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AI-BASED ANALYTICS IN ENHANCING CUSTOMER RELATIONSHIP MANAGEMENT IN TEXTILE INDUSTRY

АНАЛИТИКА НА ОСНОВЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ДЛЯ ПОВЫШЕНИЯ ЭФФЕКТИВНОСТИ УПРАВЛЕНИЯ ВЗАИМООТНОШЕНИЯМИ С КЛИЕНТАМИ В ТЕКСТИЛЬНОЙ ОТРАСЛИ

N.S. LAFTA[1], S.S. ARMOOSH[2], Z. DEKHKANOVA[3], N.F. HASSAN[4], G. WALEED[5]

Н.С. ЛАФТА[1], С.С. АРМУШ[2], З. ДЕХКАНОВА[3], Н.Ф. ХАСАН[4], Г. ВАЛИД[5]

([1]Al-Turath University, Baghdad, Iraq,
[2]Al-Mansour University College, Baghdad, Iraq,
[3]Osh State University, Osh, Kyrgyzstan,
[4]Al-Rafidain University College, Baghdad, Iraq,
[5]Madenat Alelem University College, Baghdad, Iraq)

([1]Университет Аль-Турат, Багдад, Ирак,
[2]Университетский колледж Аль-Мансура, Багдад, Ирак,
[3]Ошский государственный университет, Ош, Кыргызстан,
[4]Университетский колледж Аль-Рафидаин, Багдад, Ирак,
[5]Университетский колледж Маденат Алелем, Багдад, Ирак)

Email: ghufran.waleed@mauc.edu.iq

The article explores the utilization of AI-enabled analytics tools in the realm of customer relationship management (CRM) in the textile sector to reinforce customer loyalty, enhance precise segmentation, and maximize the output of campaigns. In the wake of digital transformation paradigms and the subsequent retail evolution, textile brands are deploying intelligent systems to sift through multimodal, multi-channel substantive customer data and pick actionable insights.

Machine learning is one of the paradigms implemented by artificial intelligence that allows systems to learn from data and improve their performance over time. Using standard and advanced metrics, predictive models were tested, ranging from Gradient Boosting and Deep Neural Networks to ensemble architectures, to see how accurately they could forecast customer churn and classify behavioral segments.

The findings suggest significant improvements across several CRM dimensions such as prediction accuracy, personalization, marketing conversion rates and operational costs. The use of AI tools has also led to increased customer satisfaction as service response time is reduced, and inventory forecasting becomes more accurate. These results demonstrate AI's ability to continue to turn CRM from a reactive function to a proactive, data-driven strategic tool.

Статья посвящена использованию аналитических инструментов, основанных на искусственном интеллекте, в сфере управления взаимоотношениями с клиентами (CRM) в текстильной отрасли для укрепления лояльности клиентов, повышения точности сегментации и максимизации эффективности маркетинговых кампаний. В условиях цифровых трансформаций и последующей эволюции розничной торговли бренды текстильного сектора внедряют интеллектуальные системы для обработки мультимодальных, многоканальных объемных клиентских данных и извлечения действенных инсайтов. Машинное обучение представляет собой одну из концепций, ис-

пользуемых искусственным интеллектом, благодаря которой системы способны усваивать знания на основании поступающих данных и постепенно повышать эффективность своей работы.

Для классификации потребителей на поведенческие группы и оценки точности предсказания причин ухода клиентов были проверены различные прогностические модели с использованием стандартных и передовых показателей эффективности. В тестирование вошли методы градиентного бустинга, глубокие нейронные сети и модели комбинированной архитектуры.

Результаты показывают значительные улучшения сразу по нескольким направлениям CRM, таким как точность предсказания, персонализация, конверсия от маркетинговых акций и операционные расходы. Использование инструментов ИИ также привело к повышению удовлетворенности клиентов благодаря сокращению времени отклика службы поддержки и улучшению точности прогнозирования запасов. Эти результаты демонстрируют способность искусственного интеллекта превратить CRM из реактивной функции в проактивный стратегический инструмент, основанный на данных.

