Scholarly Research Journal for Interdisciplinary Studies
Online ISSN 2278-8808, SJIF 2026 = 8.727
https://www.srjis.com/issues_data/297
Peer Reviewed & Refereed Journal, JULY-AUG 2026, Vol- 15/96
https://doi.org/10.5281/zenodo.22787196

ARTIFICIAL INTELLIGENCE-DRIVEN CRM AND PREDICTIVE ANALYTICS FOR B2B CUSTOMER LIFETIME VALUE PREDICTION: A REVIEW

Komalpreet kaur
Assistant Professor University - Punjab Institute of Technology under Maharaja Ranjit Singh Punjab Technical University (PIT College)
Email.id - commerceacademy0001@gmail.com

Paper Received On: 20 JULY 2026
Peer Reviewed On: 24 AUG 2026
Published On: 01 SEPT 2026

Abstract

The concept of Customer Lifetime value (CLV) is fast gaining importance in business-to-business (B2B) companies and is being used as a strategic metric to allocate resources, enhance customer relationships, minimize customer attrition and discover potential revenue sources. In this review, we explore the impact of predictive analytics and artificial intelligence (AI) in customer relationship management (CRM) on B2B Customer Lifetime Value (CLV) estimation and decision-making. The paper gathers the latest secondary literature to synthesize the progress made in customer-data integration, feature engineering, machine learning, deep learning, segmentation, churn prediction, revenue forecasting, and real-time CRM decision support. It contrasts classic statistical models with more recent models based on Artificial Intelligence (AI) and assesses how each type of model requires, is easier to interpret, more flexible and applicable, and how well each one can be used in management practice. It highlights the benefits of machine-learning and ensemble methods for heterogeneous B2B customer portfolios, and the benefits of sequential methods and deep learning methods in instances of dynamic and complex behavioural histories. But implementation is limited by fragmented data, unexplainable models, privacy issues, algorithmic bias, lack of generalizability, concept drift, and adoption issues. Based on the paper, effective CLV management with the help of AI should combine predictive performance, explain ability and governance, human judgement, and continuous learning. It demonstrates how CLV can be made more than a financial metric, and can become a dynamic decision-making tool used for retention, account prioritisation, personalisation and the creation of sustainable B2B relationship value in various industrial markets, through the application of AI-powered CRM. Customer Lifetime Value (CLV) is an essential metric for organizations to maintain customer satisfaction and retain their clientele base.

Keywords: *Customer Lifetime Value, Predictive Analytics, Artificial Intelligence, B2B Customer Relationship Management, Machine Learning*

1. INTRODUCTION

1.1 B2B Customer Relationships and Value Management.

B2B relationships involve many decision makers, long sales cycles, negotiated offerings and high dollar accounts. CLV represents the value of the relationship, net of the costs of acquisition and renewal, and helps in acquiring new customers, renewing existing customers, pricing, services, and cross-selling (Venkatesan & Kumar, 2004; Gupta et al., 2006). This information is connected to decisions through marketing analytics (Basu et al., 2023).

1.2 Customer Lifetime Value as a Strategic Metric

CLV is a combination of the value of the customer's purchases, retention, costs and discounts that help to identify valuable customers from unprofitable or vulnerable ones. It enables customer selection (Venkatesan & Kumar, 2004); links marketing investment and firm value (Gupta et al., 2006); relies on high quality, accurate data, features, and validation (Nie et al., 2024).

1.3 AI/CRM/Predictive Analytics Transformation

Digital CRM amalgams interactions, service, usage, campaigns, contracts, and deals. Beyond descriptive reporting (Ozay et al., 2024), AI transforms these signals into predictions and recommendations, elevating CRM's functionality.AI takes these signals and turns them into predictions and recommendations, taking CRM's functionality beyond descriptive reporting. Despite the progress in the field of B2B marketing analytics, models need to be resolved with human decisions throughout the relationship life cycle (Amoozad Mahdiraji et al., 2024).

There is one multiple-choice question in this section. This section contains one multiple choice question.

