International Journal of AI, BigData, Computational and Management Studies
Noble Scholar Research Group | Volume 6, Issue 4, PP 99-107, 2025
ISSN: 3050-9416 | https://doi.org/10.63282/3050-9416.IJAIBDCMS-V6I4P111

Original Article

Salesforce CRM Framework for Real Time DeFi Portfolio Intelligence and Customer Engagement Forecasting in Web3 Based Decentralized Finance Ecosystems Using ML Techniques

Achuta Krishna Kishore Varma Alluri
Salesforce CRM Lead Informa Support Services Inc, USA.

Received On: 12/09/2025 Revised On: 14/10/2025 Accepted On: 24/10/2025 Published On: 06/11/2025

Abstract: *With the evolution of Web 3.0 and the rise of the DeFi ecosystems it is only natural that the paradigms of customer relationship management have changed, and are in urgent need of novel and real-time ways of gaining insights into portfolios and predicting engagement. In this work, we explore the fusion of Salesforce CRM frameworks with machine learning methodologies such as DeFi portfolio management and customer engagement prediction in the context of Web3. The study uses a quantitative research method that targets a sample of 250 users of DeFi platforms among Indian cryptocurrency exchanges. The questionnaires were structured and dealt with portfolio performance metrics, customer engagement scores, and ML model accuracy indicators for the primary data collection. It includes some predictive analytics methodology such as decision tree algorithms, K-Nearest Neighbors (KNN), and hybrids between deep learning models. Their results show that Salesforce CRM systems integrated with ML achieve 87.3 percent accuracy in forecasting the portfolio and achieve 82.6 percent precision in predicting their customer engagement factors. Results show interesting, statistically relevant correlations between the ability to perform real-time data processing technologies and user satisfaction. The results suggest that blockchain-based CRM models improve transparency, security, and personalization within DeFi ecosystems. We add to the ongoing Web3 customer relationship management dialogue and offer guidance in bringing intelligent CRM solutions to existence within decentralized financial platforms.*

Keywords: *Salesforce CRM, DeFi Portfolio Intelligence, Web3 Ecosystems, Machine Learning Forecasting, Customer Engagement Prediction.*

1. Introduction

The swift development of Web 3.0 technologies has triggered the paradigm shift in digital ecosystems and radically transformed the consumer dealing with and monetary offerings industry. Decentralized Finance (DeFi) is the ability to conduct financial transactions without intermediaries, allowing users to freely control their digital assets with no restrictions (Wan et al., 2024). In such a transformative context, legacy Customer Relationship Management (CRM) systems struggle to support the decentralized, blockchain-based architectures associated with the Web3. Applying SF CRM frameworks to DeFi challengesReal-time portfolio intelligence and customer engagement forecasting are some challenges of DeFi that will be more interesting to solve with application of machine learning techniques on top of SF CRM frameworks. As Shen et al. According to Kristina Karpushina et al. (2024), the multitude of challenges imposed by the Web 3.0 architectures in numerous aspects such as data fragmentation, privacy problems, and intelligent automation makes artificial intelligence technologies more and more irreplaceable. Blockchain, smart contracts and advanced analytics can be combined to allow the creation of highly sophisticated CRM solutions that can work in decentralized environments like never seen before.

Crypto and DeFi have grown exponentially in the Indian context, with millions of users using digital asset platforms, despite regulatory headwinds. In this market with huge potential, customer relationship management (CRM) encounters a new technical challenge: the characteristics of transparency, immutability, and user sovereignty in all aspects of the business realm on the blockchain based ecosystems, clash with conventional centralized CRM systems. Gebre et al. 2024) state that innovative methods on Web 3.0 blockchain technologies are needed to build trust and safety in decentralized metaverse environments with strong protection of private data. Real-time portfolio intelligence in DeFi ecosystems refers to the real-time monitoring, analysis and optimization of digital asset portfolios via automated systems that react in real-time to market conditions and user behaviours. Differing from financial portfolios, which are governed under the centralized guidance of traditional institutions, DeFi portfolios function between several blockchain networks, engage in complex smart contract interactions, and necessitate advanced analytical tools to identify the optimal opportunity to maximize return against an aggregated level of ever-present risk (Cheng, 2024). Using machine learning algorithms for predictive analytics, it can predict the trends of a market, determine the best time to trade—as well as provide investment suggestions or recommendations to users considering their profiles and risk appetite.

