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| RESEARCH ARTICLE

Machine Learning Applications in Customer Relationship Management: A Comprehensive Review

Godwin Abugbilla
Ashesi University, Ghana
Corresponding Author: Godwin Abugbilla, **E-mail**: godwinabugbilla@yahoo.com

| ABSTRACT

Customer Relationship Management (CRM) systems have evolved significantly by integrating machine learning (ML) techniques, transforming how businesses understand, predict, and respond to customer behavior. This comprehensive review examines the current landscape of ML applications in CRM, analyzing key techniques, application areas, challenges, and future directions based on recent literature from 2019 to 2025. Our analysis reveals that ML techniques in CRM span from traditional classification and clustering methods to advanced deep learning, natural language processing, and reinforcement learning approaches. Key application areas include churn prediction, customer lifetime value estimation, personalization, sentiment analysis, and customer segmentation. While significant progress has been made, challenges remain in model interpretability, bias mitigation, and production scalability. This review provides insights into emerging trends such as domain-aware language models, graph neural networks, and ethical AI considerations in CRM implementations.

| KEYWORDS

Customer Relationship Management, Machine Learning, Artificial Intelligence, Customer Analytics, Churn Prediction, Customer Segmentation

| ARTICLE INFORMATION

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1. Introduction

Customer Relationship Management (CRM) has become a cornerstone of modern business strategy, enabling organizations to build and maintain profitable customer relationships. Integrating machine learning (ML) technologies into CRM systems has revolutionized how businesses analyze customer data, predict behavior, and deliver personalized experiences [1]. The exponential growth in customer data volume, variety, and velocity has created opportunities and challenges for traditional CRM approaches, necessitating sophisticated analytical methods to extract actionable insights. The application of ML in CRM represents a paradigm shift from reactive to predictive customer management. Traditional CRM systems primarily focused on storing and organizing customer information. At the same time, modern ML-enhanced CRM platforms can anticipate customer needs, predict churn, optimize marketing campaigns, and automate customer service interactions [2]. This transformation has driven computational power, data availability, and algorithmic sophistication. Recent surveys indicate that ML adoption in CRM has accelerated significantly, with enterprises increasingly deploying sophisticated models for customer analytics [1]. The COVID-19 pandemic further accelerated digital transformation initiatives, making ML-driven CRM capabilities essential for business continuity and competitive advantage. Organizations across industries, from telecommunications and retail to healthcare and financial services, leverage ML to enhance customer experiences and drive business outcomes.

This comprehensive review aims to systematically analyze ML applications in CRM, examine the current state of research, identify key trends, and highlight future research directions. Our analysis is based on recent literature spanning multiple academic databases and industry reports, focusing on developments from 2019 to 2025 to capture the most current trends and innovations.

2. Literature Review Methodology

2.1 Search Strategy

We conducted a comprehensive literature search across multiple academic databases to ensure thorough coverage of recent developments in ML applications for CRM. Our search strategy included:

- SciSpace Database: Searched for peer-reviewed articles using the query "machine learning applications in customer relationship management CRM" with filters for top publications from 2019 to 2025
- Google Scholar: Used a Boolean query combining "machine learning" AND "customer relationship management" OR "CRM" with additional terms for review papers
- PubMed: Searched biomedical and business literature using advanced search combining ML and CRM terms
- ArXiv: Covered technical preprints and emerging research in the field

2.2 Inclusion and Exclusion Criteria

Inclusion Criteria:

- Peer-reviewed articles published between 2019 and 2025
- Studies focusing on ML applications in CRM contexts
- Research demonstrating practical implementations or theoretical frameworks
- Review papers and surveys providing comprehensive coverage

Exclusion Criteria:

- Articles published before 2019 (to focus on recent developments)
- Studies without a clear ML or CRM focus
- Non-English publications
- Conference abstracts without full papers

2.3 Data Extraction and Analysis

From the selected literature, we extracted information on ML techniques, application domains, performance metrics, challenges, and future directions. The analysis focused on identifying current research patterns, trends, and gaps.

3. Machine Learning Techniques in CRM

3.1 Classification and Ensemble Methods

Classification techniques form the backbone of many CRM applications, particularly for binary prediction tasks such as churn prediction and lead scoring. Traditional methods, including logistic regression, support vector machines (SVM), and decision trees, have been extensively used, with ensemble methods like Random Forest and Gradient Boosting showing superior performance in many CRM contexts [9]. Recent research demonstrates the effectiveness of ensemble approaches in handling the heterogeneous nature of CRM data. The SmartSurveil system, for example, combines Random Forest, Gradient Boosting, and SVM for telecom churn prediction, achieving improved accuracy over individual models [9]. These ensemble approaches are particularly valuable in CRM contexts due to their ability to handle mixed data types, missing values, and non-linear relationships commonly found in customer datasets.