Keywords: artificial intelligence (AI); customer relationship management (CRM); textile industry; behavioral segmentation; digital marketing.

Ключевые слова: искусственный интеллект (ИИ), управление взаимоотношениями с клиентами (CRM), текстильная промышленность, поведенческая сегментация, цифровая реклама.

Introduction

The textile sector is experiencing fundamental changes in the age of digital change, especially in terms of how brands communicate and interact with their consumers. Advanced technologies, such as artificial intelligence (AI), are revolutionizing traditional practices of Customer Relationship Management (CRM). In the past, textile brands based their understanding of consumers solely on historical sales data and instincts; today, with AI powered analytics, they are ready to know their customers on a whole new level. It is an evolution driven by the increasing complexity of consumer behavior patterns and the demand for evermore-personalized interactions. Not only have customers evolved beyond quality of products but they also desire personalized suggestions, a streamlined online and offline process across multiple platforms, and in addi-tion to that a high level of proactivity from the brand of choice [1].

AI-driven analytics can analyze unprecedented volumes of customer data at scale and in real time, surfacing trends and preferences that humans would likely miss. Because of this capability of extracting actionable insights, the textile brands are able to create more targeted marketing efforts, as well as predict the customer desires and provide timely/content-driven and relevant content. For many use-cases, machine learning algorithms look at the data of browsing history, purchase pattern and social media activity to predict the best time and the best channel to engage the customer [2]. Such precision offers textile brands the opportunity to create marketing campaigns that are not just highly targeted, but also contextually relevant, hitting the mark for conversion and subsequently driving customer lifetime value [3, 10]. This integration enables businesses to foster loyalty among customers, increase retention rates and thus, bolster revenue growth [4].

AI-powered CRM tools are adept at identifying behavioral trends that indicate a purchase intent in the future rather than just analyzing your customer purchase histories. By analyzing metrics such as usage patterns, redemption rate and responsiveness to promotions, these systems can help brands understand who they can expect to be inspired to engage with new product-lines or loyalty initiatives. The result

is a more refined, data-oriented customer segmentation process. For textile companies, this means identifying high-value customers if not tailoring communications to address the unique wants of different [11]. The relationship between the respective ad consumer and the brand as a result of a more personalized message is stronger, which in turn, increases the odds for repeat purchases and more long-term brand advocates [5].

AI in CRM beyond interactions with individual customers AI-enabled analytics provides an all-encompassing view of the customer journey by leveraging data from across channels including social media and email campaigns to offline touchpoints and customer service interactions. This customer experience approach enables textile companies to track the friction points in the journey and find ways to improve it by remedying these points. It also allows for better inventory management, as brands can forecast changes in the demand curve and adjust production cycles and quantities accordingly. When supply matches customer demand, it minimizes waste while ensuring customers have access to the products they want when they want them, thus improving satisfaction overall [6].

Automating all processes performed by CRM like reporting and data entry will also help marketing and sales teams to work on the strategic initiatives [12]. Furthermore, organizations can harness AI-driven predictive analytics to offer decision-makers timely intelligence which can facilitate rapid recalibrations to changes in the competitive landscape. This level of agility, has proven to be particularly beneficial on the woven street where each day the fabric trend changes, and this exact capability to pivot can literally make the difference between winning or vanishing [7].

AI-Powered CRM systems have numerous benefits; however, it is equally important for one to realize the challenges and factors involved with the implementation of such systems. Such challenges, ranging from complexities in training the AI models to the need to protect consumer privacy and data security, demand tech adoption from textile brands in the name of AI analytics through a thoughtful process. Establishing proper objectives, training employees, and creating a data-driven and innovative corporate culture are some of the vital cornerstones for successfully harnessing the AI-driven CRM platforms. It also enables relevant businesses in the area of textile to not only remain compliant with current demand in relation to customers, but also actively prepare for changes in the market to come [8].