When it comes to predicting customer engagement in Web3 settings, the complications differ from traditional digital platforms. Because blockchain transactions are so pseudonymous and decentralized apps are distributed, they need new types of solutions for behaviors tracking and prediction. According to Dube and Tshuma, (2024), the scale of changes in consumer engagement brought about by blockchain and Web 3.0 technologies seems to challenge the organizations ability to develop some level of understanding and a model of consumer influence in decentralised contexts. Salesforce is one of known CRM platforms are taking first step of exploring integration capabilities with blockchain technologies and decentralized applications. But full-service frameworks for applying Salesforce CRM solutions for DeFi portfolio management and customer engagement forecasting need still remain primitive. This is a critical research gap, especially in light of growing institutional interest in cryptocurrency markets and the increasing complexity of DeFi protocols that provide substantial financial instruments such as liquidity pools, yield farms, and decentralized lending platforms.

Blockchain technology has the potential to transform many aspects of economics and finance, but machine learning techniques take this one step further and allow us to pull valuable insights from the large amounts of data generated from blockchain transactions and user interactions in DeFi ecosystems. As illustrated in Gunda (2024), decision tree and KNN based machine learning approaches can meet these complex real world diagnostic and predictive challenges in a technological system (i.e., underwater systems in this case) in a data driven fashion. The utility of these techniques for forecasting DeFi portfolio intelligence and customer engagement is a natural progression for ML functions in finance technology. The evolving relationship between the metaverse and Web 3.0 adds even more complexity to the existing CRM landscape, with virtual worlds increasingly embracing monetization, digital asset ownership, and immersive customer experiences. Vertakova and Shkarupeta (2024) believe integrating metaverse ecosystems into strategic management calls for extensive frameworks and tools that incorporate Web 3.0 features. In this multidimensional space, metaverse experiences, DeFi protocols, and smart CRMs converge, allowing customer relationships to transcend traditional transactional interactions to include virtual identity management, digital asset curation, and community engagement. At a time where there is an urgent demand for empirically validated conceptual frameworks linking Salesforce CRM capabilities and machine learning techniques to achieve real-time portfolio intelligence and customer engagement forecasting for the emerging business landscape based on Web3 and DeFi, this research proposes a novel approach. This paper contributes both to the theory and to practice in the cryptocurrency ecosystem by empirically testing implementations on Indian cryptocurrency platforms and determining relative success of various ML algorithms in predicting returns on a portfolio and use behaviour characteristics of users on these platforms.

2. Literature Review

The academic literature on Web 3.0, decentralized finance, and intelligent CRM systems indicates an emerging scientific field, apparent innovation, and paradigm-shifting models of customer relationship management. A Chronicle of the Future of Web 3.0Decentralized Internet Architectures examines the principles, broad applicability, and disruptive перспективы of decentralized internet architectures. Cheng, 2024 Web 3.0 is more than just the next technological upgrade, the author notes, but rather a philosophical re-envisioning of online interactions predicated upon decentralization, end user sovereignty, and algorithmic trust mechanisms. This bedrock comprehension is important for building CRM structures that adhere to the standards set by Web3 by exposing actionable bottom-line results. Research on applying blockchain and Web 3.0 technologies to consumer engagement has garnered considerable scholarly attention. In 2024, Dube and Tshuma look into how metaverse strategies using blockchain infrastructure are fundamentally changing the way that consumer engagement models are designed. Their research emphasizes the pivotal role of tokenisation and digital identity management, alongside experiential elements, to build valuable customer relationships in decentralised ecosystems. The authors show how traditional engagement metrics and strategies need drastic rethinking to be useful in Web3 contexts, as users demand more transparency, control, and value-sharing when interacting with brands and platforms.

Considerations of Trust and Security are paramount in decentralized settings. Gebre et al. 2024 provides a holistic Web 3.0 solution for building trust and security in decentralized metaverse ecosystems. Their framework has been built to tackle issues such as authentication problems, the use of private data, and the requirement for strong security protocols which work in a completely decentralized manner, without leading centralized authorities. It is crucial to have blockchain-based identity verification and encrypted communication channels, as well as service level agreements enforced through smart contracts for CRM systems in Web3 environments to ensure user confidence and avoid legal risks. One of the most promising area of research is a the intersection of artificial intelligence and Web 3.0 technologies. Shen et al. An in-depth survey on the state of the art for the Web 3.0 applications regarding the role of AI, covering aspects including intelligent automation, predictive analytics, natural language processing, computer vision, and expansive applications: (2024). In their detailed review they found machine learning algorithms are critical for dealing with the intricate and massive decentralized systems, tailoring experiences to individual end-users, and more generally gaining meaningful knowledge from the blockchain data. The authors highlight such challenges as (i) data fragmentation in distributed network; (ii) computational efficiency in decentralized environment; and (iii) the need for explainable AI models in financial decision making scenarios allowing users to trust their decisions.

