

PREDICTIVE DATA SCIENCE AND MLOPS FRAMEWORKS FOR AI-DRIVEN MARKETING ANALYTICS AND DECISION SUPPORT

Rahul Gupta, Ananya Desai & Vivek Kulkarni

School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

ABSTRACT

The rapid growth of Artificial Intelligence (AI), predictive data science, and Machine Learning Operations (MLOps) has transformed modern marketing by enabling organizations to make faster, more accurate, and data-driven decisions. Businesses increasingly rely on predictive analytics to understand customer behavior, forecast market trends, evaluate marketing campaign performance, and optimize strategic decision-making. However, many organizations continue to face challenges related to model deployment, scalability, continuous monitoring, data quality, and the integration of machine learning models into real-world business environments. This study proposes a Predictive Data Science and MLOps framework for AI-driven marketing analytics and decision support that integrates predictive modeling, automated machine learning deployment, continuous model monitoring, and intelligent business analytics into a unified system. The proposed framework enhances marketing efficiency by enabling organizations to generate accurate customer insights, optimize resource allocation, improve campaign effectiveness, and support evidence-based decision-making. MLOps practices ensure that predictive models remain reliable, scalable, secure, and continuously updated as new marketing data become available. The study adopts a quantitative research approach to evaluate the effectiveness of the proposed framework using data collected from marketing professionals, business analysts, and data scientists. The expected findings indicate that integrating predictive data science with MLOps significantly improves forecasting accuracy, marketing performance, customer segmentation, and organizational decision-making. Furthermore, the framework supports continuous model improvement while reducing operational risks associated with machine learning deployment. This study contributes to the growing field of AI-driven marketing analytics by presenting a practical framework that combines predictive intelligence with modern MLOps practices to improve business performance, strategic planning, and competitive advantage in dynamic marketing environments.

KEYWORDS: Predictive Data Science, MLOps, Artificial Intelligence, Marketing Analytics, Decision Support.

Article History

Received: 05 Jun 2025 | Revised: 07 Jun 2025 | Accepted: 14 Jun 2025

INTRODUCTION

Artificial Intelligence (AI) has become one of the most influential technologies driving innovation in modern marketing. Organizations increasingly rely on AI-powered systems to analyze customer behavior, forecast market trends, personalize marketing campaigns, and support strategic business decisions. The rapid growth of digital platforms and the continuous generation of large volumes of customer data have created new opportunities for businesses to apply predictive data

science in understanding consumer preferences and improving marketing performance. As a result, predictive analytics has become a valuable tool for organizations seeking to gain competitive advantages through data-driven decision-making (Jordan & Mitchell, 2015). Predictive data science combines statistics, machine learning, and artificial intelligence to analyze historical and real-time data for forecasting future outcomes. In marketing, predictive models assist organizations in identifying potential customers, predicting purchasing behavior, estimating customer lifetime value, detecting market trends, and optimizing advertising strategies. Mahajan et al. (2025) demonstrated that predictive Bayesian models provide reliable approaches for measuring marketing campaign effectiveness by improving prediction accuracy and supporting evidence-based marketing decisions. Similarly, Provost and Fawcett (2013) emphasized that predictive analytics enables organizations to transform business data into actionable knowledge that enhances operational performance and strategic planning. Although predictive models provide valuable business insights, deploying machine learning models into production environments presents several operational challenges. Many organizations struggle with model deployment, scalability, continuous monitoring, version control, data management, and model maintenance. Machine learning models often experience performance degradation due to changing customer behavior, evolving market conditions, and data drift. Consequently, organizations require systematic approaches that ensure predictive models remain accurate, reliable, and continuously updated throughout their operational lifecycle (Sculley et al., 2015). Machine Learning Operations (MLOps) has emerged as an effective solution for managing the complete lifecycle of machine learning systems. MLOps integrates software engineering, DevOps principles, automation, and machine learning practices to support efficient model development, deployment, monitoring, maintenance, and continuous improvement. According to Dutta et al. (2026), MLOps enables organizations to operationalize machine learning models by improving collaboration among data scientists, software engineers, and business stakeholders while ensuring scalable and reliable AI deployment. Modern MLOps frameworks automate model retraining, performance monitoring, validation, and deployment, allowing organizations to respond quickly to changing business environments. Marketing analytics has also evolved significantly through the integration of AI technologies. Organizations now utilize machine learning algorithms to segment customers, personalize advertisements, optimize pricing strategies, predict customer churn, and improve marketing return on investment. AI-powered decision support systems analyze complex datasets in real time, enabling marketing managers to make informed strategic decisions based on predictive insights rather than intuition. The combination of predictive data science and MLOps therefore provides organizations with a comprehensive framework for developing intelligent marketing systems capable of adapting to dynamic market conditions. Despite the growing adoption of predictive analytics and MLOps, existing studies often examine predictive modelling and machine learning deployment separately. Limited research has integrated predictive data science, MLOps practices, AI-driven marketing analytics, and decision support into a unified framework capable of supporting end-to-end business intelligence. This gap highlights the need for a comprehensive framework that combines predictive modelling, automated deployment, continuous monitoring, and intelligent decision support for modern marketing environments. Therefore, this study proposes a Predictive Data Science and MLOps Framework for AI-Driven Marketing Analytics and Decision Support. The framework integrates predictive machine learning models with automated MLOps practices to improve marketing performance, enhance forecasting accuracy, optimize business decision-making, and support sustainable organizational growth. The study contributes to the advancement of marketing analytics by providing a practical model that enables organizations to deploy trustworthy, scalable, and intelligent AI solutions for competitive business success.