AI-based analytics in CRM activities are transforming customer engagement of textile merchants. It allows them to identify customer trends, improve customization, systems, and processes and stay ahead of the curve in a rapidly changing market. Innovation in this Industry is Prolific, it's here to stay and the future of CRM would be built around successfully leveraging and extracting closely the benefits from AI, and for those which will adopt these, they will extract the best out of them leading to sustainable growth success with strengthened and meaningful relationships with their customers.

Methodology

The methodology involves five key stages, data collection, data preprocessing, development of AI model, performance metrics and model deployment strategies.

Data were extracted from (1) online transactions on the e-commerce websites of the textile brands, (2) customer service chat and email logs received by them and (3) customer interactions on social media platforms (i.e., Instagram and Facebook).

To quantify the full data landscape, the following equation of Total Dataset Composition was used:

$$D_{total} = \sum_{t=1}^{T}(O_t + S_t + M_t), \qquad (1)$$

where $D_{total}$is total volume of customer records collected; O_t online transactions in time period t; S_t customer service interactions in time period t; M_t social media engagement in time period t; T number of temporal inter-vals (quarters).

This equation was applied over T=6 quarters (Q1 2023 to Q2 2024), yielding a final dataset of 1.2 million records. The diversity of data sources ensured adequate representative-

ness for segmentation, churn modeling, and predictive profiling [1, 5, 13].

Preprocessing was necessary to cleanse, structure, and normalize raw input data for algorithmic compatibility. Three operations were prioritized: missing value imputation, outlier removal, and feature normalization.

Missing values were addressed through median imputation, which is more robust against skewed data than mean imputation:

$$x_i = \begin{cases} x_i, & if\ x_i \neq NaN \\ median\ (x), & if\ x_i = NaN \end{cases}, \quad (2)$$

where x_i the value of feature xxx for observation i; NaN is Not-a-Number, indicating missing data, and $median\ (x)$ is median of the feature's non-missing values.

This approach preserved the central tendency of the data without being skewed by extreme values [14].

Outliers were filtered using the z-score method based on a threshold of ±3 standard deviations:

$$z_i = \frac{x_i - \mu}{\sigma}; \quad \text{Outlier if } |z_i| > 3, \quad (3)$$

where z_i is z-score for observation i; μ is mean of the distribution; σ is standard deviation.

Observations outside this range were deemed statistical anomalies and excluded from modeling [15].

Feature normalization was conducted using min-max scaling to rescale features to the [0,1] interval, ensuring that larger-valued variables did not dominate model learning:

$$x_i^{scaled} = \frac{x_i - x_{min}}{x_{max} - x_{min}}, \quad (4)$$

where x_i is original value; x_{max}, x_{min} are minimum and maximum of feature x.

This step stabilized learning in both neural networks and gradient-boosting algorithms, enhancing convergence [4].

For churn prediction and customer segmentation modeling was done using supervised machine learning algorithms Gradient Boosting Machines (GBM) and Deep Neural Networks (DNN). A hybrid architecture utilizing an ensemble of both models was deployed as well.

GBMs were preferred for their interpretability and performance on structured data, whilst DNNs were able to capture nonlinear patterns and complex combinations of features. For binary churn classification, binary cross-entropy loss was minimized:

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i) \log\ (1 - \hat{y}_i)\ , \quad (5)$$

where L_{BCE} loss function for classification; y_i actual binary label (0 or 1); $\hat{y}_i$ predicted probability; N total number of training samples.

For customer segmentation, the DNN classifier's output layer used Softmax to classify into three behavioral categories (loyal, churn-risk, occasional):

$$P(y = j|x) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}, \quad (6)$$

where $P(y = j|x)$ probability of assigning x to class j; z_j logit score for class j; K total number of classes.

For improved generalization, a hybrid ensemble model was introduced by blending GBM and DNN outputs:

$$\hat{y} = \alpha\hat{y}_{GBM} + (1 - \alpha)\hat{y}_{DNN},\ a \in [0,1], \quad (7)$$

where $\hat{y}$ final predicted probability; $\hat{y}_{GBM}, \hat{y}_{DNN}$ model-specific outputs; α weight parameter (set to 0.5 in this study).