2. CONCEPTUAL AND THEORETICAL FOUNDATION FOR B2B CLV

2.1 A Description and Economic Justification of CLV

The discounted present value of expected net account contribution that includes revenue, margin, service cost, retention, and uncertainty. Different assumptions must be made in contractual and non-contractual settings. Its modelling features are described by Gupta et al. (2006) and its function as a resource allocator is shown by Venkatesan and Kumar (2004).

2.2 Traditional, Probabilistic, and Statistical Approaches

CLV is based on revenue, margin, recency, frequency, and monetary value; traditional CLV also includes revenue, margin, recency, frequency, monetary value, assumptions about purchase, assumptions about retention. Pareto/NBD models make inferences about activity based upon transaction timing (Fader et al., 2005). Curiskis et al. (2023) tackle the problem of heterogeneous B2B SaaS accounts with lump-sum prediction and hierarchical ensembling..

Table 1. Eligibility and analytical classification framework for the review

Dimension	Included Evidence	Excluded or Limited Evidence
Topic	CLV; B2B customer analytics; AI-CRM; churn, retention, propensity, segmentation, and revenue prediction	Records unrelated to customer value or customer-management decisions
Publication type	Peer-reviewed journal and conference papers; selected scholarly reviews; seminal CLV studies	Promotional webpages, unsupported opinion, duplicate records, and sources without adequate scholarly detail
Context	B2B evidence prioritized; transferable consumer or sector studies used with explicit contextual caution	Context-specific claims generalized to B2B without analytical justification
Data and method	Studies explaining customer data, features, models, validation, or implementation	Purely technical methods with no relevant customer or CRM outcome
Outcome	CLV, churn, retention, revenue, purchase/expansion propensity, segmentation, or sales decision support	Outcomes not connected to customer relationship value
Synthesis use	Conceptual, methodological, comparative, and managerial evidence	Unverifiable performance claims or incomparable metrics treated as universal benchmarks

Source: Authors' review framework.

2.3 Distinctive Characteristics of B2B Customer Value

In B2B, errors and hierarchy, timing, and identity of customer may be important as customer can be a user, a buyer, a site, a subsidiary, a contract, and a product. Curiskis et al. (2023) name heterogeneity, several offerings and temporal restrictions. Predictions are also only of value when the salesperson is aware of them and applies them (Habel et al., 2024).

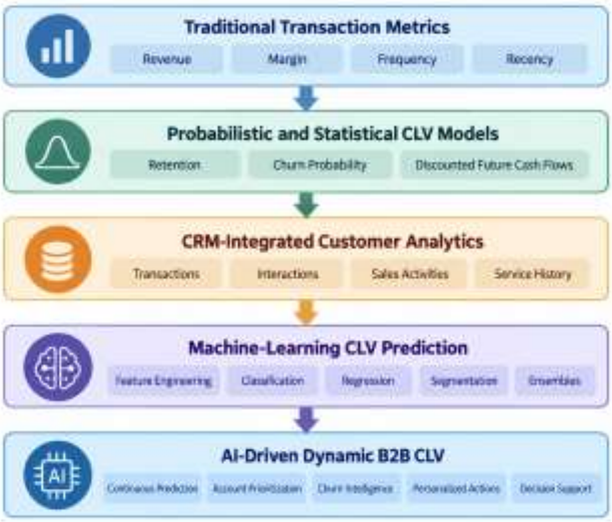
2.4 Relationship Marketing and CRM: Foundations

CRM brings together information about relationships between entities in sales, marketing and service; AI introduces prediction, recommendation, and learning (Ozay et al., 2024). Keegan et al (2024) demonstrate that changes in implementation involve changes in tools, rules, and responsibilities. A second channel of impact is the potential for opacity or depersonalization (Peruchini et al., 2024) resulting from poor governance.