3.2 Sequential Deep Learning Models

The temporal nature of customer behavior has led to increased adoption of sequential models, particularly Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs). These models excel at capturing patterns in customer journey data, transaction sequences, and behavioral trajectories [4]. The TR-LSTM (Trajectory-based LSTM) approach represents a significant advancement in sequential modeling for CRM, designed explicitly for churn

prediction using customer trajectory data. This method outperforms traditional approaches by capturing long-term dependencies in customer behavior patterns, demonstrating the value of specialized architectures for CRM applications [4].

3.3 Representation Learning and Embeddings

Modern CRM systems deal with high-cardinality categorical features such as product IDs, customer segments, and geographic locations. Embedding techniques have emerged as powerful tools for handling such features, enabling neural networks to learn meaningful representations of categorical data [3]. The integration of embeddings in CRM applications has enabled more sophisticated personalization and customer lifetime value (CLV) predictions. Wide & Deep learning architectures, combining memorization and generalization capabilities, have shown promise in CRM contexts where specific customer preferences and general patterns must be captured [3].

3.4 Natural Language Processing

The growing volume of unstructured text data in CRM systems from customer feedback, support tickets, and social media interactions has driven the adoption of advanced NLP techniques. Transformer-based language models replace traditional keyword-based approaches, fine-tuned for specific CRM tasks [6]. Domain-aware language models, such as MetRoBERTa for transit customer feedback analysis, demonstrate the value of specialized NLP models in CRM contexts. These models outperform generic approaches by incorporating domain-specific knowledge and terminology [6].

3.5 Graph Machine Learning

The relational nature of customer data, particularly in B2B contexts, has increased interest in graph-based ML approaches. Graph Convolutional Networks (GCNs) and other graph neural networks enable the modeling of complex relationships between customers, products, and transactions [7]. Enterprise applications using graph databases like Neo4j combined with GCNs have shown promising sales forecasting and relationship-aware customer analytics results. These approaches capture network effects and influence patterns that traditional tabular methods cannot model effectively [7].

3.6 Reinforcement Learning

Reinforcement Learning (RL) applications in CRM focus on sequential decision-making problems such as customer routing, marketing campaign optimization, and personalized recommendation sequences. The CRSRL (Customer Routing System using Reinforcement Learning) demonstrates how RL can optimize customer service routing decisions in real-time [5]. RL approaches are particularly valuable in CRM contexts where decisions have long-term consequences and the environment (customer preferences, market conditions) changes dynamically. Deep Q-learning and policy gradient methods have shown promise in marketing automation and customer journey optimization.

4. Key Application Areas

4.1 Churn Prediction

Churn prediction remains one of the most critical and well-studied applications of ML in CRM. The ability to identify customers likely to discontinue service enables proactive retention strategies and significantly impacts business profitability. Modern approaches combine multiple data sources, transactional, behavioral, and interaction data to build comprehensive churn prediction models. Recent advances include trajectory-based approaches that model customer behavior as sequences of states and transitions. The TR-LSTM model explicitly addresses the temporal dynamics of customer churn, achieving superior performance compared to static feature-based models [4]. These sequential approaches are particularly valuable in subscription-based businesses where customer engagement patterns evolve.

4.2 Customer Lifetime Value (CLV) Prediction

CLV prediction has evolved from simple statistical models to sophisticated ML systems capable of real-time, personalized value estimation. Modern CLV systems integrate multiple components: churn prediction, purchase

frequency modeling, and monetary value estimation, often using ensemble approaches to combine predictions [3]. High-performance turnkey CLV systems now enable daily scoring across diverse retail brands, incorporating feature embeddings and multi-stage frameworks. These systems demonstrate the maturation of ML in CRM, moving from research prototypes to production-ready solutions capable of handling enterprise-scale data [3].

4.3 Customer Segmentation and Targeting

Traditional RFM (Recency, Frequency, Monetary) analysis has been enhanced with advanced clustering techniques and graph-based methods. Modern segmentation approaches incorporate behavioral patterns, preference modeling, and social network effects to create more nuanced customer segments. Graph-based segmentation methods are particularly valuable in B2B contexts where customer relationships and influence patterns significantly impact purchasing decisions. GCN-based approaches on customer relationship graphs have shown superior performance in sales forecasting and lead prioritization [7].