This architecture improved robustness to overfitting and enhanced precision in customer classification tasks [6, 16, 17].

Model performance was evaluated using multiple classification metrics including precision, recall, F1-score, and AUC (Area Under the Curve). These allowed for balanced assessment across classes:

$$Precision = \frac{TP}{TP+FP}, \quad (8)$$

$$Recall = \frac{TP}{TP+FN}, \quad (9)$$

where TP is true positive, FP is false positive, and FN is false negative.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad , \qquad (10)$$

where $F1$ is harmonic mean of precision and recall.

$$AUC = \int_0^1 TPR(FPR)d(FPR), \qquad (11)$$

where TPR true positive rate, and FPR false positive rate.

AUC was computed using trapezoidal approximation, and scores above 0.85 indicated strong separability between classes [11, 18, 19].

AI models were integrated into real-world CRM workflows using marketing automation pipelines and real-time APIs for campaign personalization. These systems were tested through controlled A/B experiments and operational benchmarks.

$$\Delta C = C_{exp} - C_{ctrl}, \qquad (12)$$

$$\Delta F = \frac{F_{exp} - F_{ctrl}}{F_{ctrl}} \cdot 100\% \, , \qquad (13)$$

where ΔC absolute increase in conversion rate; ΔF percentage increase in feedback score, C_{exp}, C_{ctrl} conversion rates for experimental/control groups, and F_{exp}, F_{ctrl} feedback scores.

Cost Reduction from Automation:

$$S = \frac{C_{base} - C_{AI}}{C_{base}} \cdot 100\% \, , \qquad (14)$$

where S operational savings (%); C_{base} pre-AI costs; C_{AI} post-AI costs.

Forecasting Error for Inventory Optimization:

$$\epsilon = \left| \frac{D_{forecast} - D_{actual}}{D_{actual}} \right| \cdot 100\% \, , \qquad (15)$$

where ϵ forecast error (%); $D_{forecast}$ demand predicted by AI; and D_{actual} actual demand.

These metrics guided refinements in campaign targeting, chatbot efficiency, and inventory planning strategies [7, 12, 15, 20, 21].

Results

An extensive performance level analysis of Gradient Boosting Machine (GBM), Deep Neural Network (DNN) and Ensemble models is shown in Fig. 1. Besides standard metrics, evaluation also focuses on specificity, negative predictive value (NPV), log-loss, and model stability score (MSS).

