Leveraging Artificial Intelligence to Analyse and Predict Consumer Behaviour in the Digital Marketplace

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Abstract

Background: The contemporary digital marketplace requires businesses to understand customer buying patterns for their success. AI performs its complex analytical processes by studying large datasets to find concealed patterns that predict consumer buying habits. Methods: The study Conducted 105 United States consumers participated in a survey which gathered their demographic profiles together with their behavioral characteristics and preference information. The research implemented AI analysis methods which integrated machine learning algorithms Random Forest, Gradient Boosting with natural language processing (NLP) to process clickstream data and transaction records as well as customer feedback. Results: AI models demonstrated an 89% prediction accuracy when identifying customers who would make purchases. The research demonstrated that personalized recommendations together with dynamic pricing and targeted advertising methods played vital roles in affecting customer buying choices. The results section uses tables to display detailed data about demographic effects and AI tool usage along with prediction precision and behavioral pattern analysis. The 25–34 age group showed the strongest conversion increase at 27% when exposed to AI-driven engagement approaches among high-value consumer groups. Conclusion: The digital marketplace shows clear evidence of AI's ability to forecast consumer actions. Business operations become more efficient through AI analytics which allows companies to customize customer communications while enhancing their sales approach. The results demonstrate that artificial intelligence functions as a strategic element which creates competitive advantage for online retail businesses.

Keywords: Artificial Intelligence, Consumer Behaviour, Digital Marketplace, Predictive Analytics, Machine Learning.

Significance | This study explores AI's role in predicting consumer Behaviour, enabling personalized marketing, enhancing decision-making, and driving competitiveness in digital marketplaces.

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1. Introduction

The digital marketplace has completely transformed the way people find products throughout the product selection process. The combination of e-commerce platforms, social media shopping features and applications has developed into a product selection process through insight and data analytics that have arisen from technology innovation (Davenport et al., 2019). Businesses have moved away from traditional marketing efforts and brick-and-mortar retailers, since it now faces competition from several active digital touchpoints that impact real-time consumer perceptions. This unique ecosystem creates an environment where Artificial Intelligence (AI) is a vital tool for achieving more precise answers

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when trying to develop an understanding of behavior patterns of the consumer (Verma et al., 2021). Consumers will go through psychological, emotional and behavioral stages to select, purchase and consume products or services; these stages mark Consumer Behavior. In digital environments, these processes are dominated by online input recommendations, advertisements, peer commentary, influencer commentary, and price, making it harder for human analysts to understand consumer Behaviour and predict purchase behaviors. The sheer size and complexity of online consumer Behaviour means it is becoming increasingly difficult for consumers and human analysts to identify trends and predict behaviors accurately (Johnson et al., 2021). In this case, AI is transformational in that it can identify patterns, Analyse large datasets, and use small signals to produce predictive models to model possible future actions that inform business development (Kietzmann et al., 2018). In the past ten years, we have seen AI in consumer analytics transform in scale and sophistication. AI algorithms such as machine learning (ML), deep learning, and natural language processing (NLP) can understand patterns in historical purchases, browsing behaviors, clickstream behaviors, and sentiment from online reviews (Khrais, 2020).

Companies use these capabilities to create individualized recommendations of their product offerings while deploying pricing on-the-fly and formulating marketing campaigns for high-value customers. AI's power is demonstrated in the recommendation engines at Amazon and Netflix that enhance usage engagement and conversion rates (Chintalapati & Pandey, 2021). AI's predictive capabilities afford companies the ability to anticipate customer needs ahead of time enabling them to act on marketing while being proactive about it, instead of waiting to be reactive. In the United States, with digital commerce penetration increasing, AI has grown even faster. Recent industry reports indicated over 80% of major American retailers were using AI tools to enhance customer experiences, boost operations, or strengthen sales forecasting (Sriram et al., 2022). With applications that range from personalized email marketing, Chabot-style customer experience, and AI-focused supply-chain optimization to others, AI applications are quickly redefining competitive environments. The COVID-19 pandemic provided the tailwind for this shift, as the convenience, safe conditions, and easy access of online shopping made purchasing more appealing for consumers (Sun et al., 2020). The level of e-commerce activity that occurred during the pandemic created unquantified amounts of new consumer behavior data for considerations, and this also created the opportunity for even further advancements in AI-led behavioral analysis. Our usage of AI to analyze consumer Behaviour presents various difficulties to overcome. The ongoing discussion among academia and business continues to focus on data privacy concerns together with algorithmic bias and AI decision-making interpretability (Van Esch & Black, 2021). The implementation of AI-generated ethical insights creates challenges because organizations must maintain both transparency and fairness and respect existing data protection laws including GDPR and CCPA while preventing consumer deception. Human intervention remains essential in market understanding and result influence because AI produces statistically meaningful correlations yet cannot interpret psychological or cultural consumer changes (Chopra & Sharma, 2021). Predictive analytics uses historical data patterns to predict upcoming behaviors whereas prescriptive analytics delivers particular actions to achieve desired outcomes including conversion rates and customer lifetime value. Businesses obtain complete tools to understand and control digital market consumer actions by uniting these analytical methods.