2.5 Moving to AI-Enhanced Dynamic CLV

Machine learning is capable of capturing non-linear patterns; ensembles of learners; deep learning for sequences. Mena et al. (2024) model time-varying RFM churn, and Nie et al. (2024) highlight the acquisition-to-validation workflow. Algorithmic segmentation is a tool which enables value and risk grouping but is not always assessed (Salminen et al., 2023). Figure 1 summarizes the evolution of the SDV.

Figure 1. Evolution from traditional transaction metrics to AI-driven dynamic B2B CLV



Source: Authors' conceptual synthesis based on Venkatesan and Kumar (2004), Gupta et al. (2006), Curiskis et al. (2023), and Ozay et al. (2024).

3. REVIEW METHODOLOGY

3.1 Review Design and Scope

A review in the form of an integrative one was conducted on B2B CLV, AI, CRM, analytics, and sales literature without the pooling of effects. The process is described in figure 2.

3.2 Source of Information and Search Strategy.

CLV, B2B, CRM, AI, and predictive-analytics terms were used to search Scopus, Web of Science, IEEE Xplore, Emerald, Springer, Wiley and Taylor and Francis.

3.3 Eligibility and Screening Criteria.

Available CLV or associated CRM research provided conceptual, empirical, methodological or managerial support. Duplicated, promotional, inaccessible, irrelevant and unsupported recordings were eliminated. The criteria are indicated in table 1.

3.4 Classification and Evidence Coding of studies.

Coding of the studies was based on context, data, target, model, evaluation and CRM use. The outcome and models were classified into the categories of analysis applied in the synthesis.

3.5 Synthesis, Quality and Limitations.

Thematic and comparative synthesis determined the capabilities, data requirements, temporal processing, interpretability and deployment. Measurements were anchored on initial validation; thus, tables and figures reflect qualitative associations.

Figure 2. Structured literature-review and thematic-synthesis process

Source: Authors' review framework.

4. AI-DRIVEN CRM AND PREDICTIVE ANALYTICS FOR B2B CLV PREDICTION

4.1 AI-Enabled CRM Systems in B2B Customer Management

The CRM with AI facilitates account priorities, opportunities, recommendations, and coordinated decisions (Ozay et al., 2024; Keegan et al., 2024). Value is based on relationship processes and salesperson discretion (Amoozad Mahdiraji et al., 2024; Habel et al., 2024), whereas adoption needs data readiness and human acceptance (Peruchini et al., 2024). The system is summarized in Table 2 and Figure 3.

Table 2. AI-enabled CRM capabilities supporting B2B customer lifetime value prediction

AI-Enabled CRM Capability	**Primary Information Utilized**	**Contribution to CLV Management**	**Typical Managerial Application**
Unified customer intelligence	Transactions, contracts, service and interaction history	Creates an account-level analytical view	Key-account assessment
Predictive scoring	Historical and behavioral variables	Estimates future value, churn, purchase or renewal likelihood	Account prioritization
Intelligent segmentation	Value, RFM and behavioral attributes	Differentiates customers by value and relationship pattern	Resource allocation
Recommendation support	Customer profile and predicted outcomes	Identifies appropriate next actions	Cross-selling and retention
Sales/service augmentation	CRM records, interaction history	Improves salesperson access	Account preparation and service

	and generated insights	to customer intelligence	
Continuous learning	New interactions and realized outcomes	Allows models to reflect changing customer behavior	Model monitoring and CRM adaptation

Source: Authors' synthesis of secondary literature based on Ozay et al. (2024), Keegan et al. (2024), Habel et al. (2024), and Peruchini et al. (2024).