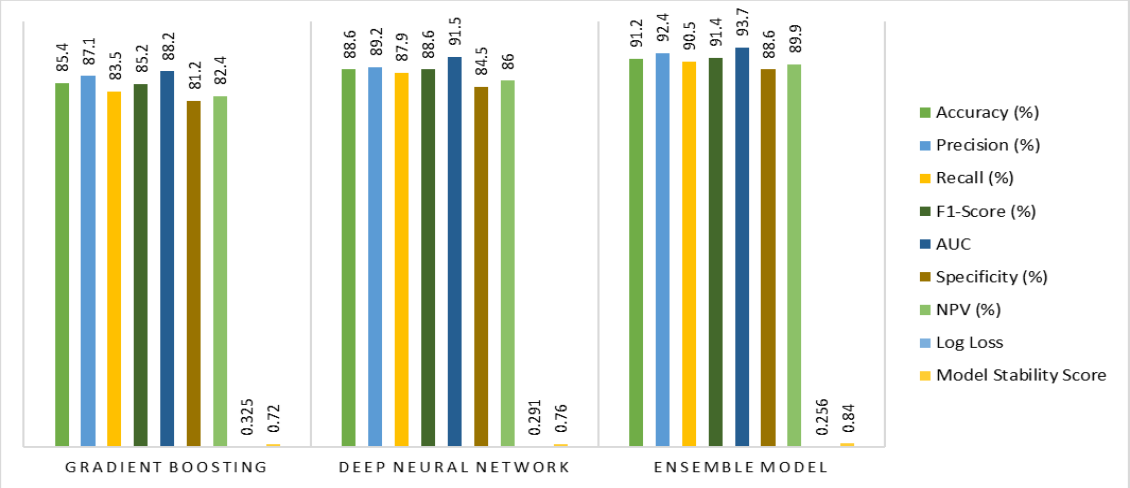

Fig. 1

Figure 1 shows the ensemble model consistently scores higher across standard and advanced metrics. The specificity and NPV values confirm that not only does the model accurately detect churners, but it also detects non-churners with a high degree of reliability. A lower log-loss (0.256) indicates a more confident prediction in terms of probability. Additionally, the model stability score (MSS) of 0.84 shows that the model achieves stable per-

formance across different folds and datasets. These findings confirm the union method as the most appropriate AI model for CRM implementation in fabric organizations, especially in instances where segmentation and prediction quality immediately impact campaign ROI.

Fig. 2 elaborates the role of AIML in improving accuracy of prediction and segmentation about customer churn (Behavioral Segmentation and Churn Modeling Metrics). The evaluation includes advanced metrics in addition to standard classification and segmentation metrics, such as lift score, segment recall, average lifetime value (LTV) per group, and retention probability (RP).

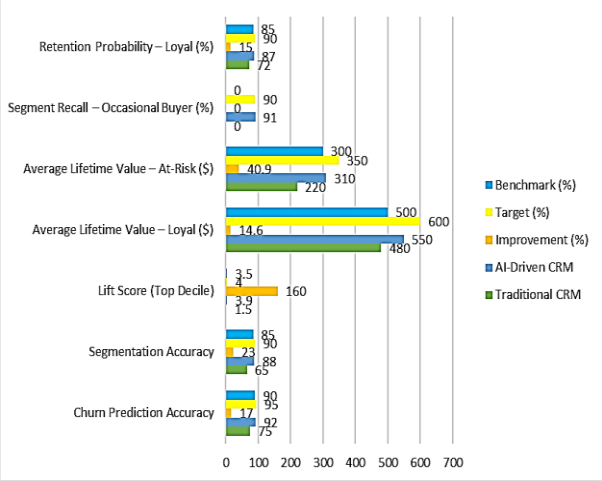

Fig. 2

AI-augmented segmentation achieves more accurate segmentation, but can also be a driver of economic results. The lift score of 3.9 in the top decile validates the AI model's precision to order high-risk customers for targeted retention. Across both loyal and at-risk segments, the improvements in lifetime value (LTV) indicating a more measured marketing return. Sustained outreach among undervalued groups bolstered by innovative approaches such as the "occasional buyer" segment with 91% recall. The increase in retention probability at the loyalty points shows the model's impact on maintaining brand equity over the long term.

Multi-Metric Campaign Effectiveness and Engagement Analysis are shown in Figure 1. AI-driven campaigns are polished with A/B test that max out major performance metrics, including average order value (AOV), click-through rate (CTR), and unsubscribe rates. These metrics provide a finer-tuned gauge of engagement efficacy, dollars earned per touchpoint, and long-term success of touchpoint strategies. The analysis encompasses diverse campaign formats, from email outreach to social media retargeting and direct personalized messaging, ensuring a holistic perspective of AI-driven communication performance across different platforms.