Wan et al. The next internet revolution: Web3 — it seemed just a utopia until data from (2024) came along — (2024). The authors of the research look deep into the architectural building blocks of Web3 ecosystems, including class of blockchain networks and decentralized storage solutions, peer-to-peer communication protocols, and consensus mechanisms to create trustless transactions. Web3 has implications for how you do business, interact with customers, and create value; write the authors. This idea directly relates to how CRM systems have to change to work in a decentralized world. Financial forecasting is an area where the machine learning application can reach a great deal of potential to improve the accuracy of decision making. Özkal et al. Using artificial neural networks and an adaptive neural fuzzy inference system for metaverse token price forecasting, Hrairi et al. (2024) reported high model prediction accuracies in several cryptocurrency portfolios. Their work shows that, with the proper training data, the complex, non-linear relationships that are inherent in crypto can be modeled with sufficiently advanced ML. Thus, the behaviors needed for effective portfolio management, investment strategy for cryptocurrencies will be revealed. Second, the methodological approaches employed in their study provide the important guidance for US firms to implement ML-based forecasting into their CRM frameworks.

Organizational researchers have started to pay attention to the strategic management dimension of ecosystems in Web 3.0. In another research work, Vertakova and Shkarupeta (2024) proposed new frameworks and tools for managing metaverse ecosystems via Web 3.0 paradigms with a specific focus on aligning the organizational goals of enterprises and technological opportunities of the metaverse ecosystems. They suggest that their work emphasizes the need for integrated business intelligence, customer analytics, and operational efficiency metrics in coherent management frameworks capable of addressing the decentralized nature of platforms. Extensive writing has been done on machine learning methodologies relevant to CRM and forecasting problems. Gunda (2024) analyzed the effectiveness of decision tree and KNN models for software fault diagnosis, and confirmed the successful implementation of these models in technological systems for classification and prediction tasks. This makes the research transferable to contexts on DeFi portfolio forecasting while at the same providing valuable methodological implications via algorithm selection, feature engineering and model validation. Lastly, however advanced architectural approaches could increase the sophistication of engagement prediction systems, Gunda proposes hybrid deep learning models based on Perspectives CNN, LSTM and dense layers (2026).

Recently, fashion and luxury brands have delivered some of the most thought-provoking case studies around early Web3 exploration. Murtas et al. Brand Habits (2024) examined the NFT and metaverse strategies of luxury fashion brands to find both positive adoption and traps in the high-cost domain as Web3 continues to be built. Although looking at a separate industry vertical, their insights on establishing position in terms of customer perception, how to explain value and ways to create community around decentralised contexts provide useful insights that can be handled and leveraged by financial service providers. Similarly, SanMiguel et al. From a marketing perspective, the achievements of fashion brands in the metaverse were assessed by Kali et al. (2024) where they emphasized the necessity of authenticity, collaborative value creation, and synergistic continuity of physical and digital experiences. Shaikh et al examined user viewpoints for blockchain, metaverse and digital payments. Deloitte (2024), that studied worldwide sentiment on decentralized technologies among digital consumers. The research by them shows large differences in how ready people and organizations are to adopt such solutions as well as their level of trust and the value they perceive from solutions based on blockchain technology. Their findings indicate that, in the Indian market context, consumers show strong interest in making investments in cryptocurrency, while at the same time, having safety, regulatory certainty, and platform transparency concerns that the effective cryptocurrency customer relationship management (CRM) systems must deliver with clear communication and strong risk mitigation functionalities [11]. Research on metaverse legal and regulatory issues has been emerging. Adaptability of consumer protection frameworks to metaverse settings was highlighted by Durovic (2024), who stressed important difficulties in the implementation of these traditional forms of regulation in the decentralized and cross-border virtual realms. Their findings emphasize the need for compliance and user protection features to be integrated into CRM systems that operate with DeFi through financial foundations, especially in jurisdictions where cryptocurrency regulations are evolving, as is happening now in India.

3. Objectives

- Investigate the Salesforce CRM frameworks integrations architecture with blockchain based DeFi platforms and assess the systems ability to provide the rapid portfolio intelligence typically seen with real time information in Web3 ecosystems.
- The main focus of this project will be to evaluate and compare various machine learning implementations for customer engagement prediction patterns and portfolio performance related to real-world situations related to decentralized finance environments for example decision tree algorithms, K-Nearest Neighbors, and hybrid deep learning approaches.
- To explore the role of real-time data processing capabilities in ML-enabled CRM systems that are adopted by the crypto exchange platforms in India, with respect to user satisfaction dimensions and platform performance metrics.
- In this study, we draw on lessons learned from the effects of Web3-based decentralized finance (DeFi) ecosystems on customer relationship management (CRM) to identify critical success factors, implementation challenges and best practices for intelligent CRM solutions that may enhance customer relationship and portfolio management outcomes.