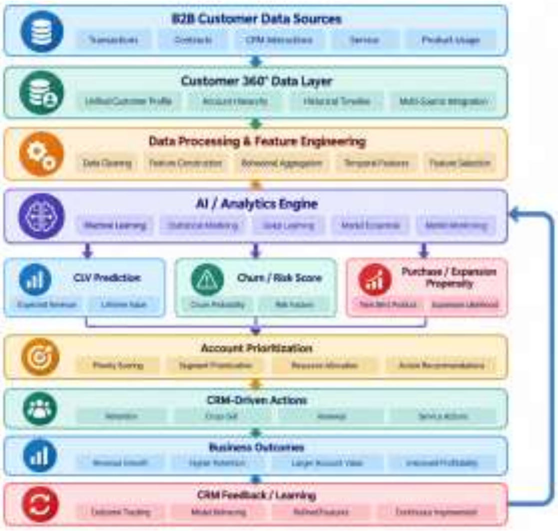


Figure 3. Integrated AI-driven CRM architecture for B2B CLV prediction

Source: Authors' conceptual synthesis based on Ozay et al. (2024), Amoozad Mahdiraji et al. (2024), and Keegan et al. (2024).

4.2 Customer Data Integration and Feature Engineering

B2B CLV combines CRM, transaction, contract, service, engagement and account-history data. The important consideration is not the volume of data, but useful representations (Basu et al., 2023; Ozay et al., 2024). Temporal features are stressed on by Curiskis et al. (2023) and time varying RFM is demonstrated by Mena et al. (2024). Table 3 and Figure 4 show the pipeline.

Table 3. Secondary-literature synthesis of customer-data and feature families for B2B CLV prediction

Feature Family	**Illustrative Variables**	**Analytical Relevance to B2B CLV**
Transactional	Revenue, order value, purchase frequency, recency	Reveals economic contribution and purchasing pattern
Relationship	Account tenure, renewal history, relationship duration	Represents relationship maturity and continuity
Product/contract	Number of products, subscriptions, contract value, product breadth	Captures account depth and expansion potential
Engagement	Contact frequency, campaign response, platform usage	Indicates relationship activity

Service	Complaints, tickets, resolution history, service contacts	Provides potential satisfaction and churn signals
Temporal	Changes in RFM, declining activity, recent growth	Captures dynamic customer behavior
Derived value/risk	Predicted churn, propensity and segment membership	Supports forward-looking CRM decisions

Source: Synthesized from Curiskis et al. (2023), Mena et al. (2024), Basu et al. (2023), and Ozay et al. (2024).

Figure 4. Customer-data integration and feature-engineering pipeline

Source: Authors' synthesis based on Curiskis et al. (2023), Mena et al. (2024), and Nie et al. (2024).

4.3 Machine Learning Models for CLV Prediction

Customer patterns are captured in a nonlinear fashion by machine learning models such as regression, trees, boosting, and ensembles (Curiskis et al., 2023; Kasem et al., 2024). Hierarchical ensembling works for heterogeneous B2B accounts (Curiskis et al., 2023) and churn evidence is in favour of engineered tree ensembles (Suh, 2023; Sagming et al., 2024). Selection should be influenced by aspects such as horizon, sparsity, explainability, error costs and deployment. Alternatives are compared in Table 4 and Figure 5.

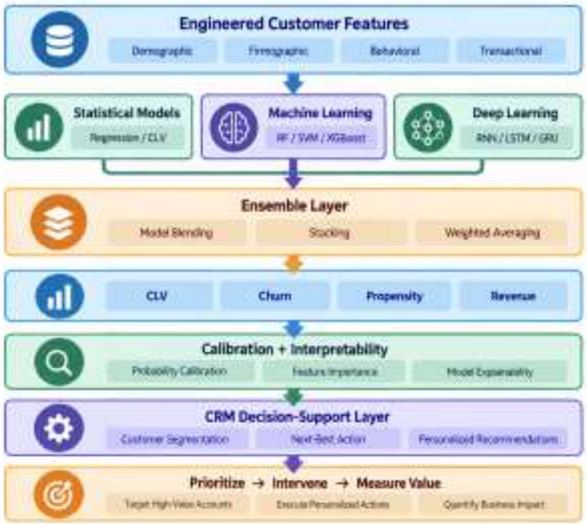
Table 4. Comparative synthesis of modelling approaches applicable to B2B CLV prediction