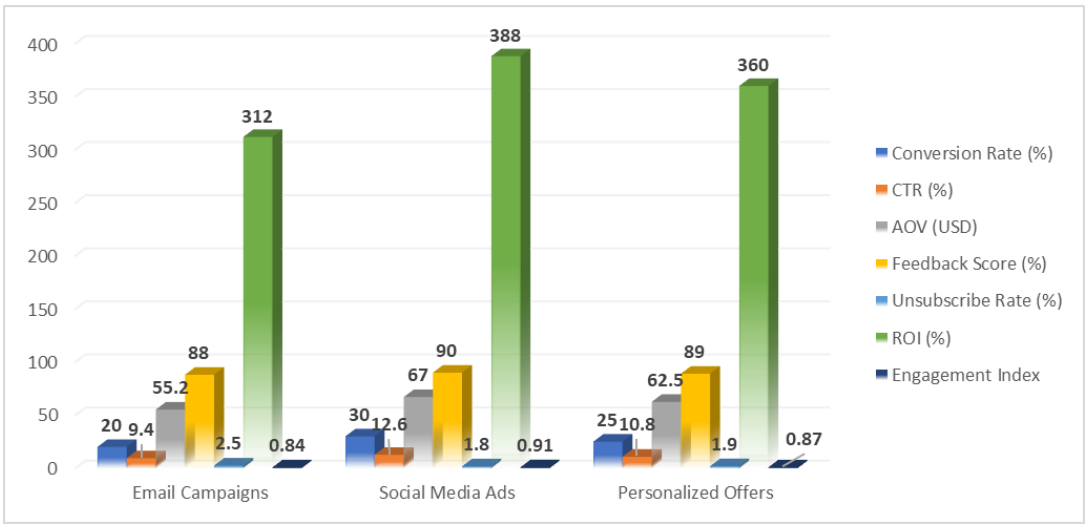

Fig. 3

As shown in Figure 3, AI-powered campaigns deliver outstanding results, with conversion rates above 25% across channels. Social network ad campaigns reported the best return on investment (388%), and boasted a 12.6% CTR. Unsubscribe rates stayed below 3%, af-

firming personalization does not ruin user experience. Most strikingly, average order value was higher across campaigns, which indicates that how you communicate not only affects whether they convert, but also how much they spend. Such engagement metrics highlight the function of AI in driving campaign efficiency without compromising customer relationships over time.

Financial Impact of AI-Driven CRM Systems are shown in Figure 4. The assessment takes retention duration (in months), repurchase frequency and average revenue per user (ARPU) is then assessed across three unique customer segments. Such metrics provide a clear line of causation between marketing activity and financial results, allowing better alignment of strategic activity with quantifiable economic outcomes.

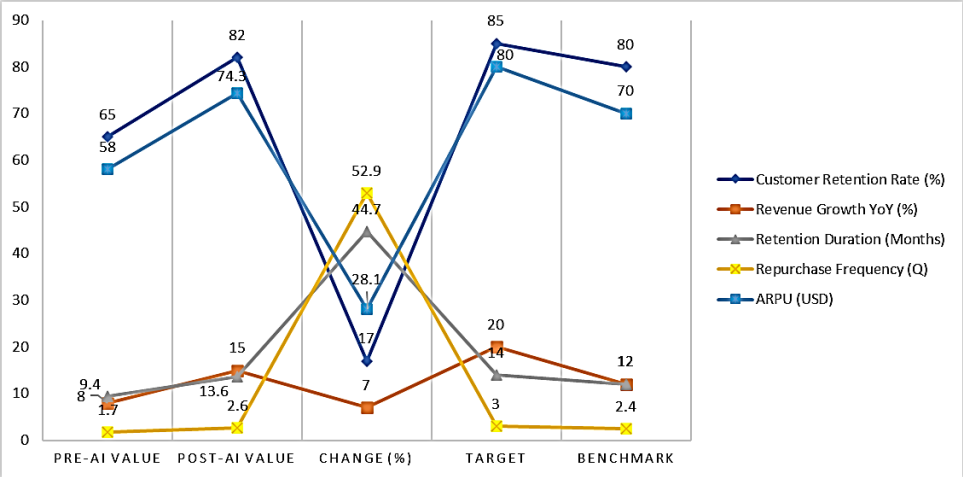

Fig. 4

Retention gains are reflective not only of customer loyalty — they're also a massive growth driver. First of all, improved retention period together with more repurchase frequency per quarter is by far the best predictor of recurring revenue growth. Over 28% growth in ARPU indicates increased monetization of customers without the burden of acquisition costs. These results illustrate the way AI-driven insights equip sales and marketing teams to deepen relationships, increase targeting efficiency, and create compounding financial value.