4.4 Personalization and Recommendation Systems

Personalization in CRM extends beyond product recommendations to include personalized pricing, communication timing, and channel selection. Modern systems use deep learning architectures that simultaneously handle multiple objectives, relevance, diversity, and business constraints. Embedding-based approaches enable sophisticated personalization by learning dense representations of customers, products, and contexts. These representations can be used across multiple CRM tasks, from recommendation to pricing optimization, providing consistent personalization across customer touchpoints [3].

4.5 Sentiment Analysis and Customer Feedback Processing

Analyzing customer feedback, reviews, and social media mentions has become crucial for CRM systems. Advanced NLP techniques enable real-time sentiment monitoring, topic extraction, and automated response generation. Domain-specific language models, such as MetRoBERTa for transit customer feedback, demonstrate significant improvements over generic NLP approaches. These specialized models understand industry-specific terminology and context, enabling more accurate sentiment analysis and topic classification [6].

4.6 Customer Service Automation and Routing

ML-powered customer service systems can automatically route inquiries to appropriate agents, predict resolution times, and even provide automated responses for common queries. Reinforcement learning approaches optimize routing decisions based on agent expertise, customer priority, and workload balance. The CRSRL system exemplifies how RL can maximize customer service operations, learning optimal routing policies that adapt to changing conditions and customer needs [5]. These systems significantly improve service efficiency while maintaining customer satisfaction.

5. Current Challenges and Limitations

5.1 Model Interpretability and Explainability

Despite their superior performance, many ML models used in CRM operate as "black boxes," making it difficult for business users to understand and trust their predictions. This lack of interpretability poses significant challenges in regulated industries and business decision-making processes requiring clear justification. Recent research emphasizes the need for explainable AI (XAI) in CRM applications, particularly for high-stakes decisions like credit scoring or customer prioritization. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are being integrated into CRM systems to provide model explanations [13].

5.2 Data Quality and Bias

CRM systems often suffer from data quality issues, including missing values, inconsistent formatting, and biased sampling. These issues can significantly impact ML model performance and lead to unfair or discriminatory outcomes. Bias detection and mitigation have become critical concerns, particularly as CRM systems influence customer treatment and business decisions. Recent surveys highlight the prevalence of bias in customer interaction

data and the need for systematic approaches to bias detection and mitigation. This includes both algorithmic bias (unfair model predictions) and data bias (unrepresentative training data) [13].

5.3 Distribution Shift and Model Drift

Customer behavior and market conditions change, leading to a distribution shift that can degrade model performance. CRM models trained on historical data may become less accurate as customer preferences evolve or market conditions change. This challenge is particularly acute in dynamic industries and during periods of significant change (such as the COVID-19 pandemic). Domain generalization techniques are being developed to create more robust CRM models that maintain performance across different contexts and time periods [14]. These approaches focus on learning invariant features that generalize across different distributions.

5.4 Scalability and Production Deployment

Moving ML models from research prototypes to production-ready CRM systems presents significant technical challenges. Issues include real-time prediction requirements, system integration, model versioning, and performance monitoring. Many organizations struggle with the operational aspects of ML deployment, including infrastructure requirements and maintenance overhead. Turnkey ML systems represent one approach to addressing scalability challenges, providing pre-built solutions that can be deployed across different business contexts with minimal customization [3]. However, these solutions may sacrifice flexibility for ease of deployment.

5.5 Privacy and Regulatory Compliance

Using customer data for ML applications raises significant privacy concerns and regulatory compliance requirements. Regulations such as GDPR in Europe and CCPA in California impose strict data collection, processing, and customer consent requirements. These regulations impact how CRM systems collect and use customer data for ML applications. Privacy-preserving ML techniques, including differential privacy and federated learning, are being explored for CRM applications. These approaches enable ML model training while protecting individual customer privacy, though they often involve trade-offs in model performance.

6. Recent Trends and Innovations (2019-2025)

6.1 Large Language Models and Conversational AI

The emergence of large language models (LLMs) has transformed customer service and CRM interactions. ChatGPT, Claude, and other conversational AI systems are being integrated into CRM platforms to provide automated customer support, generate personalized communications, and analyze customer feedback at scale. Domain-specific LLMs trained on industry data show particular promise for CRM applications. These models better understand industry terminology, regulations, and customer concerns than generic models, enabling more effective customer interactions [6].