Model Family	Typical Strength	Principal Limitation	Potential B2B CLV Use
Linear/regularized regression	Transparency and straightforward estimation	Restricted nonlinear representation	Baseline monetary-value prediction
Decision trees	Human-readable decision structure	Instability/overfitting when used alone	Account classification
Random forest	Handles nonlinearities and feature interactions	Reduced interpretability	CLV and churn prediction

Support vector machines	Effective classification in complex feature spaces	Scaling and interpretation challenges	Risk classification
Gradient boosting/XGBoost	Strong performance on structured tabular data	Requires tuning and explanation	CLV, propensity, and churn
Hierarchical/stacked ensembles	Combines heterogeneous predictive patterns	Greater maintenance complexity	Multi-product B2B accounts
Neural/deep models	Represents complex or sequential relationships	Higher data and computational needs	Dynamic customer behavior

Source: Secondary-literature synthesis based on Curiskis et al. (2023), Kasem et al. (2024), Suh (2023), Sagming et al. (2024), and Mena et al. (2024).

Figure 5. Layered predictive architecture for AI-driven B2B CLV modelling



Source: Authors' synthesis of recent predictive-analytics evidence (Curiskis et al., 2023; Mena et al., 2024; Imani et al., 2025).

4.4 Deep Learning and Advanced Predictive Models

Deep learning is good for things that have a sequence or are unstructured. In Mena et al. (2024), the authors determined that there was no improvement by the combination of classifiers and that recurrent models worked well for RFM churn in the case of time-varying churn. Ensembles continue to perform well with tabular data (Imani et al., 2025). The primary use cases of generative AI in CRM are enhancing communication and knowledge management in customer service (Grewal et al., 2025).

4.5 Customer Segmentation and Behavioral Prediction

Segmentation helps to translate the forecasted value into tailored account treatment. RFM clustering is a summary of transactions and machine learning is a context of behaviours.

B2B segments must also consider bringing into account buying centres, product portfolios, stages of a relationship, and account heterogeneity (Amoozad Mahdiraji et al., 2024). Table 5 is a mapping of the analysis states with CRM responses.

Table 5. Linking predictive customer states with B2B CRM actions

Analytical Customer State	Predictive Interpretation	Suggested CRM Response	CLV Objective
High value-low risk	Valuable and stable account	Relationship reinforcement	Protect current CLV
High value-high churn risk	Valuable but vulnerable account	Priority retention intervention	Prevent major value loss
Moderate value-high growth propensity	Expansion potential	Cross-sell/up-sell activity	Increase future CLV
New/high-potential account	Insufficient history but promising behavior	Onboarding and relationship development	Accelerate value creation
Low engagement-recoverable	Declining interaction	Re-engagement intervention	Restore future contribution
Persistently low value	Low expected incremental return	Selective servicing	Improve resource efficiency

Source: Authors' secondary synthesis based on Kasem et al. (2024), Curiskis et al. (2023), Habel et al. (2024), and Amoozad Mahdiraji et al. (2024).

4.6 Churn, Retention, and Revenue Forecasting

CLV is influenced by churn, retention, and revenue predictions. Links to value and intervention economics are needed for risk scores (Habel et al., 2024). Benefits (Habel et al., 2024), feature quality, imbalance and validation (Sagming et al., 2024; Imani et al., 2025) remain important as they are affected by customer characteristics and by responses of salespeople. The feedback loop is given in Figure 6.

Figure 6. Closed-loop predictive CRM and B2B CLV decision process

Source: Authors' conceptual synthesis based on Habel et al. (2024), Ozay et al. (2024), and Basu et al. (2023).

4.7 Real-Time Analytics and CRM-Based Decision Support

Value and risk and propensity indicators can be updated in real time when there are CRM events. While analytics must link customer data with action by management (Basu et al., 2023; Labib, 2024), recommendations need to be within the understanding, the workflow, and are governed (Keegan et al., 2024; Habel et al., 2024). Figure 6 brings monitoring and recalibration back to the outcomes.

