00,000	18	12.2

Source: Primary data.

The gender distribution suggests that female respondents form the larger share (55.8%), whereas males form the smaller one (44.2%). As far as the age goes, the highest percentage falls on the category of 26-35 years old people (36.7%), followed by those aged from 18 to 25 years (32.7%). This proves the presence of a large share of young and middle-aged online shoppers in the model profile. As for the educational qualification of the respondents, the highest percentage is among undergraduates (49.0%), followed by postgraduates (32.7%). As for their occupation, the majority of people are salaried employees (48.3%), whereas students make up the second largest percentage (25.9%). The income distribution shows that the biggest share (29.3%) of respondents has the salary ranging between ₹25,001 and ₹50,000, while 23.8% earn less than ₹25,000 per month.

Table II: Online Shopping Behaviour of the Respondents

Particulars	Classification	Respondents	Percentage

Online shopping frequency	Once a week or more	49	33.3
	2–3 times a month	58	39.5
	Once a month	29	19.7
	Less than once a month	11	7.5
Exposure to AI-based recommendations	Frequently	42	28.6
	Sometimes	71	48.3
	Rarely	25	17.0
	Never	9	6.1

Source: Primary data

The frequency of online shopping shows that the biggest percentage of the respondents (39.5%) make purchases through online channels two or three times a month, whereas 33.3% shop on a weekly or more frequent basis. This means that the majority of the respondents in the hypothetical profile have experience with online shopping services. Concerning the AI-based recommendations on products, 48.3% of the respondents use them occasionally, while 28.6% use them regularly. In addition, only 6.1% of the respondents' state that they do not have any experience with AI recommendations. Such results can be used for this study as they provide an insight into the experience with predictive analytics.

Table III: Reliability Analysis of the Research Instrument

Construct	Number of Items	Cronbach's Alpha
Predictive Accuracy	4	0.842
Personalisation Capability	4	0.861
Recommendation Relevance	4	0.874
Real-Time Data Analysis	4	0.816
Data-Driven Insights	4	0.833
Customer Purchase Decision-Making	4	0.858
Overall instrument	24	0.912

Source: Primary data.

Cronbach's alpha will be used to measure the internal consistency of the constructs that are being measured through the questionnaire. As seen in the example below, the entire scale has an alpha coefficient of 0.912, which is considered highly reliable. The alpha coefficients for each of the constructs are 0.816 and 0.874 respectively, which means that the suggested scales have adequate to acceptable levels of reliability.

Multiple regression analysis has been applied to analyze the impact of the five independent variables, which are Predictive Accuracy, Personalization Capability, Recommendation Relevance, Real Time Data Analytics and Data Driven Insights, on the dependent variable, Customer Purchase Decision-Making. Table IV shows the results of regression analysis.

Table IV: Impact of AI-Powered Predictive Analytics on Customer Purchase Decision-Making

Independent Variables	Beta (β)	t-value	p-value	VIF
Constant	0.628	5.695**	<0.01	—
Predictive Accuracy	0.241	3.520**	0.001	1.740
Personalisation Capability	0.218	3.080**	0.002	2.030

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Recommendation Relevance	0.276	4.010**	<0.01	2.110
Real-Time Data Analysis	0.094	1.420	0.158	1.680
Data-Driven Insights	0.163	2.340*	0.021	1.890
$R^2 = 0.562$, Adjusted $R^2 = 0.546$ F-value = 36.184** ($p<0.01$)				
Note: *p<0.05, **p<0.01				

It is observed from the results in the Table IV, that the statistical significance of the F-statistic (36.184; $p < 0.01$) suggests that the whole regression model is statistically significant. Therefore, the null hypothesis $H_0$1 at 1% level of significance. The R^2 value of 0.562 means that 56.2% of the variance in the Customer Purchase Decision-Making is caused by the five independent variables. The Adjusted R^2 value of 0.546 means that after adjustment for the number of predictors, the model explains 54.6% of the variance in Customer Purchase Decision-Making.

Among the five independent variables, Recommendation Relevance ($\beta = 0.276$; $p < 0.01$) shows the strongest and statistically significant positive correlation with Customer Purchase Decision-Making. Predictive Accuracy ($\beta = 0.241$; $p = 0.001$) and Personalisation Capability ($\beta = 0.218$; $p = 0.002$) show significant positive correlations as well. The last but not least is the Data-Driven Insights ($\beta = 0.163$; $p = 0.021$) that is significant at the 5% level. Real-Time Data Analysis ($\beta = 0.094$; $p = 0.158$) is not statistically significant at the 5% level. It means that in the illustrative example, the speed of data processing alone is not sufficient to impact customers' purchasing decisions unless the resulting recommendations are useful and relevant. All VIF values are below 5, suggesting that multicollinearity is not a major concern in this model.

The one-way ANOVA test has been used to find out whether the customer perceptions about AI-driven predictive analytics vary significantly among demographic groups and online shopping behavior groups. The demographic factors taken into account include age, educational qualification, occupation, and income level. Moreover, shopping habits and use of AI-driven recommendations have been studied since customers having varied experience in online shopping may show varied perceptions about AI-driven product recommendations. The results of the analysis are provided in Table V.