6.2 Automated Machine Learning (AutoML)

AutoML platforms democratize ML in CRM by enabling business users without deep technical expertise to build and deploy ML models. These platforms automate feature engineering, model selection, and hyperparameter tuning, making ML more accessible to CRM practitioners. Integrating AutoML into CRM platforms enables rapid experimentation and model iteration, allowing businesses to quickly adapt to changing customer behavior and market conditions. However, these automated approaches may miss domain-specific insights that expert data scientists would incorporate.

6.3 Real-time and Edge Computing

The demand for real-time personalization and immediate response to customer behavior has driven the adoption of edge computing and real-time ML inference in CRM systems. This enables instantaneous personalization, fraud detection, and customer service routing. Streaming ML architectures that can update models in real-time as new customer data arrives represent a significant advancement in CRM capabilities. These systems can adapt to changing customer behavior without requiring full model retraining.

6.4 Multi-modal Learning

Modern CRM systems integrate data from multiple sources and modalities, such as text, images, voice, and behavioral data. Multi-modal learning approaches can combine these diverse data types to create a more comprehensive customer understanding. For example, combining customer service call transcripts (text), voice sentiment analysis (audio), and transaction data (structured) can provide a more complete picture of customer satisfaction and likely future behavior.

6.5 Ethical AI and Responsible ML

There is growing emphasis on ethical considerations in CRM ML applications. This includes fairness in customer treatment, transparency in decision-making, and accountability for automated decisions that affect customers. Responsible ML practices are being integrated into CRM development processes, including bias testing, fairness metrics, and ethical review processes for ML model deployment [13]. These practices are becoming essential for regulatory compliance and maintaining customer trust.

7. Future Research Directions

7.1 Federated Learning for CRM

Federated learning enables multiple organizations to collaboratively train ML models without sharing sensitive customer data. This approach has significant potential for CRM applications, particularly in industries where data sharing is restricted but collaborative learning could benefit all participants. Future research should explore federated learning architectures designed explicitly for CRM use cases, including cross-industry customer behavior modeling and collaborative fraud detection systems.

7.2 Causal Inference and Treatment Effect Estimation

Moving beyond correlation to causation is crucial for effective CRM decision-making. Causal inference techniques can help identify which marketing interventions drive customer behavior changes, enabling more effective resource allocation. Research in causal ML for CRM should focus on treatment effect estimation for marketing campaigns, pricing strategies, and customer service interventions. This includes developing methods to handle most CRM data's observational nature.

7.3 Quantum Machine Learning

While still in early stages, quantum computing has potential applications in CRM, particularly for optimization problems such as customer segmentation, resource allocation, and portfolio optimization. Quantum ML algorithms may provide computational advantages for certain types of CRM problems. Research should explore which CRM applications could benefit from quantum computing and develop quantum-classical hybrid approaches that leverage the strengths of both paradigms.

7.4 Sustainable and Green ML

The environmental impact of large-scale ML systems is becoming a significant concern. Future CRM systems should consider energy efficiency and carbon footprint in their design and operation. Research directions include developing more efficient ML algorithms, optimizing model deployment for energy efficiency, and creating sustainability metrics for CRM ML systems.

7.5 Human-AI Collaboration

Rather than replacing human decision-making, future CRM systems should focus on augmenting human capabilities. This includes developing interfaces that effectively communicate ML insights to business users and enable human oversight of automated decisions. Research should explore how to design human-AI collaboration frameworks that leverage the strengths of both humans (creativity, empathy, domain expertise) and AI (pattern recognition, scale, consistency) in CRM contexts.

8. Industry Adoption Patterns

8.1 Enterprise Implementation

Large enterprises have been early adopters of ML in CRM, with significant investments in data infrastructure, ML platforms, and specialized talent. Enterprise CRM systems increasingly include built-in ML capabilities for everyday use cases such as lead scoring, churn prediction, and customer segmentation. The trend toward "turnkey" ML solutions reflects the need for standardized, reliable ML capabilities that can be deployed across different business units and use cases [3]. These solutions balance customization needs with operational efficiency.

8.2 Small and Medium Enterprise (SME) Adoption

SMEs face different challenges in ML adoption, including limited resources, expertise, and data volume. Cloud-based CRM platforms with integrated ML capabilities make advanced analytics more accessible to smaller organizations. Future research should address the specific needs of SMEs, including developing ML approaches that work effectively with smaller datasets and require minimal technical expertise to deploy and maintain.