5. THE COMPARATIVE SYNTHESIS AND EVALUATION OF EXISTING APPROACHES

5.1 Comparison of traditional, statistical, and AI-based models of CLV

There's no one best model. Machine learning is used for nonlinear, heterogeneous data (Curiskis et al., 2023); and Mena et al. (2024) demonstrates that architecture needs to match customer histories. Ensembles introduce robustness but come at the expense of added maintenance and governance costs (Imani et al., 2025). Table 6 contrasts flexibility, data needs, interpretation, temporal handling and deployment.

Table 6. Comparative evaluation of major CLV modelling paradigms

Evaluation Dimension	Traditional / Statistical	Conventional Machine Learning	Ensemble Learning	Deep / Sequential Learning
Data requirement	Low-moderate	Moderate-high	Moderate-high	High
Nonlinear relationships	Limited unless specified	Strong	Strong	Strong
High-dimensional features	Moderate	Strong	Strong	Strong
Temporal-sequence modelling	Limited/manual engineering	Moderate	Moderate	Strong
Interpretability	Generally high	Model dependent	Moderate-low	Generally lower
Computational burden	Low	Moderate	Moderate-high	High
Ease of deployment	Relatively high	Moderate	Moderate	Lower
B2B heterogeneity handling	Moderate	Strong	Particularly useful	Strong when sufficient data exist
Appropriate role	Transparent baseline	Flexible prediction	Robust heterogeneous prediction	Sequential/complex-data modelling

Note: Ratings are qualitative secondary-literature synthesis rather than results from an original experiment. Source: Curiskis et al. (2023), Mena et al. (2024), Imani et al. (2025), and Kasem et al. (2024).

5.2 Model Performance and Evaluation Metrics

Estimation, classification, ranking and allocation should be included in CLV evaluation. These measures include MAE, RMSE, MAPE, R-squared, precision, recall, F1, ROC-

AUC, calibration and segment separation as described by Kasem et al., 2024. Financial error cost is important as it can be concealed by the lack of balance and accuracy-only reporting of the business value (Imani et al., 2025).

5.3 Data Requirements and Model Interpretability

In contrast to the traditional CLV, machine learning can include features like behavioural or contextual data, while transaction and retention information is more suited for traditional CLV. In addition to the traditional CLV, machine learning can incorporate features such as behavioural or contextual data, which are more appropriate for traditional CLV than transaction and retention data. Large datasets and infrastructure (Mena et al., 2024) are required for deep models. Predictive gains must outweigh costs of data, explanation, and implementation as salespeople have to have reasons for account priorities (Habel et al., 2024).

5.4 Business Value and Strategic Applications in B2B CRM

Prioritizing accounts that can generate value from actions highlights the importance of CLV in AI. This focus on accounts where action can create value underscores the role of CLV in AI. Integrated CRM coordinates knowledge (Ozay et al., 2024; Peruchini et al., 2024), but judgment is still a crucial factor in situations where no context is provided for the relationships from the historical data (Keegan et al., 2024). Figures 3-6 and Tables 2-6 are tied together in predicting, intervening, outcomes and learning.

6. CHALLENGES AND RESEARCH GAPS

6.1. Data Quality, Integration and Data Availability

B2B CRM data can also be incomplete, include duplicated accounts, inconsistent identifiers, sparse histories, and disconnections, compromising the reliability of features and calibration (Ozay et al., 2024; Curiskis et al., 2023). For CLV to be operational, therefore, identity resolution, temporal alignment, governance, and continuous quality monitoring are prerequisites.

6.2 Explainability, Bias, Privacy, and Ethical Issues

Bias, privacy, and explainability risks arise with AI-driven CLV. Obscure priorities and skewed histories can lead to arbitrary targeting or services (Bozorgpanah & Torra, 2024; Batool et al., 2025). Governance and human oversight is required when combining behavioural and transactional signals as this increases their exposure to privacy (Kaponis & Maragoudakis, 2026). There should be a section on generalizability and dynamic B2B customer behaviour. A section of generalizability and dynamic B2B customer behaviour should exist. The value of B2B relationships varies by industry, contract, company size and buying cycles, with models not necessarily being reliably transferable (Curiskis et al., 2023). Behavior changes also cause concept drift (Imani et al., 2025). To keep performance over time, external validation, monitoring, recalibration, and retraining are required.