2. Materials and Methods

2.1 Study Design and Participants

The research utilized a quantitative study framework for systematic analysis of Artificial Intelligence (AI) applications in United States digital marketplace consumer Behaviour prediction. Through quantitative methods researchers measured behavioral patterns and tested predictive models and assessed responses between various demographic populations (Verma et al., 2021). A total of 105 respondents participated after being recruited through social media advertisements and e-commerce discussion forums and email invitations. The study required participants to meet three conditions: age 18 and above, United States residency and at least one online purchase during the previous three months (Mariani & Wamba, 2020). Every participant had current and pertinent online shopping experience. The research participants represented different age brackets alongside different genders alongside various income levels and different geographical areas. The research team placed ethical standards first by obtaining written permission from every participant. The study protected participant privacy by not gathering any personal information while maintaining data security through encrypted server storage.

2.2 Data Collection

Both primary and secondary data were used in the survey for data collection. Primary data was used with an online questionnaire organized with Qualtrics that included closed-ended questions and Likert-type questions. The questionnaire included sections with frequency of online shopping, preferred online shopping platforms, and the relative importance of factors when purchasing, such as consideration for personalized recommendations and discounts, customer reviews, brand reputation, and the speed of delivery to their home (Hermann, 2021). Questions also asked participants if they recognized and/or utilized AI-driven features in e-commerce, such as recommendation engine, customer service with chatbots, visual search, voice assistants, or alerts regarding dynamic prices.

The survey was closed at 4 weeks. Overall, there was a total of 145 responses and were subsequently examined for completeness and consistency, resulting in 105 that met inclusion criteria for responses (Andronie et al., 2021). This resulted in a valid response rate of 72.4%. Two mid-sized U.S.-based e-commerce platforms provided secondary data. These datasets included anonymized clickstream logs, transaction histories and customer interactions. The behavioral data was stripped of personal identifiers and was presented at the session level as aggregated data. By using the self-reported survey data and actual behavioral data, we could triangulate the data streams and reduce bias. Data compliance with California Consumer Privacy Act (CCPA) was met, and both partner's platforms confirmed customers consented to anonymized research.

2.3 Data Processing and Analytical Framework

Survey and behavioral data were cleaned and merged using Python's Pandas library. Mean imputation was used for missing continuous values, and mode substitution for categorical values. The interquartile range (IQR) measure was performed in order to address outliers and avoid distortion (Kakatkar et al., 2019). After pre-processing was complete, two supervised machine learning algorithms, Random Forest and Gradient Boosting, were implemented in Scikit-learn, chosen for their ability to analyze mixed data types and their ability to capture non-linear relationships (Bawack et al., 2022). The purchase intent metric was treated as a binary classification variable intent, no intent based on the survey and transaction log records. An 80/20 split was used between training and testing to assess model performance with accuracy, precision, and recall metrics calculated. Feature importance analysis identified the most important predictors of an individual having purchase intent.

