Advances in Consumer Research
ISSN (Print): 0098-9258
ISSN(Online): 3079-1766

Vol. 2, Issue 2 (2025) https://acr-journal.com/

Machine Learning for Product Development: Predicting Consumer Preferences and Market Trends

Dr. Asad ullah[*1], Arif Deen[2], Syed Arshad Hussain[3], Dr.Naim Ayadi[4]

[1]Assistant Professor, Department of Management Studies, Middle East College, Muscat, Oman
Email ID: contactasad1985@gmail.com
[2]Senior Lecturer, Department of Management Studies, Middle East College, Muscat, Oman
Email ID: deen.arif01@gmail.com
[3]Senior Lecturer, Department of Management Studies, Middle East College, Muscat, Oman
Email ID: syedarshadhussain92@gmail.com
[4]Senior Lecturer, Department of Management Studies, Middle East College, Muscat, Oman
Email ID: naim150107@gmail.com

Cite this paper as: Dr. Asad ullah, Arif Deen, Syed Arshad Hussain, Dr.Naim Ayadi, (2025) Machine Learning for Product Development: Predicting Consumer Preferences and Market Trends. *Advances in Consumer Research*, 2 (2), 873-878.

KEYWORDS
Machine learning (ML), Product Development, prediction, Market trends.
)

ABSTRACT
Product administrators may now make better choices about costs, advertising, and development of products thanks to machine learning (ML), which is transforming analytical forecasting. They may search through enormous databases for unseen relationships or trends using this equipment, which gives them fresh perspectives on how decisions are made. A person pursuing a career in machine learning product management has to be well-versed in statistical analysis, mathematics, and the constraints of adaptive programming. To predict future trends and make better judgments about managing products, advanced machine learning algorithms can evaluate previous sales data. Additionally, they may use consumer preferences for items to tailor recommendations to make items and services stand out and inspire fresh, clever ideas for internet marketing. Managers of products may also benefit from using machine learning technologies to set goals for developing products and discover features that consumers find most useful.

1. INTRODUCTION

The research on buyer preferences focuses on the beliefs and tastes influencing consumers' purchasing decisions. Machine learning Market analysts rely heavily on forecasting technology since it makes precise forecasts. Decision-making has been made easier and procedures have been relieved by big-data systems and data linkage. Gaining insight into customer behaviour is essential for company expansion and advertising. The examination of consumer behaviour centres on societal, demographic, and emotional factors. Meaningful technical improvements in Indian companies have increased managing clients in the modern age. Analytics has unlocked the full potential of studying customer behaviour on product creation and brought cutting-edge solutions for managing consumers. Analytics solutions identify correlations between purchasing intents and demographics to assist companies in comprehending their intended customer base and market conditions. Decision-makers in charge of planning and execution may make decisions with confidence thanks to analytics' assistance in getting vital data to them. Better and more tailored insights are produced by predictive analysis, and these insights help businesses make choices that support raising customer happiness and choosing efficient marketing tactics. The primary goal of this study is to analyse and forecast market conditions and consumer habits using ML techniques and guided prediction techniques.