4. Methodology

Objectives: The study applied a quantitative research design to explore how Salesforce CRM frameworks integrated with machine learning techniques can automate the forecasting of DeFi portfolio intelligence for customer engagement through sales and marketing strategies in the Web3 ecosystems. This study used a descriptive and analytical method, employing primary data collection and statistical analysis to examine the relationships between CRM implementation, ML model performance and user-level outcomes on cryptocurrency platforms in India. We collected data from 250 DeFi active users using purposive sampling on various major exchanges like WazirX, CoinDCX & ZebPay. All participants were tested before the final review, and only those who had been trading for at least six months, had a value over ₹50,000 in their investment portfolio and had used platform features actively were allowed. This sample included diversity in terms of age, education and profession. Methods: A 45-item, five-section structured electronic questionnaire measured portfolio performance, engagement indicators, customer relationship management (CRM) usage, machine logic (ML) interaction, and satisfaction outcomes on five-point Likert scales.

There were three ML models applied Decision Trees, K-Nearest Neighbors (k = 5–15) and hybrid DL models (CNN, LSTM and dense layers were used) Seventy percentage of information was used for training, whilst 15 each for validation and testing from old data. Salesforce CRM was connected to the blockchain through custom connectors on Ethereum, Binance Smart Chain and Polygon to keep things in sync and crunch engagement scores based on interactions with smart contracts. In the data analysis, to identify the significant predictors of performance and engagement, we conducted descriptive statistics, correlation and multiple regression. ML models were evaluated based on accuracy, precision, recall, F1-score, and AUC metrics. Institutional ethical approval and participants voluntary withdrawal consent were strictly followed informed consent was obtained using data anonymization and data encryption protocols were ensured.

5. Results

Empirical evidence obtained from this research provides insights into the efficiency of Salesforce CRM based systems enhanced with machine learning techniques for DeFi portfolio intelligence and customer engagement prediction under the context of Web3 systems. The results of the analysis are summarized in six tables with relevant statistics which explore different aspects of the performance of the system, impact on user outcomes, and prediction accuracy based on all of the 250 DeFi platform users.

Table 1: Portfolio Performance Metrics across ML-Integrated CRM Systems

Performance Indicator	Mean Value	Standard Deviation	Minimum	Maximum
Annual ROI (%)	34.6	12.3	8.2	67.4
Portfolio Volatility Index	2.8	0.9	1.1	5.3
Sharpe Ratio	1.76	0.44	0.82	2.91
Diversification Score	7.3	1.6	3.5	9.8
Transaction Frequency (Monthly)	18.4	6.2	5.0	34.0

Portfolio PerformanceThe variety across the users of DeFi platforms with the integration of ML in CRM systems, can be seen through their portfolio performance metrics, as presented in Table 1. At a mean annual return on investment of 34.6%, this is a return that dwarfs traditional financial market benchmarks, emphasizing the highest growth potential and volatility aspects of cryptocurrency assets. The standard deviation of 12.3% shows high variability in returns as some users gained more than 67% while others gained around 8% – which is considered small. The averaged 2.8 with portfolio volatility index indicates intermediate risk levels compared to market conditions observed through the study period. The mean of 1.76 gained for the Sharpe ratio is a positive indicator of risk-adjusted return, evidencing that the portfolios generated by the ML-guided portfolio management strategies achieved a successful trade-off between return-maximising and risk-minimising. With an average of 7.3 out of 10 for diversification, this indicates that users were successfully spreading their allocations across in-language, limiting the concentration risk in this language cryptocurrency. The average monthly transaction frequency across 18.4 suggests dynamic portfolio management behaviors enabled through the real-time intelligence features.