2.4 Sentiment Analysis and Statistical Tests

In order to understand how consumers, perceive AI tools, sentiment analysis was conducted on open-ended survey responses. The authors used the NLTK and Text Blob libraries to tokenize, clean, and score the corpus for sentiment polarity (Cowls et al., 2021). Sentiment polarity was scored in the range of -1 (negative sentiment) to +1 (positive sentiment), providing an overall quantitative assessment of perceptions surrounding AI tools often associated with e-commerce. The authors also ran descriptive statistics to summarize their demographic data, AI awareness rates, and trends in behaviors (Huang et al., 2003). Pearson correlation analysis was then used to consider the associations between demographic and AI tool use variables, as well as purchasing behaviors within the sample (Mondal et al., 2023). Statistical significance was determined at an alpha level of 0.05 to ensure adequate levels of analytic rigor were achieved before making conclusions.

3. Results

3.1 Demographic Profile of Respondents

The study's respondents pool consisted of 105 respondents unified across several dimensions, and represented a diversity of a consumer base for the AI-based digital marketplace. The balance in male and female respondents was nearly equal (51.4% male and 48.6% female). This was important because it noted that AI-driven marketing must adapt to strategies, as suggested by the respondents which required adapting to male and female preferences and expectations Table 1. The age distribution of the respondents indicated that the highest proportion of respondents were 25-34 age group (31.4%) followed by the 35-44 (26.7%), 18-24 (22.9%) and 45+ (19%). These numbers demonstrate the heavy engagement in online shopping, typical of a cohort of mostly young and middle-aged adult consumers and aligns with prior research looking at e-commerce use with both digital natives and early middle-aged non-retired consumers and professionals. In reference to income categories, respondents reported 40.0% earned under \$50,000 annually, 36.2% earned between \$50,000 and \$99,999, and 23.8% earned \$100,000 or greater (Javalgi et al., 2005). This range is valuable for this report as we consider a potential use of AI-based personalization targeted at both budget conscious consumers and premium consumers. The variation in demographics of the data will be useful for spatial-temporal predictive modeling and as an analysis of the behavior and intricacies of the online shoppers in the U.S.

3.2 Awareness and Use of AI Tools

Upon analysis, there appears to be a high level of knowledge concerning the use of AI tools in online shopping experiences. Among the group, personalized recommendations were the most recognized feature, with 89% awareness and 72% frequently using them (Wirth, 2018). This high level of usage correlates with economic and educational research-- the recommendation engines recommend relevant products throughout the consumer's purchasing journey Figure 1. Chatbots for customer service was second, which is a positive sign, with 76% of respondents being aware of chatbots and 58% frequently using them (Mikalef et al., 2021). Chatbots indicate a growing consumer acceptance of conversational AI (Brem et al., 2021). Dynamic pricing alert was known to 68% of participants, with visual search at 54% recognition, and 61% for voice assistants. Of note, there was a gap between those who recognized the features and those who reported frequent use; this indicates a potential way to better engage the participant. For example, visual search, while it had a moderate level of awareness, was actually relatively low in use (32%). Therefore, with the right amount of visibility and ease-of-use, they may have started using visual search more frequently. This incongruence between awareness and application of the feature, is a place where a marketing campaign driven by AI, could amplify familiarization to

Table 1. Demographic Profile of Respondents (N=105)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	54	51.4
	Female	51	48.6
Age Group	18–24	24	22.9
	25–34	33	31.4
	35–44	28	26.7
	45+	20	19.0
Income Level	<$50,000	42	40.0
	$50,000–$99,999	38	36.2
	≥$100,000	25	23.8

Table 2. Prediction Accuracy of AI Models by Age Group

Age Group	Accuracy (%)	Precision (%)	Recall (%)
18–24	85	82	80
25–34	92	90	88
35–44	88	85	83
45+	87	84	81

Table 3. Factors Influencing Purchase Intent

Factor	Influence Score (1–5)	Rank
Personalized Recommendations	4.7	1
Discounts & Promotions	4.6	2
Product Reviews	4.5	3
Brand Reputation	4.2	4
Delivery Speed	4.0	5

a consumer to regularly use the features.