LITERATURE REVIEW

Predictive data science has become an essential component of modern marketing analytics because it enables organizations to transform large volumes of business data into meaningful insights that support strategic decision-making. The increasing availability of customer data from digital platforms, e-commerce websites, social media, and customer relationship management systems has encouraged businesses to adopt predictive analytics for improving marketing performance. Predictive data science combines statistics, machine learning, artificial intelligence, and data mining techniques to identify patterns, forecast future outcomes, and optimize business operations (Jordan & Mitchell, 2015). Consequently, organizations can make informed decisions based on data-driven evidence rather than intuition. Artificial Intelligence has significantly improved marketing analytics by enabling businesses to automate customer segmentation, predict purchasing behaviour, optimize pricing strategies, and personalize marketing campaigns. Goodfellow et al. (2016) explained that deep learning models have transformed predictive analytics by improving the ability of AI systems to analyze complex datasets and generate highly accurate predictions. Similarly, Mahajan et al. (2025) demonstrated that Bayesian predictive models effectively measure marketing campaign performance by estimating campaign impact and supporting evidence-based decision-making. These findings highlight the growing importance of predictive modelling in improving organizational competitiveness. Machine Learning Operations (MLOps) has emerged as an important discipline for deploying and maintaining machine learning models in real-world business environments. Traditional machine learning projects often face challenges related to model deployment, version control, continuous monitoring, reproducibility, and collaboration between data scientists and software engineers. Sculley et al. (2015) described these challenges as technical debt within machine learning systems, emphasizing the need for structured operational frameworks. Dutta et al. (2026) further explained that MLOps integrates machine learning with DevOps practices to automate model development, testing, deployment, monitoring, and maintenance, thereby improving operational efficiency and model reliability. Modern MLOps frameworks support the complete lifecycle of machine learning models by enabling automated retraining, continuous integration, continuous deployment (CI/CD), performance monitoring, and governance. Zaharia et al. (2018) introduced MLflow as an open-source platform that simplifies experiment tracking, model deployment, and lifecycle management for machine learning applications. These technological advancements enable organizations to deploy predictive models more efficiently while ensuring consistent performance under changing market conditions. Marketing analytics has also evolved through the integration of predictive modelling and MLOps. Businesses increasingly utilize AI-powered predictive systems to forecast customer demand, evaluate advertising performance, estimate customer lifetime value, predict customer churn, and optimize marketing investments. Davenport and Harris (2017) argued that organizations capable of effectively utilizing analytics achieve superior business performance and sustainable competitive advantage. Similarly, Kotler et al. (2022) emphasized that data-driven marketing enables organizations to develop customer-focused strategies that improve market responsiveness and profitability. Despite these technological advancements, several challenges remain. Predictive models may experience performance degradation due to changing customer behaviour, evolving market conditions, and poor-quality data. Furthermore, the absence of standardized deployment procedures often limits the scalability and long-term sustainability of machine learning systems. Existing studies have primarily examined predictive analytics and MLOps independently, with limited attention given to integrating these technologies into a unified framework for AI-driven marketing analytics and decision support. Therefore, this study proposes an integrated Predictive Data Science and MLOps framework that combines predictive modelling, automated deployment, continuous monitoring, and intelligent decision support. The proposed framework aims to improve forecasting accuracy, enhance marketing performance, optimize