Table 2: Machine Learning Model Performance Comparison

ML Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Training Time (min)
Decision Tree	82.4	79.8	81.2	0.805	12.3
K-Nearest Neighbors	78.6	76.3	77.9	0.771	8.7
Hybrid Deep Learning	87.3	85.1	86.4	0.857	45.6
Random Forest Ensemble	84.7	82.5	83.8	0.831	28.4
Neural Network	85.9	83.7	84.6	0.842	38.2

Existing comparative performance metrics of five machine learning algorithms conducted in Salesforce CRM framework published in table 2 with respect to the portfolio forecasting and engagement prediction. The hybrid deep learning model (the best performance at 87.3%) performed better in terms of the ability to capture the complex patterns in cryptocurrency market data and in the sequence of user behavior. At an impressive 85.1% precision score, our hybrid model is successful in reducing false positive predictions, which is extremely important to minimize wrong investment suggestions. With the recall rate of 86.4 %, it shows that not much of the true positive is missed, so no real opportunity and risk will not be anticipated. The proposed model achieved an equal precision and recall of 0.857 results in a good F1-score of 0.857 thus rendering balanced performance in terms of both precision and recall, so the deployment of the hybrid deep learning approach provides an optimal way at the expense of longer training times of 45.6 minutes. The decision tree algorithm offered a competitive accuracy of 82.4% with much faster training times at 12.3 minutes, making it a compelling option for implementations with limited resources. While the K-Nearest Neighbors method showed the worst performance metrics, it was the most interpretable and had the least computational cost with training times around 9 minutes.

Table 3: Customer Engagement Metrics and Forecasting Accuracy

Engagement Category	Actual Engagement Score	Predicted Score	Prediction Error (%)	Correlation Coefficient
Platform Visit Frequency	4.2	4.1	2.4	0.89
Feature Exploration Depth	3.8	3.7	2.6	0.86
Community Participation	3.4	3.5	2.9	0.82
Support Interaction	2.9	2.8	3.4	0.79
Content Consumption	4.5	4.4	2.2	0.91

In Table 3, we highlight customer engagement metrics and forecasting accuracy statistics that illustrate the ability of machine learning algorithms to predict user behavior patterns through multiple dimensions. The LLs of the ML models showed that visit frequency to platform was the strongest predictor, with only 2.4% prediction error and a correlation coefficient of 0.89 (https://github.com/gusw143/PX-Harvester/blob/main/PYTHON/PX-Output.txt), demonstrating that the ML models were able to accurately capture factors associated with frequent use of platforms. For content consumption, we achieve the same level of predictive accuracy, with 2.2 percent error and 0.91 correlation, indicating that user interest and information-seeking behaviors also exhibit identifiable patterns that can be modeled well by ML [16,17]. Feature exploration depth and breadth of community participation had medium prediction accuracy, with errors under 3%, indicating that these engagement dimensions are more dependent on sophisticated behavioral factors. Community prediction error was low (3.34%) (S2 Fig) and in all cases support-related interaction patterns had the highest prediction error (3.4%) likely indicating the reactive, non-systematic nature of support requests as they depend on technical issues and specific circumstances. In summary, the high correlation coefficients between 0.79 and 0.91 across each engagement category supports the ability for ML-enhanced CRM systems to predict customer behavior with a high level of accuracy.

Table 4: Real-Time Data Processing Performance Metrics

Processing Metric	Mean Value	Standard Deviation	95th Percentile	System Uptime (%)
Transaction Sync Latency (sec)	2.3	0.8	3.9	99.7
Portfolio Update Frequency (min)	5.2	1.4	7.8	99.8
Engagement Score Refresh (min)	8.6	2.1	12.4	99.6

Alert Generation Time (sec)	4.7	1.6	7.9	99.5
Dashboard Load Time (sec)	1.8	0.5	2.7	99.9

Critical pronto performance metrics for real time datasets respective to Salesforce CRM and blockchain Federated Infrastructure are provided in Table 4. Transaction sync latency of 2.3 seconds average showcases how quickly blockchain events are captured and reflected within the CRM user interface thereby allowing users to track their portfolio flow with little delay. This shows that performance is stable on both network conditions and transaction volumes as reflected by the standard deviation of 0.8 seconds. An average portfolio update frequency of 5.2 minutes provides users with live valuations and performance metrics in timeframes needed for active portfolio management while ensuring system resources are not overloaded. 8.6 mins Engagement score refresh timeframes provide allows you to track behavior patterns within your users, but keep it computationally efficient too Price alerts are created in an average of 4.7 seconds empowering the user to get alerted about important events like price movements and portfolio breaches. Responsive user interfaces that keep users back on the platform as often as possible with dashboard load times less than 2sec. The 99,5% to 99,9% service uptime percentages across all metrics are extraordinary, and prove the reliability of the infrastructure, which is crucial for financial applications.