6.3 Summary of Key Research Gaps

The volume of research is limited with poor longitudinal evidence, inadequate cross industry validation, and lack of explainability and economic evaluation in deployed CRM outcomes (Imani et al., 2025; Ozay et al., 2024). There is also a need for more evidence for human-AI collaboration, trust, and organizational implementation (Keegan et al., 2024; Oberg, 2026).

7. FUTURE RESEARCH DIRECTIONS AND MANAGERIAL IMPLICATIONS

7.1 Future Directions for AI Based B2B CLV Research

More dynamic, explainable, privacy-preserving, and economically assessed CLV systems should be developed in the future. Some of the priorities are temporal and multimodal representations, concept-drift adaptation, causal intervention analysis, profit-sensitive metrics, and external validation (Imani et al., 2025; Grewal et al., 2025). Prediction, explanation, judgment, outcomes and ongoing learning should be incorporated into the governance frameworks (Batool et al., 2025; Oberg, 2026).

7.2 Implications for CRM Managers and B2B Decision-Makers

Managers should consider accuracy as one criterion in implementation and set up ownership, monitoring, explanations, and intervention procedures (Habel et al., 2024; Ozay et al., 2024). The model should be as complex as needed to reflect the maturity of the data and the importance of the decisions made with it. For strategically important accounts, where the context of negotiations and trust is not recorded electronically, human intervention is still needed (Keegan et al., 2024).

8. CONCLUSION

With the help of AI, CRM integrates customer data to inform future B2B CLV decisions. The transition from financial and probabilistic approaches to machine learning, ensembles, deep learning and decision support (Curiskis et al., 2023; Ozay et al., 2024). Constraints of data quality, interpretability, privacy, bias, drift, readiness and salesperson acceptance still exist (Habel et al., 2024; Imani et al., 2025). Effective systems link together preparation, prediction, explanation, intervention, measurement, governance and judgment.

REFERENCES

Amoozad Mahdiraji, H., Sharifpour Arabi, H., & Vrontis, D. (2024). Marketing 4.0 analytics in the B2B sector: A state-of-the-art review and integrated framework. Journal of Strategic Marketing, 32(8), 965-986. https://doi.org/10.1080/0965254X.2023.2273501

Basu, R., Lim, W. M., Kumar, A., & Kumar, S. (2023). Marketing analytics: The bridge between customer psychology and marketing decision-making. Psychology & Marketing, 40(12), 2588-2611. https://doi.org/10.1002/mar.21908

Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: A systematic literature review. AI and Ethics, 5, 3265-3279. https://doi.org/10.1007/s43681-024-00653-w

Bozorgpanah, A., & Torra, V. (2024). Explainable machine learning models with privacy. Progress in Artificial Intelligence, 13, 31-50. https://doi.org/10.1007/s13748-024-00315-2

Curiskis, S., Dong, X., Jiang, F., & Scarr, M. (2023). A novel approach to predicting customer lifetime value in B2B SaaS companies. Journal of Marketing Analytics, 11, 587-601. https://doi.org/10.1057/s41270-023-00234-6

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005). Counting your customers the easy way: An alternative to the Pareto/NBD model. Marketing Science, 24(2), 275-284. https://doi.org/10.1287/mksc.1040.0098

Grewal, D., Satornino, C. B., Davenport, T., & Guha, A. (2025). How generative AI is shaping the future of marketing. Journal of the Academy of Marketing Science, 53(3), 702-722. https://doi.org/10.1007/s11747-024-01064-3

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modelling customer lifetime value. Journal of Service Research, 9(2), 139-155. https://doi.org/10.1177/1094670506293810

Habel, J., Alavi, S., & Heinitz, N. (2024). Effective implementation of predictive sales analytics. Journal of Marketing Research, 61(4), 718-741. https://doi.org/10.1177/00222437221151039