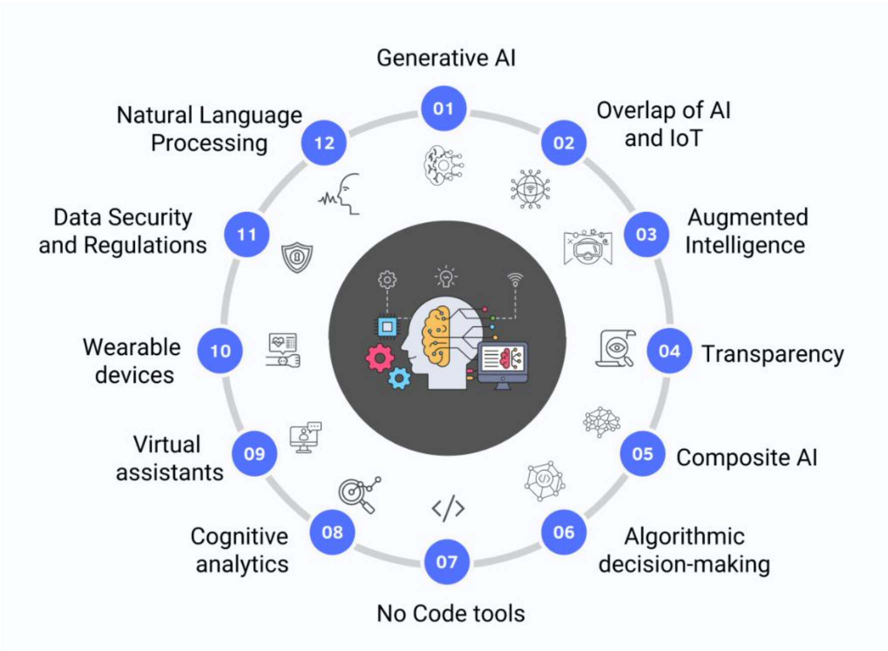

Figure 1: Emerging trends of ML tools in recent years

(Adapted from Arefin, *et al.*, 2024)

Objectives:

The key targets for the study are based on exploring several aspects of machine learning tools which can be beneficial for effective product development. There has been investigated the evolving market trends and consumer preferences through implementing different machine learning tools and algorithms. By deploying such technologies in the marketplace, businesses can effectively predict the upcoming business trends in the marketplace. Moreover, the business management can effectively anticipate the evolving preferences of the potential consumers (Yi and Liu, 2020). The study targeted to obtain an in-depth insights and knowledge about machine learning for the development of new products and innovations based on the ongoing market trends and consumer choices.

2. LITERATURE REVIEW

The review is based on the comprehensive overview of various existing studies and evidence from authentic sources. The review focuses on exploring several ML techniques and their unique applications in product marketing and development. Machine learning is generally classified into three types of learning including the reinforcement, supervised, and unsupervised learning (Ni *et al.*, 2020). Each type of ML tools has unique application in the respective fields. The use of ML tools can potentially provide significant benefits for product marketing. It can effectively help for classification, regression, and clustering of the current marketplace. The ML approach requires to follow the significant steps to determine the market analytics for product development and the steps include data collection, model training, problem statement, evaluation, and implementation (Miklosik and Evans, 2020). By going through the process, the businesses can significantly enhance data security, privacy, interoperability of the model, and automated services.

- ***Analysis of client preferences and Demands:***

The tastes and wants of customers are essential to the profitability of a product, and academics often examine these demands and tastes from several angles. These include machine learning techniques, decision simulation, improvement, and online goods reviews. Unfortunately, most emotional analysis techniques are not appropriate for customer requirements research since they are unable to filter out ineffective assessment data. This research focuses on sentiment evaluation approaches that eliminate incomplete reviews utilizing fastText via a trained filtering procedure. While the majority of the study forecasts online messages without a severity score, uncontrolled algorithms employ a list of emotive lexicons conceptually, that may not be adequate to assess customer happiness. The study suggests using VADER, an unsupervised method that outperforms human researchers in terms of F1 score, to quantify forecast customer happiness. Furthermore, product qualities may be extracted using methods to analyze sentiment to learn what customers think about them. A product ecosystem's many consumer demands may be analyzed using methods like efficient deployment, topic simulation, and obtained named element identification. This method enables the analysis of relationships between various items by grouping consumer wants inside a certain category.

- ***The process of machine learning:***

There are several steps involved in learning machine learning (ML). The investigator determines the kind of issue and type of data needed in the first step, which is issue description and dataset construction. The issue determines whether success measurements, like exactness or mean standard accuracy, are used. The framework is developed with a hold-out verification dataset, K-fold cross-validating, or repeated K-fold confirmation once the evaluation methodology is set up. After that, information is prepared and the model is trained for a particular purpose. The level of preciseness of the model ought to exceed 0.5 as the anticipated value of a random guess. The definition of the optimizer connects the model variables with the loss functions. The model will then be scaled up to see how well it extends. To ensure that the prediction can fit a broad range of functions, the optimal model strikes a compromise between under-fitting and overfitting. The next steps are regularity and tweaking, which may be completed faster and with less work thanks to recent advancements like automatic machine learning (AutoML). The model may be evaluated and put to use in the actual world when it has been improved. A prototype in production requires more care and safeguards to maintain.