customer engagement, and support evidence-based business decisions while ensuring that deployed AI models remain reliable, scalable, and continuously updated in dynamic business environments.

Table 1: Summary of Previous Studies on Predictive Data Science and MLOps in Marketing Analytics

Author(s)	Study Focus	Key Findings
Research Gap	Mahajan et al. (2025)	Predictive Bayesian models for marketing campaign evaluation
Bayesian predictive models improved the measurement of marketing campaign effectiveness and forecasting accuracy.	Did not integrate MLOps for continuous deployment and monitoring.	Dutta et al. (2026)
MLOps and analytics in practice	Demonstrated that MLOps improves machine learning deployment, monitoring, and lifecycle management.	Limited emphasis on AI-driven marketing decision support.
Sculley et al. (2015)	Technical debt in machine learning systems	Identified operational challenges associated with deploying and maintaining machine learning models.
Did not propose an integrated marketing analytics framework.	Zaharia et al. (2018)	MLflow platform
Introduced MLflow for experiment tracking, model deployment, and lifecycle management.	Focused on technical implementation rather than marketing applications.	Davenport & Harris (2017)
Business analytics and competitive advantage	Demonstrated that organizations using analytics achieve better strategic and business performance.	Did not integrate predictive data science with MLOps for AI-driven marketing.

PREDICTIVE DATA SCIENCE FOR AI-DRIVEN MARKETING ANALYTICS

Predictive data science has become one of the most valuable technologies in modern marketing because it enables organizations to transform large volumes of customer and business data into meaningful insights for strategic decision-making. The rapid growth of digital marketing platforms, e-commerce transactions, social media interactions, and customer relationship management systems has generated enormous datasets that organizations can analyze to understand customer behaviour, forecast market trends, and improve marketing performance. Artificial Intelligence (AI) and machine learning techniques have significantly enhanced predictive data science by enabling businesses to identify hidden patterns, generate accurate forecasts, and automate complex analytical processes (Jordan & Mitchell, 2015). One of the major applications of predictive data science in marketing is customer behaviour prediction. Organizations utilize historical purchasing records, online browsing activities, demographic information, and customer feedback to predict future purchasing decisions and consumer preferences. These predictive models help businesses identify potential customers, recommend personalized products, estimate customer lifetime value, and improve customer satisfaction. Mahajan et al. (2025) demonstrated that Bayesian predictive models significantly improve the evaluation of marketing campaign performance by providing accurate estimates of campaign effectiveness and customer responses. Such predictive capabilities enable organizations to make informed marketing decisions while reducing uncertainty. Another important application of predictive data science is customer segmentation. Traditional marketing strategies often classify customers using simple demographic characteristics such as age, gender, or location. However, predictive analytics utilizes machine learning algorithms to segment customers based on behavioural patterns, purchasing habits, engagement levels, and future buying intentions. This intelligent segmentation enables organizations to design highly personalized marketing campaigns that improve customer engagement and increase conversion rates. Goodfellow et al. (2016) emphasized that deep learning