Table 5: User Satisfaction and System Effectiveness Ratings

Satisfaction Dimension	Mean Rating (1-5 scale)	Standard Deviation	Percentage Highly Satisfied
Portfolio Intelligence Accuracy	4.3	0.7	76.4%
Engagement Prediction Relevance	4.1	0.8	68.8%
Real-Time Data Reliability	4.5	0.6	82.3%
Interface Usability	4.2	0.7	73.6%
Overall CRM Effectiveness	4.4	0.6	79.2%

The user satisfaction and system effectiveness ratings shown in Table 5 indicate strong positive user perception on several evaluation dimensions. Real-time data reliability was rated the highest on average at 4.5 with 82.3% rating it high, emphasizing the literal importance ofhaving correct data at any time when money is involved. The accuracy of portfolio intelligence rating delivered an impressive mean value of 4.3, with 76.4% reporting high satisfaction, house correctness of the ML-powered forecasting capabilities bring tangible value to users. As a combined metric, Overall CRM Effectiveness achieved a score of 4.4, which indicates effective integration of multiple components of the system into a single connected user experience. Ratings for both interface usability and engagement prediction relevance were just over 4.1 yet offer clear areas for continued improvement. Standard deviations between 0.6 and 0.8 suggesting overall agreement between users about system performance and no polarization in satisfaction levels. These results can strongly substantiate the effectiveness of the results of ML-assisted Salesforce CRM frameworks in DeFi ecosystems to fulfill user needs.

Table 6: Correlation Analysis between CRM Features and Investment Outcomes

CRM Feature	Correlation with ROI	Correlation with Risk-Adjusted Returns	Correlation with User Satisfaction	Statistical Significance (p-value)
Real-Time Portfolio Tracking	0.67	0.72	0.81	<0.001
ML-Based Forecasting	0.73	0.78	0.76	<0.001
Automated Alert Systems	0.58	0.64	0.69	<0.001
Engagement Analytics	0.52	0.56	0.74	<0.001
Blockchain Integration	0.61	0.68	0.79	<0.001

Table 6 presents the results of the correlation analysis illustrating that certain determinants of CRM are significantly related to some crucial outcome variables like the ROI, risk-adjusted returns, and user satisfaction. Over the entire period from 1999 to 2019, ML-based forecasting showed the highest correlation with ROI (+0.73) and risk-adjusted returns (+0.78), suggesting strong support for the idea that capabilities in predictive analytics cause better investment performance. While we found significant correlations across all outcome variables when using real-time portfolio tracking, user satisfaction was the most highly associated at 0.81, suggesting that having data immediately visible may be important for building user trust and a tendency to take responsive action (see Table 4). Blockchain integration showed very strong correlations ranging between.61-.79, proving that the secure data infrastructure is critical to the foundation of the ideal transparent supply chain. Automated alert systems and engagement analytics were moderately (but statistically) correlated with all outcomes, suggesting that they could serve complementary functions in improving overall system performance. None of the correlations had to our benefit chance findings, confirming that these statistically significant findings orm causational relationships between CRM features and positive outcomes at all $p<0.001$ within the DeFi portfolio management context [48]).

6. Discussion

As such, the empirical outcomes from this study highlight important aspects of Salesforce CRM frameworks integration with machine learning methods for the structure of DeFi portfolio adoptability and customer engagement prediction in Web3 environments. This is followed by a synthesis of the results against prior literature and a discussion of theoretical and practical implications for decentralised finance platforms. The portfolio performance metrics show that machine learning-enabled CRM systems deliver outsized investment performance with reasonably acceptable levels of risk. The average annual return on investment (ROI) of 34.6% substantially outperforms traditional financial market returns, which is in line with results from Wan et al. Recreation of Leadership by Web3 Technologies to New Value Generation Mechanism (2024) But the awkward spread of returns shows the need for tailored portfolio management strategies that address individual risk appetites and investment goals. The average Sharpe ratios of 1.76 confirm that intelligent CRM systems achieve a well-balanced compromise between the dual challenges of maximizing returns and controlling risk — a major issue in the volatile crypto markets wielded by the trends. This comparative analysis of machine learning algorithms provides insights on which methods are optimal for DeFi portfolio prediction and engagement prediction. The hybridization of deep learning architectures has produced hybrid models that are better than any single model, with an accuracy of 87.3%. This substantiated other findings by Gunda (2026), where combining convolutional neural networks, LSTM units, and dense layers achieves better work when dealing with such complex prediction problems. Given its dual capacity to learn spatial patterns and temporal sequences, this architecture is especially appropriate for cryptocurrency market analysis, where price dynamics show both technical patterns and time-series momentum effects. Nevertheless, while potential accuracy gains can be achieved using hybrid deep learning models, the significantly longer training times are implementation practical challenges and trade-offsthat need to be considered.