3. METHODOLOGY

The study adopts secondarily sourced data to provide insights about machine learning tools and its potential applications in different sectors. The data has been gathered from industry reports, historical sales information, market analytics reports, and other digital media data. Based on the obtained information, Ml algorithms are effectively used in evaluating data (Potla and Pottla, 2024). In the study, the qualitative findings are obtained by considering evidence-based studies and analytics.

Machine learning categories:

Machine learning (ML) can be classified into three primary varieties: supervision, autonomy/unsupervised, and reinforcement learning. Classes and regression are techniques used in supervised instruction, which convert inputs into outputs using labelled practice sets. Support vector machines, or SVM, random forests, and logistical and linear regression methods are a few instances of supervised learning techniques. Finding fascinating trends in data is the goal of unsupervised learning, which does not use objectives or outputs. Mapping circumstances to behaviours to optimize the numerical incentive signal is known as reinforcement learning (RL). RL Is different from supervised learning in the fact It prioritizes exploration overexploiting and Is incapable of locating concealed structures. Uses of RL involve self-driving vehicles, robotics, and games.

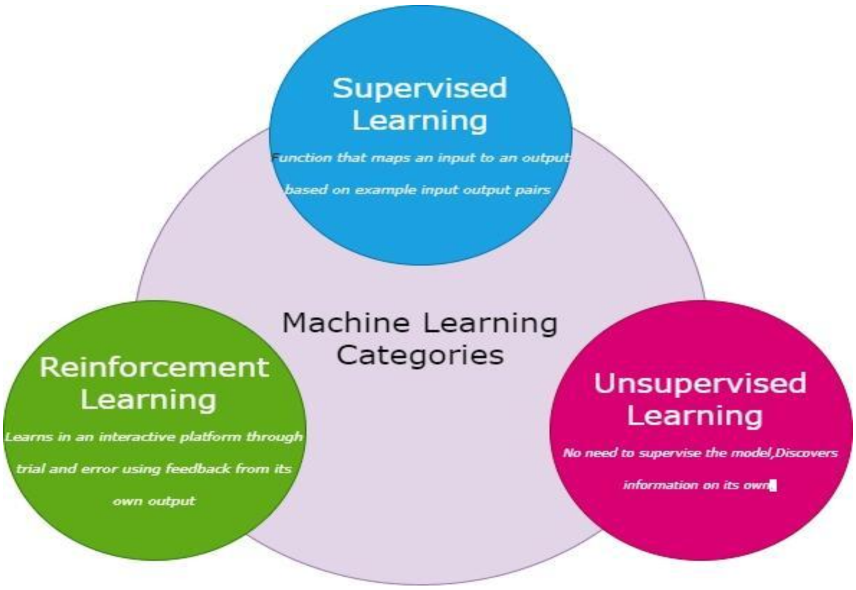

Figure 2: Machine learning categories

(Adapted from Bharadiya, 2023)

Machine learning's applicability to marketing:

Classifying and regression difficulties, grouping, imagining, decreased dimensionality, laws of association, and reinforcement-learning devices are just a few of the many benefits that machine learning (ML) brings to the marketing industry. As opposed to conventional econometric techniques, machine learning (ML) prioritizes managing big factors, attaining flexibility, and producing the most accurate out-of-sample projections (Jain *et al.*, 2021). It can manage numerous factors and can be generated in scenarios without having a predetermined hypothesis for gathering data. Predictive modelling provides a potent viewpoint for marketing creation and testing. Machine learning (ML) techniques in marketing use any combination of descriptive/exploratory or predicting approaches.