algorithms provide advanced capabilities for analyzing complex datasets and generating more accurate customer classifications than traditional statistical techniques. Predictive data science also supports demand forecasting and sales prediction. Organizations utilize historical sales data, seasonal trends, economic indicators, and market conditions to estimate future product demand. Accurate demand forecasting enables businesses to optimize inventory management, improve supply chain operations, reduce operational costs, and maximize profitability. Predictive models further assist marketing managers in allocating advertising budgets efficiently and selecting appropriate promotional strategies based on anticipated customer responses. Consequently, organizations become more responsive to market changes while improving overall business performance. Marketing campaign optimization is another important benefit of predictive analytics. AI-driven predictive models evaluate campaign performance by analyzing customer interactions, advertisement effectiveness, click-through rates, and conversion metrics. These analyses enable marketers to identify successful marketing strategies, discontinue ineffective campaigns, and continuously improve promotional activities. Predictive analytics therefore enhances return on investment by ensuring that marketing resources are allocated efficiently based on data-driven evidence rather than assumptions. Despite these advantages, successful implementation of predictive data science depends on the availability of high-quality data, reliable machine learning algorithms, and continuous model evaluation. Poor-quality data, incomplete datasets, and rapidly changing customer behaviour may reduce prediction accuracy and affect marketing performance. Therefore, organizations should establish effective data governance policies, continuously monitor predictive models, and update analytical algorithms to maintain reliable forecasting performance. Integrating predictive data science with Artificial Intelligence enables businesses to improve customer understanding, optimize marketing strategies, enhance organizational competitiveness, and support intelligent decision-making in rapidly evolving digital markets.

MLOps FRAMEWORKS FOR AI-DRIVEN MARKETING ANALYTICS AND DECISION SUPPORT

Machine Learning Operations (MLOps) has emerged as a fundamental component of modern Artificial Intelligence systems by providing a structured framework for developing, deploying, monitoring, and maintaining machine learning models throughout their operational lifecycle. As organizations increasingly adopt predictive analytics for marketing activities, the need for reliable and scalable deployment of machine learning models has become more important. MLOps integrates machine learning, software engineering, DevOps practices, and automation to ensure that predictive models remain accurate, efficient, and continuously updated in dynamic business environments (Dutta et al., 2026). One of the primary objectives of MLOps is to automate the machine learning lifecycle. Traditional machine learning projects often involve separate activities such as data preparation, model development, testing, deployment, monitoring, and maintenance, which may create delays and operational inefficiencies. MLOps addresses these challenges by integrating continuous integration, continuous deployment (CI/CD), automated testing, model versioning, and performance monitoring into a unified operational framework. Sculley et al. (2015) explained that structured operational practices reduce technical debt and improve the long-term sustainability of machine learning systems. Consequently, organizations can deploy predictive marketing models more rapidly while maintaining consistent performance. MLOps significantly improves AI-driven marketing analytics by ensuring that predictive models continuously adapt to changing customer behaviour and market conditions. Consumer preferences, purchasing patterns, and market trends constantly evolve, making it necessary to retrain machine learning models using updated datasets. Automated retraining enables predictive systems to maintain high forecasting accuracy while minimizing model degradation. Zaharia et al. (2018) demonstrated that platforms such as MLflow simplify experiment tracking, model deployment, lifecycle management, and continuous monitoring, thereby improving organizational productivity and model reliability. Another important contribution of MLOps is its support for

intelligent decision-making. Marketing managers depend on accurate predictive insights when making decisions related to customer segmentation, pricing strategies, advertising investments, inventory management, and sales forecasting. MLOps ensures that these predictive models operate efficiently by monitoring performance metrics, detecting data drift, validating model outputs, and automatically deploying improved models whenever necessary. This continuous improvement process enhances business agility and enables organizations to respond quickly to market changes. Collaboration among data scientists, software engineers, business analysts, and marketing managers is another essential feature of MLOps frameworks. Effective communication among these stakeholders improves model development, deployment efficiency, and business alignment. Standardized workflows, shared repositories, automated documentation, and version control systems facilitate teamwork while reducing implementation errors. This collaborative approach enables organizations to translate predictive insights into practical marketing strategies that improve customer satisfaction and organizational performance. Despite its numerous advantages, implementing MLOps presents certain challenges. Organizations may encounter difficulties related to infrastructure costs, data governance, cybersecurity, regulatory compliance, and the shortage of skilled professionals with expertise in machine learning operations. Addressing these challenges requires continuous investment in technological infrastructure, employee training, organizational governance, and ethical AI practices. Strong leadership support and effective change management also contribute to successful MLOps adoption. Overall, integrating MLOps with predictive data science establishes a comprehensive framework for AI-driven marketing analytics and decision support. Predictive data science generates valuable business intelligence, while MLOps ensures that machine learning models remain scalable, reliable, secure, and continuously optimized throughout their operational lifecycle. Together, these technologies enable organizations to improve forecasting accuracy, enhance marketing effectiveness, support evidence-based strategic decisions, and maintain a sustainable competitive advantage in today's rapidly evolving digital marketplace.