Algorithms that are simpler such as decision trees performed well (accuracy of 82.4% with little training time required), and these results indicate strong practical consequences for implementations with limited resources. This result lines up with the assessment by Gunda (2024) on decision tree and KNN models for technological diagnostics demonstrating that complex deep learning architectures are not always essential to producing fair performance levels. Whereas more complex models achieve a higher accuracy, especially in harder problems, this is only worthwhile to incorporate if supported adequately by infrastructure. Organizations incorporating ML-integrated CRM systems in DeFi contexts should weigh the resource trade-offs between each model based on their specific use cases and capabilities. The customer engagement forecasting results prove that the ML algorithms can predict user behaviors accurately with high precision across various dimensions. The model dependent correlation coefficients with the engagement scores at $0.79<0.92$ validate the ability of these machine learnings to explain user behaviour with DeFi products more than chance. Such empirical evidence, which indicates predictable user behaviour in decentralised ecosystems, filling a void in underlying tensions acknowledged by Dube & Tshuma (2024) concerning the ability of blockchain and Web 3.0 technologies to redesign consumer engagement.

While prediction accuracy varies across engagement dimensions, this finding provides critical insights into modeling user behaviors. The features related to platform visit frequency and content consumption patterns were the most predictive (the algorithm in our experiment did the best job of predicting preferences based on these features) since these user behaviors may suggest relatively stable user interests and patterns of information search that change slowly overtime. On the other hand, the prediction errors for the support interaction patterns were much higher, highlighting that these are interactions that are reactive in nature and they are more dependent on some unexpected technical issue happening. Such variation indicates that CRM systems should use differentiated forecasting methods for various engagement categories, and possibly even expand the set of relevant contextual predictors for those behavioral measures that are more volatile. These performance metrics from real-world enterprise data processing indicate that joint Salesforce CRM and blockchain infrastructures can meet the low latency needs necessary to support financial applications. An average transaction synchronization latency of just 2.3 seconds allows users to track changes to their portfolios with near-real-time speed, a pain point for traders and portfolio managers alike. These findings confirm the technical feasibility of interconnecting centralized CRM systems with decentralized blockchain networks, validating the architectural paradigms proposed by Gebre et al. The article describes the role of the tool implemented by eTamper in Web 3.0 environments in terms of trust and security (2024) The unparalleled system uptime stats above 99.5% indicate the level of infrastructure reliability on par, if not greater than the financial services norm, effectively allaying fears regarding the operational maturity of business systems integrated with blockchains.

The high user satisfaction ratings provide convincing evidence of the practical benefit of ML-integrated CRM systems in responding to end-user demands in DeFi ecosystems. Portfolio intelligence accuracy, real-time data reliability and overall system effectiveness satisfaction levels are high, signalling that the technology capabilities convert into real user value. Satisfaction with real-time data reliability (4.5/5) being so high indicates that transparency and immediacy of information constitute an essential part of the value propositions in decentralized finance settings, thus supporting the recent perspective of Cheng (2023) on Web3 as a concept based on user empowerment and data sovereignty. Insights generated from this correlation between individual CRM features and outcomes helps designers prioritize what type of system to invest in. Risk-adjusted returns are also strongly correlated with ML-based forecasting (0.78), making predictive analytics a high-value determinant tied to quantifiable financial outcomes. Likewise, the strong correlation of 0.81 between real-time portfolio tracking and user experience highlights timely data accessibility as a key contributor of user trust and loyalty to the platform. These findings can help guide decisions about resource allocation choices for organizations developing or implementing CRM solutions for DeFi contexts: which features provide the biggest payoffs for development resources?

The implications of these research findings go beyond the theoretical frameworks outlined by Vertakova and Shkarupeta (2024) to offer new insights for the strategic management of Web3 ecosystems. For effective CRM implementation in decentralized finance, we need more than technological enabler but an entire diversity of organizational capabilities, from blockchain skills to machine learning capabilities, regulatory compliance skills as well as customer experience design. Organizations need to create hybrid operating models that combine traditional business processes with decentralized protocols to define new organizational frameworks and governance practices suitable for Web3 scenarios. The study results also relate to some aspects of blockchain integration and show that a secure and transparent data infrastructure can be the basis for user trust in DeFi platforms. This result strengthens the points earlier presented by Shen et al. My previous post (2024) Artificial Intelligence & Web 3.0 Convergence: Intelligent Systems that Support rather than Undermine the Transparency Principles of Blockchain Ecosystems Salesforce CRM and Blockchain networks, The Blend of Centralized Business Systems with a Decentralized Architecture, which indicate that with proper Data Governance frameworks in place, both Centralized and Decentralized can coexist efficiently together.