The process of machine learning:

To solve an issue, the machine learning pipeline goes through many steps. The researcher defines the issue and gathers the information set in the first step, during which they verify the nature of the issue and identify all the inputs, results, and necessary data. The issue determines whether success measurements, this exactness or mean typical accuracy, are used (Bharadiya, 2023). Techniques like K-fold cross-validation and repeated K-fold verification are used, and the assessment methodology Is set up. After that, the data is prepared, and the model gets taught to provide the intended result. An optimizer is established, which connects both the loss operation and model settings. The model will then be scaled up to see how well it applies. To ensure that the system can fit a broad range of processes, the optimal model strikes a compromise between underfitting and excessive fitting. After that, the system is tuned and regularized, adjusted, trained, and tested again until it reaches its optimal state (Zhou, *et al.,* 2020). The work and time spent needed to establish and optimize a model has been decreased because of autoML. The model may be verified and put to use in the actual world after a suitable arrangement has been reached. A framework in production requires more care and safeguards to maintain.

To summarize, there are several steps in the machine learning process: issue description, assessment protocols, achievement measures, collecting data, scalability, periodicity, and modification.

Future directions and product developments in machine learning for marketing:

- ***Automated machine learning or autoML:***

The technique known as automated machine learning, or AutoML, makes it possible for non-experts to carry out activities like preparing data for analysis, feature design, collection and choices, method choosing, and optimization of parameters by automating the integration of machine learning or ML to situations in reality. The need for techniques that are simple enough for non-specialists to utilize has resulted from this. In advertising analytics and relationship-based marketing, autoML may be very helpful since it improves consumer connections and makes relevant, tailored offers (Arefin, *et al.,* 2024). Solving managing identities across equipment, identification numbers, categories of data, and vocabulary and style norms is necessary for analysing consumer data since customers are using a growing amount of devices. Through the mapping of the consumer journey to buy, autoML enables businesses to interact with consumers more deeply and personally, hence introducing novel approaches to advertising. It may also do intricate “what-if” analysis to measure the efficacy of different marketing campaigns and interaction pairings (Xu, *et al.,* 2022).

- ***Safety and confidentiality of data:***

Thanks to innovations like networking sites, online computing, and analytical motors, privacy and security of data are becoming more and more important. Big data industries may include several entities with various privacy standards, such as the healthcare and finance industries. Social network extraction, outsourcing records, analytics that protect security, data sharing protocols, massive graph evaluation, and cloud-enabled management of databases are some of the difficulties. For AI and ML uses, conventional confidentiality methods like k-anonymity, l- variety, and t-closeness are inadequate (Ma, and Sun, 2020).

- ***Interpretation of the model:***

AutoML seeks to solve privacy and security issues by automating complicated operations; nevertheless, it encounters obstacles since machine learning models, or “black-box structures,” do not provide a reason for their predictions. Because of this, it can be hard to clarify forecasts without the use of causal approaches, and conducting studies is costly and takes time (Birim *et al.,* 2024). To detect and reduce bias, enhance conclusions, and stay clear of moral and legal ambiguities, machine learning (ML) suggests that models be interpretable. While specific algorithms provide accessible models, many significant improvements in machine learning employ black-box approaches. Local replacements (LIME), Shapley metrics, and featured significance are examples of modelling-agnostic techniques that have been developed as a result of recent advancements in model understanding (Van Nguyen, *et al.,* 2020). Feature significance gauges how relevant a feature is to raising the prediction made by an error, which streamlines the algorithm and improves dependability. Large amounts and intricate decision models are possible using Shapley parameters, a collaborative game theory that makes forecasts by treating every feature variable as a “player” in a contest. LIME creates a fresh data set of permuted specimens and matching projections, which is then used to explicate each assumption made by black-box machine learning models.