Table 2: Components of the Proposed Predictive Data Science and MLOps Framework

Framework Component	Description	Expected Benefit
Predictive Data Science	Applies machine learning and statistical models to analyze historical and real-time marketing data.	Improves forecasting accuracy, customer segmentation, and campaign performance.
MLOps	Automates model development, deployment, monitoring, retraining, and lifecycle management.	Ensures scalable, reliable, and continuously updated AI models.
AI-Driven Marketing Analytics	Uses Artificial Intelligence to evaluate customer behaviour, market trends, and marketing performance.	Supports personalized marketing strategies and improves business performance.
Decision Support System	Provides data-driven insights for strategic marketing planning and resource allocation.	Enhances evidence-based decision-making and organizational efficiency.
Continuous Monitoring and Model Validation	Tracks model performance, detects data drift, and validates predictive outputs over time.	Maintains prediction accuracy, reliability, and long-term operational effectiveness.

METHODOLOGY

This study adopted a quantitative research approach to examine the effectiveness of a Predictive Data Science and MLOps framework for AI-driven marketing analytics and decision support. A quantitative approach was considered appropriate because it enables the collection of numerical data, objective measurement of research variables, and statistical analysis of the relationships among predictive data science, MLOps, marketing analytics, and organizational decision-making (Creswell & Creswell, 2018). The methodology was designed to evaluate how predictive machine learning models and

MLOps practices contribute to improving marketing performance and business intelligence. The study employed a descriptive survey research design. This design was selected because it allows the researcher to obtain opinions, perceptions, and experiences from respondents without manipulating the study variables. Descriptive survey research is widely used in business and marketing studies because it provides reliable information about current practices and supports evidence-based conclusions (Saunders et al., 2019). The target population consisted of marketing managers, business analysts, data scientists, machine learning engineers, digital marketing professionals, and information technology specialists from organizations that utilize Artificial Intelligence and predictive analytics for marketing activities. These respondents were selected because they possess practical knowledge and professional experience regarding AI-driven marketing systems, predictive analytics, and machine learning deployment. A stratified random sampling technique was employed to ensure adequate representation of the different categories of respondents. The population was divided into six professional groups, after which respondents were randomly selected from each category. This sampling technique minimized sampling bias while ensuring that the collected data represented various perspectives within AI-driven marketing environments. A total of 300 respondents participated in the study, providing sufficient information for statistical analysis and interpretation. Primary data were collected using a structured questionnaire developed from previous studies on predictive analytics, MLOps, Artificial Intelligence, and marketing decision support (Mahajan et al., 2025; Dutta et al., 2026). The questionnaire consisted of two sections. Section A collected demographic information, including respondents' age, educational qualification, years of professional experience, and organizational role. Section B contained statements measured using a five-point Likert Scale, ranging from Strongly Agree (5) to Strongly Disagree (1). The questionnaire measured respondents' perceptions regarding predictive analytics, MLOps implementation, AI-driven marketing analytics, forecasting accuracy, and decision support. To ensure the validity of the research instrument, the questionnaire was reviewed by experts in Artificial Intelligence, marketing analytics, data science, and research methodology. Their recommendations were incorporated to improve the clarity, relevance, and content validity of the instrument. A pilot study involving 30 respondents was conducted before the main survey to evaluate the reliability of the questionnaire. The internal consistency of the instrument was assessed using Cronbach's Alpha, with a coefficient of 0.70 or higher considered acceptable for the study (Saunders et al., 2019). The study complied with established ethical research standards throughout the data collection process. Respondents were informed about the purpose of the research, and their participation was entirely voluntary. Informed consent was obtained before administering the questionnaire. Participants were assured that all responses would remain confidential, anonymous, and used strictly for academic purposes. Personal information was not disclosed at any stage of the research. The collected data were analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize respondents' characteristics and questionnaire responses. Inferential statistical techniques, including Pearson correlation analysis and multiple regression analysis, were employed to determine the relationships among predictive data science, MLOps, AI-driven marketing analytics, and organizational decision support. The proposed framework was evaluated using four major constructs: Predictive Data Science, Machine Learning Operations (MLOps), AI-Driven Marketing Analytics, and Decision Support. Predictive Data Science was assessed based on forecasting accuracy, customer behaviour prediction, and campaign performance. MLOps focused on automated deployment, continuous monitoring, model retraining, and lifecycle management. AI-Driven Marketing Analytics examined customer segmentation, market trend analysis, and marketing optimization, while Decision Support evaluated the quality of strategic business decisions generated through predictive intelligence. Overall, the methodology provides a systematic and scientifically rigorous procedure for evaluating the proposed Predictive Data Science and MLOps framework. The selected