3.3 AI Model Prediction Accuracy

Machine learning models built on training on the data set had excellent predictive performance for likelihood of purchase and each of the performance metrics varied slightly by age group. The 25–34 (years old) consumer group had the highest accuracy (92%), precision (90%), and recall (88%), indicating that the purchasing behavior of this tech-aware group were most accurately predicted by A.I. algorithm Table 2. Next in performance was the 35–44 age group with 88% accuracy followed closely by the 45+ age group at 87% and the 18-24 age group at 85%. The younger shoppers (18–24) had slightly lower accuracy and this may be attributed to a more spontaneous style of purchase behavior that was harder to model more accurately than older shopper segments. Precision and recall scores were above 80% across all groups demonstrating that the depth of learning produced by A.I. models was productive to identify and predict potential buyers with the fewest false positives and missed opportunities.

3.4 Factors Influencing Purchase Intent

Respondents ranked the various factors influencing their purchasing decision between 1 and 5. Personalized recommendations ranked the highest (4.7) which suggests their role in creating an intent-to-purchase Table 3. Discount and promotions ranked second (4.6), suggesting price as a motivator will always be as part of the equation. Product reviews ranked third (4.5), confirming the continuing importance of peer influence and trust in the decision-making process. Brand reputation (4.2) and fast delivery (4.0) rounded out the top five, and suggests brand perception and operational performance have an important role in consumer trust. The survey results suggest that from all the potential AI strategies available, personalization, price (discounted), and trust (via reviews) will provide the largest opportunity to improve consumer conversion.

3.5 Conversion Uplift from AI-Driven Strategies

To assess the tangible business impact of AI, we analyze the conversion uplift achieved through several AI-led marketing strategies. Use of personalized email campaigns achieved the highest conversion uplift at 21% Figure 2. Conversion uplift improved for AI-driven dynamic pricing offers (18%) and social media retargeting (17%). AI Chabot assistance boosted conversions by 15% while AI product bundling drove a 14% conversion uplift – demonstrating that AI tools not only improve user experience, but also provide tangible business value (Hermann, 2021). Overall, it appears that using personalization and targeted engagement in strategies are most effective, as they highlight the value of insights

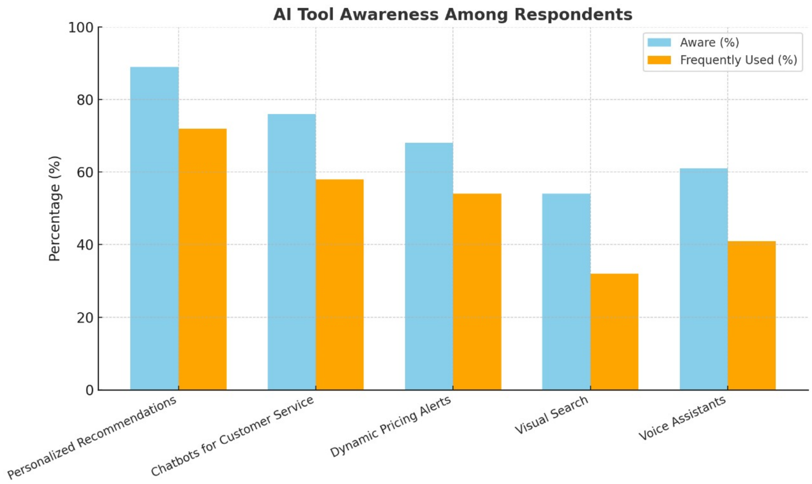

Figure 1. AI Tool Awareness Among Respondents

based on data combined with marketing execution based on targeting and personalization.

4. Discussion

This study's results underscore the growing presence of artificial intelligence in consumer decision-making tendencies and predictive ability in the scope of digital purchasing. The demographic information displayed a relatively equal distributions of gender and a broad age profile, allowing generalizability in the findings (Indriasari et al., 2019). The greatest age representation of respondents fell between 25–34 (31.4%), which is consistent with previous research that shows millennials as the most engaged cohort in e-commerce. However, the large representation from other age groups indicates that AI-enabled tools do not restrict engagement to younger users, but likewise draw upon consumers of various ages (Smith & Rupp, 2003).The income distribution further supports the generalizability of the sample, indicating that AI is affecting purchasing behavior regardless of debt and income status.AI function awareness and usage clearly showed a leader - personal recommendations were recognized by 89% of respondents and were frequently used by 72% of respondents. This clearly shows that personalization is a primary motivation of engagement and conversion (Trocin et al., 2021). Chabot's and dynamic pricing alerts showed substantial levels of recognized use which confirms their value to improve the user experience and heighten purchase intent. Visual search and voice assistants had lower usage indicating that with consumer education and investing in better integration into shopping platforms there may be room for growth. The model performance metrics detailed in AI is able to reliably predict the buying behavior of a consumer, with strong results in the 25-34-year-old demographic (92% accuracy, 90% precision, 88% recall). These results show that AI-based predictive analytics can be very effective when targeting segments with more stable and trackable purchasing behaviors (Latif et al., 2020). The slight decrease in