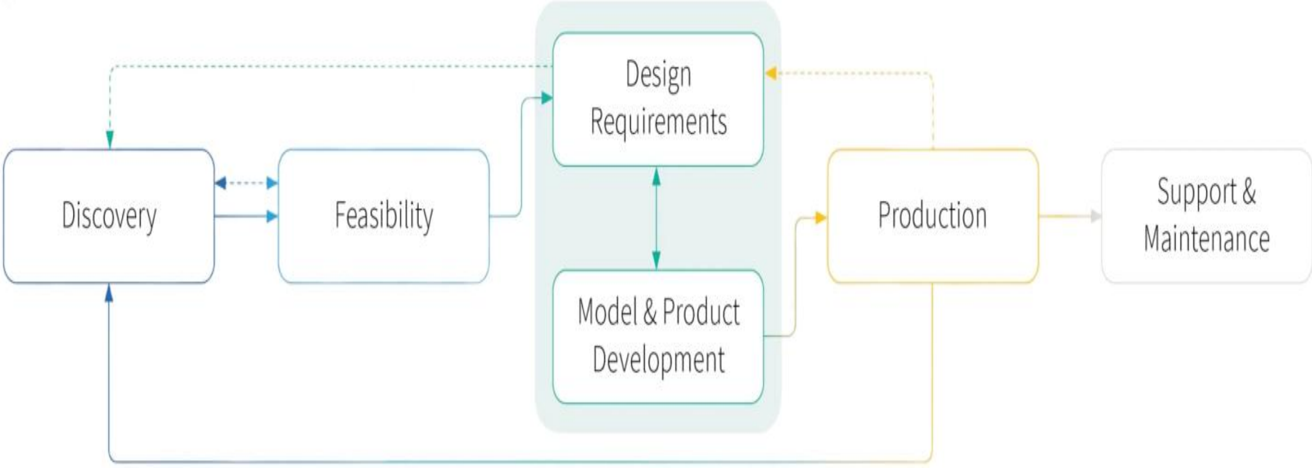

Figure 3: Model for ML-based product development

(Adapted from Potla and Pottla, 2024)

- ***Bayesian machine learning:***

With a few adjustments, the stages of classical machine learning (ML) are followed by the Bayesian machine learning (BML) approach. Its foundation is an evolutionary process that explains the creation of data and includes unclear model variables. Prior views about these guidelines, which take the shape of distributes across potential outcomes for the factors, are included in the equation. The facts are characterized as experiences made via the generating processes (Aamer, *et al.*, 2020). An Improved belief about the settings is derived from the new dispersion of the attributes after the execution of the instruction procedure. BML is especially helpful once there are numerous uncertain model variables, limited data is accessible, the scholar wants to quantify the range of ambiguity for the outcomes, or the investigator has preconceived notions regarding uncertain parameter values or data creation (Martínez, *et al.*, 2020). For a study on marketing, BML provides benefits like analytical insights, accessible processes, interpreted outcomes, and forecast accuracy. The field of advertising is already changing as a result of recent machine learning advancements, and as additional advertising experts use ML, these effects will only grow more noticeable.

4. CONCLUSION:

The needs, applications, and effects of machine learning (ML) for marketing purposes are covered in this text. An introduction to artificial intelligence (AI) and machine learning (ML), including its primary techniques, methods, and applicability to advertisement, is given, along with information on how ML may be learned by marketing scientists. Some of the shortcomings of the area, like the “recombination crisis” brought on by inadequate statistical strength, inferior methods for testing, and sound analytical techniques, may be lessened with the use of machine learning. The use of natural language processing, recognition of speech, virtual or augmented reality, and freely available web apps are also covered in this article. Advances in equipment, such as quantum computation, will also have a big influence on the area. Millions of customers are now impacted by ML’s marketing applications globally, which provide substantial potential and problems for advertisers.

REFERENCES

[1] Arefin, S., Parvez, R., Ahmed, T., Ahsan, M., Sumaiya, F., Jahin, F. and Hasan, M., 2024, May. Retail Industry Analytics: Unraveling Consumer Behavior through RFM Segmentation and Machine Learning. In 2024 IEEE International Conference on Electro Information Technology (eIT) (pp. 545-551). IEEE. https://ieeexplore.ieee.org/abstract/document/10609927/