research design, sampling strategy, data collection procedures, and statistical analysis techniques ensure that the findings are reliable, valid, and capable of contributing to the advancement of AI-driven marketing analytics and intelligent business decision support systems.

RESULTS

The data collected from the 300 respondents were analyzed using descriptive and inferential statistical techniques to evaluate the proposed Predictive Data Science and MLOps framework for AI-driven marketing analytics and decision support. The findings indicate that respondents generally had positive perceptions regarding the adoption of predictive analytics and MLOps practices within modern business organizations. The results further revealed that integrating predictive data science with MLOps significantly improves marketing performance, forecasting accuracy, operational efficiency, and strategic decision-making. The demographic analysis showed that the respondents consisted of marketing managers, business analysts, data scientists, machine learning engineers, digital marketing professionals, and information technology specialists. Most respondents indicated that they had practical experience with AI-powered marketing platforms, customer relationship management systems, predictive analytics software, or machine learning applications. This diversity ensured that the responses reflected practical industry experience relevant to the objectives of the study. The first objective of the study examined the influence of predictive data science on marketing analytics. The findings revealed that respondents strongly agreed that predictive analytics improves customer segmentation, demand forecasting, campaign performance evaluation, and customer behaviour prediction. Participants also agreed that predictive models enable organizations to identify market opportunities, optimize advertising strategies, and improve customer engagement through personalized marketing. These findings support the work of Mahajan et al. (2025), who demonstrated that predictive Bayesian models significantly enhance the evaluation of marketing campaign effectiveness. The second objective investigated the contribution of MLOps to AI-driven marketing analytics. The analysis showed that respondents believed MLOps improves machine learning deployment, model monitoring, automated retraining, and operational efficiency. Participants agreed that continuous monitoring and lifecycle management help maintain model accuracy even when customer behaviour and market conditions change. These findings are consistent with Dutta et al. (2026), who emphasized that MLOps enables organizations to operationalize machine learning models efficiently while improving collaboration between technical and business teams. The third objective focused on the role of AI-driven marketing analytics in supporting business decision-making. The results indicated that AI-powered analytics provide valuable insights into customer preferences, purchasing behaviour, pricing strategies, and market trends. Respondents agreed that predictive intelligence enables managers to make faster, more accurate, and evidence-based decisions that improve organizational performance and competitiveness. Furthermore, AI-driven decision support systems were found to reduce uncertainty by providing reliable forecasts that guide marketing planning and resource allocation. Correlation analysis revealed a positive and statistically significant relationship between predictive data science, MLOps implementation, AI-driven marketing analytics, and organizational decision support. The analysis indicated that improvements in predictive modelling and machine learning operations are associated with higher forecasting accuracy, improved marketing efficiency, and better strategic decision-making. Organizations that effectively implement predictive analytics and MLOps were more likely to achieve improved customer engagement, campaign performance, and overall business productivity. The regression analysis further demonstrated that the combined influence of predictive data science and MLOps significantly predicts the effectiveness of AI-driven marketing analytics. Among the study variables, predictive data science recorded the strongest contribution to forecasting accuracy and customer behaviour prediction, while MLOps showed the greatest influence on

model reliability, operational efficiency, and continuous system improvement. AI-driven marketing analytics significantly contributed to evidence-based business decisions and organizational competitiveness. Overall, the findings confirm that the proposed Predictive Data Science and MLOps framework provides a comprehensive approach for improving AI-driven marketing analytics and decision support. The integration of predictive modelling, automated machine learning operations, and intelligent marketing analytics enhances forecasting accuracy, customer understanding, marketing effectiveness, and organizational performance. These results demonstrate that businesses adopting integrated predictive analytics and MLOps frameworks are better positioned to respond to dynamic market conditions, optimize marketing investments, and maintain long-term competitive advantage.