8.3 Industry-Specific Adaptations

Different industries have developed specialized approaches to ML in CRM based on their unique characteristics and requirements:

- ✓ Telecommunications: Focus on churn prediction and network optimization
- ✓ Retail: Emphasis on personalization and inventory optimization
- ✓ Financial Services: Priority on fraud detection and risk assessment
- ✓ Healthcare: Integration with patient care and regulatory compliance
- ✓ Manufacturing: B2B relationship management and supply chain integration

8.4 Regulatory and Compliance Considerations

Industries with strict regulatory requirements (financial services, healthcare, telecommunications) face additional challenges in ML deployment. Compliance requirements influence model selection, data usage, and deployment practices. Developing "compliant-by-design" ML systems that incorporate regulatory requirements from the beginning represents an essential trend in enterprise CRM adoption.

9. Performance Metrics and Evaluation Methods

9.1 Business-Centric Metrics

CRM ML applications require evaluation metrics that align with business objectives rather than purely technical metrics. Key business-centric metrics include:

- ✓ Customer Lifetime Value Impact: Measuring how ML interventions affect long-term customer value
- ✓ Retention Rate Improvement: Quantifying the effectiveness of churn prediction and retention campaigns
- ✓ Revenue Attribution: Connecting ML predictions to actual revenue outcomes
- ✓ Cost Reduction: Measuring operational efficiency gains from ML automation

9.2 Model Performance Metrics

Traditional ML metrics remain important for technical evaluation:

- ✓ Accuracy and Precision/Recall: For classification tasks like churn prediction
- ✓ Mean Squared Error: For regression tasks like CLV prediction
- ✓ Area Under Curve (AUC): For ranking and probability-based predictions
- ✓ F1-Score: Balancing precision and recall for imbalanced datasets standard in CRM

9.3 Fairness and Bias Metrics

Ensuring fair treatment across different customer segments requires specialized metrics:

- ✓ Demographic Parity: Equal treatment across protected groups
- ✓ Equalized Odds: Equal accurate positive and false favorable rates across groups

- ✓ Individual Fairness: Similar treatment for similar customers

9.4 Operational Metrics

Production CRM systems require monitoring of operational performance:

- ✓ Prediction Latency: Time required to generate predictions
- ✓ System Throughput: Number of predictions per unit time
- ✓ Model Drift Detection: Monitoring for changes in model performance over time
- ✓ Data Quality Metrics: Ensuring input data meets quality standards

10. Conclusion

Machine learning has fundamentally transformed customer relationship management, enabling organizations to move from reactive to predictive customer engagement strategies. Our comprehensive review of recent literature (2019-2025) reveals a mature and rapidly evolving field with significant practical impact across industries. The landscape of ML techniques in CRM has expanded beyond traditional classification and clustering to include sophisticated deep learning, natural language processing, graph neural networks, and reinforcement learning approaches. These techniques address diverse CRM challenges from churn prediction and customer lifetime value estimation to real-time personalization and automated customer service.

Key findings from our analysis include:

- ✓ Technical Maturity: ML applications in CRM have moved from research prototypes to production-ready systems capable of handling enterprise-scale data and real-time decision-making requirements.
- ✓ Diverse Application Portfolio: CRM ML applications span the entire customer lifecycle, from acquisition and onboarding to retention and win-back campaigns, with measurable business impact.
- ✓ Integration Challenges: Despite technical advances, organizations face challenges in model interpretability, bias mitigation, and production scalability that require ongoing research and development attention.
- ✓ Ethical Considerations: The field has increasingly recognized the importance of ethical AI practices, including fairness, transparency, and accountability in customer-facing ML applications.
- ✓ Industry Adoption: Large enterprises lead in ML adoption, while SMEs benefit from cloud-based solutions and turnkey ML platforms that democratize access to advanced analytics.

Looking forward, several trends will shape the future of ML in CRM:

- ✓ Conversational AI Integration: Large language models and conversational AI will become standard components of CRM systems, enabling more natural and effective customer interactions.
- ✓ Real-time Adaptation: Systems will increasingly adapt to changing customer behavior in real-time, using streaming ML and edge computing architectures.
- ✓ Privacy-Preserving Approaches: Federated learning and differential privacy techniques will enable collaborative ML while protecting customer privacy.
- ✓ Human-AI Collaboration: Future systems will focus on augmenting rather than replacing human decision-making, creating more effective hybrid approaches.
- ✓ Sustainable ML: Environmental considerations will influence ML system design, emphasizing efficiency, sustainability, and performance.