[2] Bharadiya, J.P., 2023. Machine learning and AI in business intelligence: Trends and opportunities. International Journal of Computer (IJC), 48(1), pp.123-134. https://scholar.googleusercontent.com/scholar?q=cache:1WYuCwcc8BcJ:scholar.google.com/+Machine+Learning+for+Product+Development:+Predicting+Consumer+Preferences+and+Market+Trends&hl=en&as_sdt=0,5&as_ylo=2020

[3] Ma, L. and Sun, B., 2020. Machine learning and AI in marketing–Connecting computing power to human insights. International Journal of Research in Marketing, 37(3), pp.481-504. https://www.sciencedirect.com/science/article/abs/pii/S0167811620300410

[4] Martínez, A., Schmuck, C., Pereverzyev Jr, S., Pirker, C. and Haltmeier, M., 2020. A machine learning framework for customer purchase prediction in the non-contractual setting. European Journal of Operational Research, 281(3), pp.588-596. https://www.sciencedirect.com/science/article/abs/pii/S0377221718303370

[5] Van Nguyen, T., Zhou, L., Chong, A.Y.L., Li, B. and Pu, X., 2020. Predicting customer demand for remanufactured products: A data-mining approach. European Journal of Operational Research, 281(3), pp.543-558. https://www.sciencedirect.com/science/article/abs/pii/S037722171930668X

[6] Xu, Z., Zhu, G., Metawa, N. and Zhou, Q., 2022. Machine learning based customer meta-combination brand equity analysis for marketing behavior evaluation. Information Processing & Management, 59(1), p.102800. https://www.sciencedirect.com/science/article/abs/pii/S0306457321002788

[7] Zhou, F., Ayoub, J., Xu, Q. and Jessie Yang, X., 2020. A machine learning approach to customer needs analysis for product ecosystems. Journal of mechanical design, 142(1), p.011101. https://asmedigitalcollection.asme.org/mechanicaldesign/article-abstract/142/1/011101/956266/A-Machine-Learning-Approach-to-Customer-Needs

[8] Ni, D., Xiao, Z. and Lim, M.K., 2020. A systematic review of the research trends of machine learning in supply chain management. International Journal of Machine Learning and Cybernetics, 11, pp.1463-1482. https://www.researchgate.net/profile/Du-Ni/publication/338101452_A_systematic_review_of_the_research_trends_of_machine_learning_in_supply_chain_management/links/5dfe473692851c8364907c6c/A-systematic-review-of-the-research-trends-of-machine-learning-in-supply-chain-management.pdf

[9] Miklosik, A. and Evans, N., 2020. Impact of big data and machine learning on digital transformation in marketing: A literature review. Ieee Access, 8, pp.101284-101292. https://ieeexplore.ieee.org/iel7/6287639/8948470/09103568.pdf

[10] Potla, R.T. and Pottla, V.K., 2024. AI-Powered Personalization in Salesforce: Enhancing Customer Engagement through Machine Learning Models. Valley International Journal Digital Library, pp.1388-1420. https://vipublisher.com/index.php/vij/article/download/487/461

[11] Jain, P.K., Pamula, R. and Srivastava, G., 2021. A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews. Computer science review, 41, p.100413. https://arxiv.org/pdf/2008.10282

[12] Birim, S., Kazancoglu, I., Mangla, S.K., Kahraman, A. and Kazancoglu, Y., 2024. The derived demand for advertising expenses and implications on sustainability: a comparative study using deep learning and traditional machine learning methods. Annals of Operations Research, 339(1), pp.131-161. https://link.springer.com/content/pdf/10.1007/s10479-021-04429-x.pdf

[13] Aamer, A., Eka Yani, L. and Alan Priyatna, I., 2020. Data analytics in the supply chain management: Review of machine learning applications in demand forecasting. Operations and Supply Chain Management: An International Journal, 14(1), pp.1-13. https://journal.oscm-forum.org/journal/journal/download/20201206171323_Paper_1_Vol._14_No_._1,_2021_.pdf

[14] Yi, S. and Liu, X., 2020. Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review. Complex & Intelligent Systems, 6(3), pp.621-634. https://link.springer.com/content/pdf/10.1007/s40747-020-00155-2.pdf

❖❖❖❖❖