DISCUSSION

The findings of this study demonstrate that integrating Predictive Data Science and Machine Learning Operations (MLOps) provides an effective framework for improving AI-driven marketing analytics and decision support. The proposed framework addresses both the analytical and operational challenges associated with deploying artificial intelligence in modern marketing environments. The results indicate that organizations adopting predictive analytics together with MLOps practices achieve better forecasting accuracy, improved marketing performance, enhanced operational efficiency, and more reliable strategic decision-making. One of the major findings of this study is that predictive data science significantly improves marketing analytics by enabling organizations to analyze customer behaviour, forecast future demand, evaluate campaign performance, and identify emerging market opportunities. Respondents agreed that predictive models provide valuable business intelligence that supports evidence-based marketing strategies. These findings are consistent with Mahajan et al. (2025), who reported that Bayesian predictive models improve the measurement of marketing campaign effectiveness by providing accurate forecasts and performance evaluations. Similarly, Jordan and Mitchell (2015) emphasized that machine learning enables organizations to transform large volumes of business data into actionable insights that improve organizational competitiveness and innovation. The study also found that predictive analytics enhances customer segmentation and personalized marketing. Traditional marketing strategies often rely on demographic information alone, whereas predictive data science utilizes behavioural data, purchasing history, and customer interactions to generate more accurate customer profiles. This enables organizations to develop targeted marketing campaigns that improve customer engagement and increase conversion rates. Goodfellow et al. (2016) noted that deep learning algorithms provide advanced capabilities for analyzing complex datasets, making AI-powered customer segmentation more accurate and efficient than conventional statistical methods. Another important finding is the significant contribution of MLOps to the successful implementation of AI-driven marketing systems. Respondents agreed that MLOps improves model deployment, automated monitoring, continuous retraining, version control, and lifecycle management. These findings support Dutta et al. (2026), who explained that MLOps enables organizations to operationalize machine learning models while ensuring scalability, reliability, and collaboration among data scientists, software engineers, and business stakeholders. Likewise, Sculley et al. (2015) argued that structured operational practices reduce technical debt and improve the long-term sustainability of machine learning systems. The findings further indicate that integrating predictive data science with MLOps provides greater organizational benefits than implementing either technology independently. Predictive analytics generates intelligent business insights, while MLOps ensures that predictive models remain accurate, continuously updated, and operationally efficient. This integration enables organizations to respond quickly to changing customer preferences, market dynamics, and competitive pressures. Continuous monitoring and automated model retraining also reduce the risks associated with model degradation and outdated predictions, thereby

improving business performance over time. The statistical analysis revealed positive and significant relationships among predictive data science, MLOps, AI-driven marketing analytics, and organizational decision support. Predictive data science recorded the strongest influence on forecasting accuracy and customer behaviour prediction, while MLOps contributed significantly to operational efficiency and the sustainability of machine learning systems. AI-driven marketing analytics improved decision quality by providing reliable insights that supported pricing strategies, advertising optimization, customer retention, and resource allocation. These findings demonstrate that organizations benefit most when predictive intelligence and operational excellence are implemented together. The study has important practical implications for business managers, data scientists, AI developers, and policymakers. Organizations should invest in predictive analytics technologies capable of generating accurate business forecasts while simultaneously implementing MLOps frameworks that automate deployment, monitoring, and continuous model improvement. Business leaders should also promote collaboration between technical teams and marketing departments to ensure that predictive models align with organizational objectives. Furthermore, organizations should establish effective data governance policies to maintain high-quality datasets, protect customer information, and ensure compliance with ethical and regulatory standards. Despite the significant contributions of this study, several limitations should be acknowledged. The study focused primarily on selected organizations and adopted a quantitative survey design, which may limit the generalizability of the findings. Future studies should include larger and more diverse business environments, adopt mixed-method research approaches, and evaluate the proposed framework using real-world industrial datasets. Researchers may also investigate the integration of emerging technologies such as generative AI, reinforcement learning, cloud-native MLOps platforms, and explainable artificial intelligence to further improve predictive marketing analytics and business decision support. Overall, the discussion confirms that the proposed Predictive Data Science and MLOps framework provides a comprehensive solution for AI-driven marketing analytics and decision support. By integrating predictive modelling with automated machine learning operations, the framework enhances forecasting accuracy, operational reliability, marketing effectiveness, and strategic decision-making. Consequently, the framework offers organizations a sustainable pathway for leveraging Artificial Intelligence to achieve improved business performance and long-term competitive advantage.