The continued evolution of ML in CRM will require interdisciplinary collaboration between computer scientists, business strategists, ethicists, and domain experts. Success will depend on technical innovation and addressing practical deployment challenges, regulatory requirements, and ethical considerations. As organizations increasingly rely on ML-driven CRM systems for competitive advantage, the importance of responsible development and deployment practices cannot be overstated. The future of ML in CRM lies not just in more sophisticated algorithms, but in creating systems that are fair, transparent, sustainable, and ultimately beneficial for both businesses and their customers.

References

[1] D. Ozay, M. Jahanbakht, A. Shoomal, and S. Wang, "Artificial Intelligence (AI)-based Customer Relationship Management (CRM): a comprehensive bibliometric and systematic literature review with outlook on future research," Enterprise Information Systems, 2024. doi: [10.1080/17517575.2024.2351869](https://doi.org/10.1080/17517575.2024.2351869)

[2] N. Singh, P. Singh, and M. Gupta, "An inclusive survey on machine learning for CRM: a paradigm shift," Journal / Springer, 2020.

[3] Y. Yan and N. Resnick, "A high-performance turnkey system for customer lifetime value prediction in retail brands," Qme-quantitative Marketing and Economics, 2023. doi: [10.1007/s11129-023-09272-x](https://doi.org/10.1007/s11129-023-09272-x)

[4] B. Zhu, C. Qian, X. Pan, and H. Chen, "A trajectory-based deep sequential method for customer churn prediction," in ICML Proceedings, 2020. doi: [10.1145/3409073.3409083](https://doi.org/10.1145/3409073.3409083)

[5] C. Long, Z. Liu, X. Lu, Z. Hu, and Y. Wang, "CRSRL: Customer Routing System Using Reinforcement Learning," in IJCAI Proceedings, 2019. doi: [10.24963/IJCAI.2019/952](https://doi.org/10.24963/IJCAI.2019/952)

[6] M. Leong et al., "MetRoBERTa: Leveraging Traditional Customer Relationship Management Data to Develop a Transit-Topic-Aware Language Model," arXiv, 2023. Available: http://arxiv.org/abs/2308.05012v1

[7] S. Henna and S. K. Kalliadan, "Enterprise Analytics using Graph Database and Graph-based Deep Learning," arXiv, 2021. Available: http://arxiv.org/abs/2108.02867v1

[8] Y. Huang, J. D. Leu, B. Lu, and Y. Zhou, "Risk Analysis in Customer Relationship Management via Quantile Region Convolutional Neural Network-Long Short-Term Memory and Cross-Attention Mechanism," arXiv, 2024. Available: http://arxiv.org/abs/2408.12113v1

[9] X. Shi, Y. Zhang, L. Zhang et al., "Revolutionizing market surveillance: customer relationship management with machine learning," PeerJ Computer Science, 2024. doi: [10.7717/peerj-cs.2583](https://doi.org/10.7717/peerj-cs.2583)

[10] P. P. Šimović, D. Horvatic, and E. W. Sun, "Classifying variety of customers' online engagement for churn prediction with mixed-penalty logistic regression," arXiv, 2021. Available: http://arxiv.org/abs/2105.07671v2

[11] G. Wanganga and Y. Qu, "A Deep Learning based Customer Sentiment Analysis Model to Enhance Customer Retention and Loyalty in the Payment Industry," in International Conference on Computational Science, 2020. doi: [10.1109/CSCI51800.2020.00086](https://doi.org/10.1109/CSCI51800.2020.00086)

[12] Y. Liang, X. Zhou, X. Yuan, and Y. Chen, "Optimization of pharmacy membership management system based on big data: Sleeping member activation and awakening methods using ANN modeling," Heliyon, 2024. doi: [10.1016/j.heliyon.2024.e39482](https://doi.org/10.1016/j.heliyon.2024.e39482)

[13] A. Bias Detection et al., "Bias Detection for Customer Interaction Data: A Survey on Datasets, Methods, and Tools," IEEE Access, 2023. doi: [10.1109/access.. 2023.3276757](https://doi.org/10.1109/access.2023.3276757)

[14] H. Duan, Y. Yang, A. Abbasi, and K. Y. Tam, "Predicting Practically? Domain Generalization for Predictive Analytics in Real-world Environments," arXiv, 2025. Available: http://arxiv.org/abs/2503.03399v1