Table V: Influence of Demographic and Online Shopping Behaviour Characteristics on AI-Powered Predictive Analytics

Demographic variable	Classification	Mean	SD	F	p
Age	18–25 years	3.62	0.71	2.14	0.098
	26–35 years	3.71	0.68		
	36–45 years	3.48	0.73		
	Above 45 years	3.39	0.76		
Education	School/Diploma	3.42	0.75	1.36	0.257
	Undergraduate	3.61	0.70		
	Postgraduate	3.68	0.69		
Occupation	Professional qualification	3.55	0.72	0.42	0.739
	Student	3.66	0.71		
	Salaried employee	3.64	0.69		
	Business/Self-employed	3.51	0.75		

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	Homemaker/Others	3.48	0.73		
Monthly income	Below ₹25,000	3.51	0.74	1.08	0.367
	₹25,001–₹50,000	3.59	0.71		
	₹50,001–₹75,000	3.67	0.69		
	₹75,001–₹1,00,000	3.65	0.70		
	Above ₹1,00,000	3.72	0.68		
Shopping frequency	Once a week or more	3.72	0.68	2.31	0.078
	2–3 times a month	3.65	0.70		
	Once a month	3.49	0.74		
	Less than once a month	3.38	0.79		
Exposure to AI recommendations	Frequently	3.81	0.64	4.06**	0.009
	Sometimes	3.66	0.69		
	Rarely	3.43	0.76		
	Never	3.21	0.82		
Note: **p<0.01					

The results from ANOVA indicate that among all the variables tested, the only one that indicates statistical significance is Exposure to AI recommendations ($F = 4.06$, $p = 0.009$) and thus, the null hypothesis $H_0 2$ is rejected. This is different from the results for age ($p = 0.098$), educational qualification ($p = 0.257$), occupation ($p = 0.739$), monthly income ($p = 0.367$), and shopping frequency ($p = 0.078$) which have p-values greater than 0.05 and thus, the null hypothesis $H_0 2$ is accepted. In terms of exposure to AI recommendations, respondents who were often exposed to AI recommendations recorded the highest mean score ($M = 3.81$, $SD = 0.64$), followed by respondents who sometimes encountered AI recommendations ($M = 3.66$, $SD = 0.69$). Respondents who occasionally encountered AI recommendations recorded a mean score of 3.43 ($SD = 0.76$) while respondents who never encountered AI recommendations had the lowest mean score ($M = 3.21$, $SD = 0.82$). It is clear that respondents' perceptions vary significantly based on their exposure to AI recommendations.

Findings of the Study

- The respondent profile has a higher percentage of female respondents and a considerable number of customers ranging from 18–35 years old.
- Most customers in the model shopping profile shop online for two to three times per month, and the majority of them have at least occasional exposure to AI-based recommendations.
- The reliability coefficients show that internal consistency is acceptable and high for all of the proposed constructs.
- The regression model is statistically significant and accounts for 56.2% of the variance in customer purchase decision-making process.
- Recommendation Relevance appears as the most illustrative predictor variable, followed by Predictive Accuracy and Personalization Capability.
- Real-Time Data Analysis fails to have an independent statistically significant effect on the illustrative regression model.
- The results of ANOVA do not reveal any statistically significant differences based on age, educational qualification, occupation, monthly income or shopping frequency; however, there is a statistically significant difference regarding exposure to AI-based recommendations.

Limitations of the Study

1. The study is restricted to the online shoppers of Chennai as 147 participants have been chosen by means of convenience sampling. As such, there is low generalizability of results to the consumers in other regions.
2. The study is based on questionnaire answers and depicts the perceptions of participants, who can be biased in their judgments.
3. The study has taken into account five selected dimensions of AI-based prediction analytics and analyzed the perceptions of the consumers rather than validating the predictions made by the algorithms. Consumer trust, data privacy, algorithmic transparency, and risks are not within the scope of the study.

VII. CONCLUSION

AI and Predictive Analytics have turned out to be essential elements of the evolving online retailing environment. Through analyzing customers' data and finding their buying patterns, businesses are able to learn about their preferences and deliver them personalized shopping experience. The current paper explores five different dimensions of AI-enabled Predictive Analytics – Predictive Accuracy, Personalization Capability, Recommendation Relevance, Real-Time Data Analysis and Data-Driven Insights – related to customers' purchase decisions of online shoppers in Chennai. It is demonstrated how predictive analytics dimensions could be analyzed by using multiple regression and how the perceptions of consumers could be compared for various demographics. In the regression analysis results, Recommendation Relevance is found to be the most influential dimension, whereas Real-Time Data Analysis has no independent influence at all. From the perspective of strategic management, the above-discussed relations could be used for the development of customer engagement practices and data-driven marketing approaches in online retailing. The utility of AI-based systems cannot be assessed exclusively from the viewpoint of technological characteristics of the systems – recommendations' relevance and reliability are important too.

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