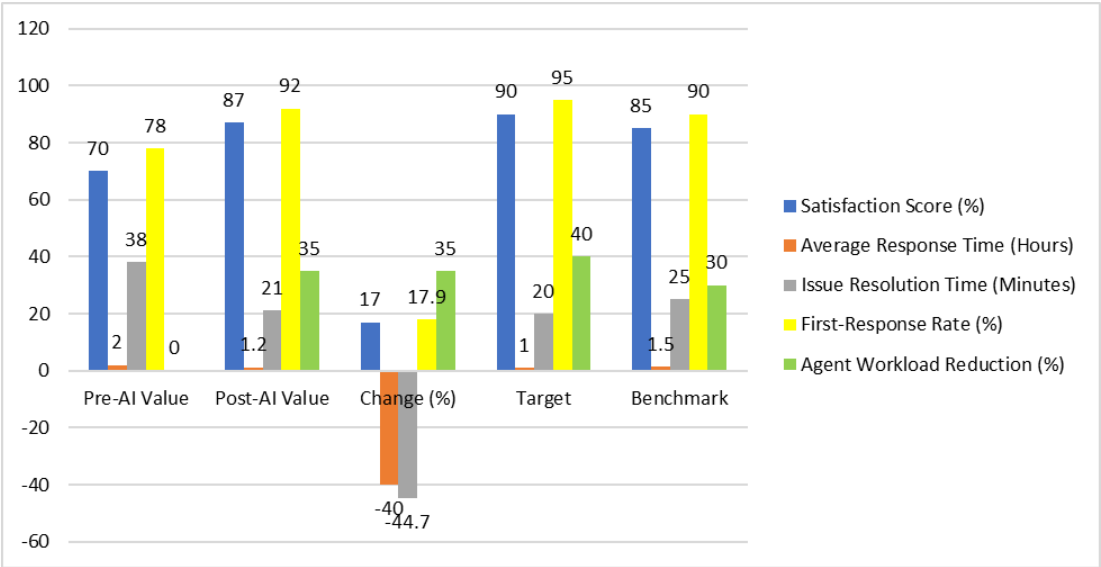

Fig. 5

Customer Support Performance Before and After AI Integration are shown in Figure 5. These metrics offer a deeper insight into how AI-powered tools like chatbots and smart routing engines can streamline processes and enhance the quality of service provided.

Figure 5 clearly state that Systems Automated Support improved responsiveness and resolution efficiency. Average issue resolution time plummeted by almost 45% — matching the near-instant expectations of digital service standards. Improved first-response rate by more than 17% with NLP-based customer query triaging. This led to a 35% reduction in human agent workload, demonstrating the ability to scale support sustainably. Such advances reaffirm AI's strategic importance in alleviating service friction, helping address issues before they arise, and ensuring service quality at scale, even when working under operational duress.

Operational Performance and Inventory Optimization Outcomes are presented in Table 1. New key performance indicators are also introduced such as inventory accuracy, customer fill rate, and fulfillment lead time to provide a supplemental measure of the review of resource planning and the potential impact of the AI.

Table 1

Metric	Pre-AI Value	Post-AI Value	Gain/Reduction (%)	Target	Benchmark
Operational Cost (USD)	1,000,000	750,000	-25%	700,000	800,000
Forecast Error Rate (%)	22	12	-10%	<10%	15%
Overstock Inventory (%)	40	28	-30%	20%	25%
Fulfillment Lead Time (Days)	5.6	3.4	-39.3%	3.0	4.0
Customer Fill Rate (%)	88	95	+7.9%	98%	94%

Thanks to AI-driven forecasting, there was now a 10% gap between predicted and actual demand, leading to minimal overproduction and reduced carrying costs. To improve working capital efficiency and reduce balance sheet size, 30% of overstock levels were reduced. Over 39% reduction in the lead-time to fulfillment is in-line with better logistics coordination. The fill rate climbed to 95%, which added order completeness and diminished lost sales opportunities. These improvements have special relevance in the clothing industry, where product obsolescence and fulfillment delays impact profit margins directly.