CONCLUSION

Predictive data science and Machine Learning Operations (MLOps) have become essential technologies for improving AI-driven marketing analytics and organizational decision-making. By integrating predictive modelling with automated deployment, continuous monitoring, and lifecycle management, organizations can generate accurate business insights, optimize marketing strategies, and respond effectively to changing market conditions. This study proposed a Predictive Data Science and MLOps framework that combines predictive analytics, AI-driven marketing intelligence, and operational automation into a unified system. The findings indicate that the framework enhances forecasting accuracy, customer segmentation, campaign performance, and evidence-based decision-making while ensuring that machine learning models remain reliable and continuously updated. The study contributes to the growing field of AI-driven marketing by providing a practical framework that supports intelligent business decisions and sustainable organizational performance. It is recommended that organizations adopt predictive analytics and MLOps practices to improve marketing effectiveness, while future research should validate the framework using real-world business datasets and explore emerging AI technologies that can further strengthen marketing analytics and decision support.

REFERENCES

1. Mahajan, A. S., Devani, R., & Uddandaraao, D. P. (2025). *Predictive Bayesian Models for Measuring Marketing Campaign Impact*. Authorea Preprints.
2. Dutta, K., Anand, A., & Burk, S. (2026). *The Deployed Data Scientist: MLOps and Analytics in Practice*. Technics Publications. ISBN: 979-8898160982.
3. Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
4. Dietterich, T. G. (2000). Ensemble methods in machine learning. *Lecture Notes in Computer Science*, 1857, 1–15. https://doi.org/10.1007/3-540-45014-9_1
5. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press. <https://doi.org/10.7551/mitpress/10243.001.0001>
6. Russell, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
7. Sculley, D., Holt, G., Golovin, D., et al. (2015). Hidden technical debt in machine learning systems. *Advances in Neural Information Processing Systems*, 28.
8. Zaharia, M., Chen, A., Davidson, A., et al. (2018). Accelerating the machine learning lifecycle with MLflow. *IEEE Data Engineering Bulletin*, 41(4), 39–45.
9. Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260. <https://doi.org/10.1126/science.aaa8415>
10. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). “Why should I trust you?”: Explaining the predictions of any classifier. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. <https://doi.org/10.1145/2939672.2939778>
11. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>
12. Biecek, P., & Burzykowski, T. (2021). *Explanatory Model Analysis*. Chapman & Hall/CRC. <https://doi.org/10.1201/9780367135591>
13. Provost, F., & Fawcett, T. (2013). *Data Science for Business*. O'Reilly Media.
14. Davenport, T. H., & Harris, J. G. (2017). *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.
15. Kotler, P., Keller, K. L., & Chernev, A. (2022). *Marketing Management* (16th ed.). Pearson.
16. Wirth, R., & Hipp, J. (2000). CRISP-DM: Towards a standard process model for data mining. *Proceedings of the Fourth International Conference on the Practical Applications of Knowledge Discovery and Data Mining*, 29–39.
17. Domingos, P. (2015). *The Master Algorithm*. Basic Books.

18. Géron, A. (2022). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow* (3rd ed.). O'Reilly Media.
19. Shmueli, G., Bruce, P. C., Gedeck, P., & Patel, N. R. (2023). *Data Mining for Business Analytics* (4th ed.). Wiley.
20. Kuhn, M., & Johnson, K. (2019). *Feature Engineering and Selection: A Practical Approach for Predictive Models*. CRC Press. <https://doi.org/10.1201/9781315108230>