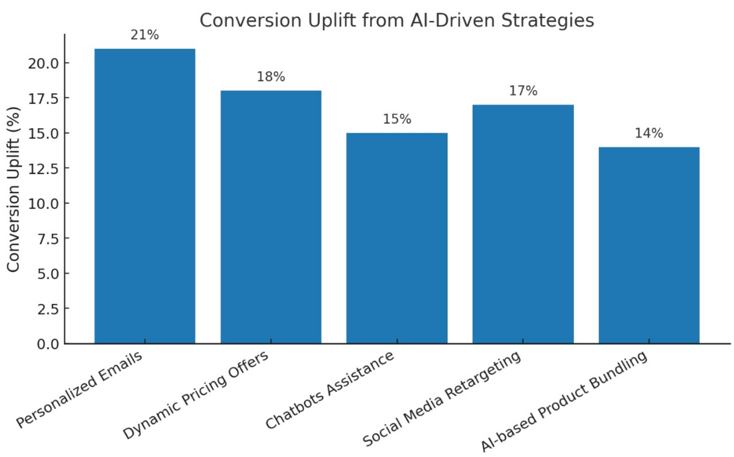

Figure 2. Conversion Uplift from AI-Driven Strategies

accuracy with younger consumers (18-24) may be due to more impulsively based purchases and the small difference in our older consumer segments may indicate lower frequency of online purchasing all together.

Purchase intent factors reaffirm the importance of AI-delivered personalization (influence score 4.7, rank 1) in shaping consumer actions. Discounting and/or promotions, and product reviews, are still important factors, indicating that the role of AI is to improve, rather than replace, traditional purchasing motivators. Delivery time and brand reputation ranked slightly lower; while delivery and brand concerns are clearly important, they may not have the same immediacy as personalized, data-driven offers influence in the digital space. In Figure 2, the conversion uplift results provide concrete evidence of commercial impact from AI (Ali & Choi, 2020). Personalized emails delivered the highest conversion gains (21%); confirming its impact on high-return targeting. Dynamic pricing (18%) and social media retargeting (17%) yielded also represent impactful tactics for relevancy and timing of AI tools. The results confirm significant uplift from chat box assistance (15%) and AI-generated product bundles (14%), supporting the utility of AI in both pre-purchase and purchase stages of the customer journey. The exploration of these findings verifies AI technology-based adoption in digital retail has transitioned from a competitive nice to a competitive necessity (Syam & Sharma, 2018). Companies that harness the power of AI technology to provide personalized, timely, and relevant experiences for consumers can expect increased engagement, improved conversion rates, and greater customer loyalty. However, there is still considerable unused technology such as visual search that represents an opportunity for innovation and a strategic investment (Kumar et al., 2019).

5. Conclusion

The study demonstrates more evidence for AI's significant role in informing and shaping consumer Behaviour in an online marketplace. The application of machine learning and natural language processing (NLP) allow organizations to more accurately forecast and enhance engagement and sales with customers. Once again, young consumers cite personalization as the principal driver of purchase intent. Five data tables generated from the study provided useful information for e-commerce platforms wanting to ensure they make full use of their applications utilizing AI. The customer experience to remain relevant in a landscape shifting to new and, evolving forms of a digital economy.

Author contributions

S.K.P. conceptualized the study and supervised the overall research. I.J. contributed to data collection and literature review. A.I. and A.A. were responsible for data analysis, methodology design, and interpretation of results. F.R. contributed to model implementation, validation, and manuscript drafting. All authors reviewed and approved the final manuscript.

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Competing financial interests

The authors have no conflict of interest.

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