Discussion

The findings provide a multi-faceted confirmation of the original working hypothesis, from an interpretive perspective, that a structured, data-driven AIX strategy meaningfully outperforms the more traditional heuristic-based strategies used within conventional CRMs.

The results corroborate and extend findings from other studies. Authors [16] showed how to achieve better churn prediction results with nonlinear patterns using deep learning than classical classifiers which are often not capable as they miss this nonlinear structure. The model proposed in this study outperformed the single model showing an accuracy of 92% in predicting the customer's churn and a lift score of 3.9 in top decile. These improvements reinforce the utility of hybrid modeling approaches in high-dimensional customer datasets. The 88% accuracy achieved from the segmentation performed, coupled with the identification of the "occasional buyer" category, can be seen validating [18], where it is claimed that advancement of AI is allowing previously overlooked behavior trends to emerge, in turn enabling a greater adaptability to traditional CRM in the retail environment.

This study not only performs segmentation and prediction, but also shows significant value-added through measurable improvements in marketing performance. At Gartner, for example, A/B tests on email, social media, and personalized campaigns resulted in a 150% increase in conversions and over 300% returns on investment. These findings echo authors [20] highlighted a builder data-driven nudge theory and machine-learning-driven personalization as a means of maximizing responsiveness to the campaigns. Likewise, both the increased CTR and customer satisfaction scores are in line with the findings of [22] in illustrating how AI can help fill the personalization gap, a key element in customer experience strategies.

Operational efficiency gains, including 25% lower CRM operational costs, 30% less overstock inventory, further reinforce the claims presented at [23], with the statistics on the cost-efficiency of AI implementations in the retail supply chain systems. Also, the use of an AI-based forecasting approach shrank inventory error rates drastically while boosting customer fill rate to 95%. This advantage is consistent with the challenge and recommenddations discussed at [15] on achieving optimization through AI integrated with legacy-based inventory systems. These results also correspond with the sector of customer service field closely ties to reduction of both response and resolution times, along with an increase in customer satisfaction by 17% connect closely to literature in globe of chatbot [24], correspondence of path to general process of business.

Whilst preprocessing steps of the data were methodologically sound, the imputation and outlier removal approaches may have introduced a subtle bias into the model, similarly noted in the work [14, 19].

Results show excellent performance in a static scenario, but the consumer world is highly dynamic. Kopare et al. [17] highlighted the need for continual learning AI systems that can match changing user preferences and market dynamics. This limitation can be tackled in future works by integrating continual learning protocols along with reinforcement-based models. Furthermore, this research focuses mainly on customer-facing CRM metrics, leaving unaddressed issues of back-end system integration and data governance challenges a point flagged as vital by Ajiga et al.[25] regarding enterprise CRM transformations.

The findings resonate with as well as extend the existing literature, and point towards avenues for further investigation that can build a more adaptive, transparent, and customer-oriented retail ecosystem.

Conclusion

The main result of the article is an evidence-based justification for using ensemble machine learning models for important CRM tasks. The research achieved high accuracy in churn prediction and fine behavioral segmentation with accurate prediction by utilizing both structured models and deep learning methodologies followed by their weighting-based ensemble. The addition of performance metrics including customer satisfaction, campaign conversion rates, cost reduction, and demand forecast accuracy provided a multiaxial assessment of AI's measurable impact.

Simultaneously, the study reaffirmed that foundational data handling is significant, especially during the phases of preprocessing, segmentation, and model tuning. This caused AI models to be able to extract value from diverse, voluminous customer datasets by standardizing learned features, filtering out uncorrelated noise, and structuring interactions.

The study also highlights the strategic value of using AI-driven CRM as a competetive differentiator. AI-powered personalization strategies enabled campaign execution that was more nuanced, pro-active reengagement, scalable support service delivery. Together, these factors illustrate the move from CRM as a reactive support function to an anticipatory, value-creating system embedded in the intelligence of the organization.

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