Imani, M., Joudaki, M., Beikmohammadi, A., & Arabnia, H. R. (2025). Customer churn prediction: A systematic review of recent advances, trends, and challenges in machine learning and deep learning. Machine Learning and Knowledge Extraction, 7(3), 105. https://doi.org/10.3390/make7030105

Kaponis, A., & Maragoudakis, M. (2026). Ethics of digital marketing in the AI era: A structured thematic review of recent research, 2023-2025. Platforms, 4(3), 17. https://doi.org/10.3390/platforms4030017

Kasem, M. S., Hamada, M., & Taj-Eddin, I. (2024). Customer profiling, segmentation, and sales prediction using AI in direct marketing. Neural Computing and Applications, 36, 4995-5005. https://doi.org/10.1007/s00521-023-09339-6

Keegan, B. J., Dennehy, D., & Naude, P. (2024). Implementing artificial intelligence in traditional B2B marketing practices: An activity theory perspective. Information Systems Frontiers, 26, 1025-1039. https://doi.org/10.1007/s10796-022-10294-1

Labib, E. (2024). Artificial intelligence in marketing: Exploring current and future trends. Cogent Business & Management, 11(1), 2348728. https://doi.org/10.1080/23311975.2024.2348728

Mena, G., Coussement, K., De Bock, K. W., De Caigny, A., & Lessmann, S. (2024). Exploiting time-varying RFM measures for customer churn prediction with deep neural networks. Annals of Operations Research, 339(1-2), 765-787. https://doi.org/10.1007/s10479-023-05259-9

Nie, D., Scriney, M., Liang, X., & Roantree, M. (2024). From data acquisition to validation: A complete workflow for predicting individual customer lifetime value. Journal of Marketing Analytics, 12(2), 321-341. https://doi.org/10.1057/s41270-022-00197-0

Oberg, C. (2026). Artificial intelligence and trust in business-to-business interactions: From decision tools to generative and reasoning AI. Journal of Business & Industrial Marketing, 41(13), 103-119. https://doi.org/10.1108/JBIM-12-2024-0936

Ozay, D., Jahanbakht, M., Shoomal, A., & Wang, S. (2024). Artificial intelligence (AI)-based customer relationship management (CRM): A comprehensive bibliometric and systematic literature review with outlook on future research. Enterprise Information Systems, 18(7), 2351869. https://doi.org/10.1080/17517575.2024.2351869

Peruchini, M., da Silva, G. M., & Teixeira, J. M. (2024). Between artificial intelligence and customer experience: A literature review on the intersection. Discover Artificial Intelligence, 4, 4. https://doi.org/10.1007/s44163-024-00105-8

Sagming, M., Heymann, R., & Visaya, M. V. (2024). Using topological data analysis and machine learning to predict customer churn. Journal of Big Data, 11, 160. https://doi.org/10.1186/s40537-024-01020-6

Salminen, J., Mustak, M., Sufyan, M., & Jansen, B. J. (2023). How can algorithms help in segmenting users and customers? A systematic review and research agenda for algorithmic customer segmentation. Journal of Marketing Analytics, 11, 677-692. https://doi.org/10.1057/s41270-023-00235-5

Suh, Y. (2023). Machine learning based customer churn prediction in home appliance rental business. Journal of Big Data, 10, 41. https://doi.org/10.1186/s40537-023-00721-8

Venkatesan, R., & Kumar, V. (2004). A customer lifetime value framework for customer selection and resource allocation strategy. Journal of Marketing, 68(4), 106-125. https://doi.org/10.1509/jmkg.68.4.106.42728

Komalpreet kaur. (2026). ARTIFICIAL INTELLIGENCE-DRIVEN CRM AND PREDICTIVE ANALYTICS FOR B2B CUSTOMER LIFETIME VALUE PREDICTION: A REVIEW. Scholarly Research Journal for Interdisciplinary Studies, 15(96), 170–182. https://doi.org/10.5281/zenodo.22787196