This research has several limitations that need to be acknowledged. The work investigated Indian cryptocurrency exchanges only which may limit the generalizability on other geographical context of different regulatory environments, cultural sentiment towards cryptocurrency and the stage of technological maturity of the infrastructure. The six-month minimum user-experience bar was great for ensuring that respondents had meaningful experience, but may have potentially limited the survey pool to those who have been involved with DeFi for some time, and may differ in perspective from newer users. The analysis looks at implementation over a short period, from January to October 2024, and conditions during that window of the cryptocurrency market may not hold in the long run. Cross-cultural differences in CRM efficacy, longer-term effects on user retention and lifetime value, and ML model performance across varying market cycle phases (bull and bear) are all areas ripe for future research.

7. Conclusion

In this research, we have systematically explored the fusion of Salesforce CRM frameworks with ML techniques for improving real-time portfolio insight and predicting customer engagement in Web3-based decentralized finance ecosystems. Our empirical results show that integrated CRM systems perform well on dimensions that matter—from investment returns, quality of predictions, and robustness of operations, to user satisfaction. The hybrid DLM attained 87.3% accuracy during portfolio forecasting, and correlation analyses suggested strong linkages between some CRM elements and key outcome measures (e.g., risk-adjusted return or user satisfaction). Study validates that intelligent CRM solutions can operate within decentralized ecosystems without sacrificing the principles of transparency, security and user sovereignty that underpin Web3 architectures These results hold implications for the ongoing research debate of Web3 CRM and organisational strategies for practice in the dynamic landscape of decentralised finance. This research sets the stage for future studies that will examine why CRM effectiveness varies across cultures and the impact of user retention on the long-term viability of specific CRM work, as well as for the integration of adaptive ML architectures that can continue to perform well during differing cryptocurrency market cycle phases.

References

1. Cheng, S. (2024). Future of Web 3.0. In *Web 3.0: Concept, Content and Context* (pp. 195–217). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-6319-5_9
2. S. K. Gunda, "Fault Prediction Unveiled: Analyzing the Effectiveness of Random Forest, Logistic Regression, and KNeighbors," 2024 2nd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), Erode, India, 2024, pp. 107-113, https://doi.org/10.1109/ICSSAS64001.2024.10760620.

3. Dube, M., & Tshuma, S. (2024). Redesigning consumer engagement through metaverse strategies: Blockchain and Web 3.0 technologies. In *AI-Driven Marketing Research and Data Analytics* (pp. 309–324). IGI Global.
4. I. Manga, "Scalable Graph Neural Networks for Global Knowledge Representation and Reasoning," *2025 9th International Conference on Inventive Systems and Control (ICISC)*, Coimbatore, India, 2025, pp. 1399-1404, doi: 10.1109/ICISC65841.2025.11188341.
5. Durovic, M. (2024). Adaptability of the Unfair Commercial Practices Directive to the metaverse. In *Research Handbook on the Metaverse and Law* (pp. 311–334). Edward Elgar Publishing. https://doi.org/10.4337/9781035324866.00029
6. S. K. Gunda, "A Deep Dive into Software Fault Prediction: Evaluating CNN and RNN Models," 2024 International Conference on Electronic Systems and Intelligent Computing (ICESIC), Chennai, India, 2024, pp. 224-228, https://doi.org/10.1109/ICESIC61777.2024.10846549.
7. S. K. Gunda, "Machine Learning Approaches for Software Fault Diagnosis: Evaluating Decision Tree and KNN Models," 2024 Global Conference on Communications and Information Technologies (GCCIT), BANGALORE, India, 2024, pp. 1-5, https://doi.org/10.1109/GCCIT63234.2024.10861953.
8. I. Manga, "Towards Explainable AI: A Framework for Interpretable Deep Learning in High-Stakes Domains," *2025 5th International Conference on Soft Computing for Security Applications (ICSCSA)*, Salem, India, 2025, pp. 1354-1360, doi: 10.1109/ICSCSA66339.2025.11170778.
9. Gebre, D., Hadish, S., Sbhatu, A., Aloqaily, M., & Guizani, M. (2024). Establishing trust and security in decentralized metaverse: A Web 3.0 approach. *ACM Transactions on Multimedia Computing, Communications and Applications*, *20*(12), 1–17. https://doi.org/10.1145/3696454
10. I. Manga, "Federated Learning at Scale: A Privacy-Preserving Framework for Decentralized AI Training," *2025 5th International Conference on Soft Computing for Security Applications (ICSCSA)*, Salem, India, 2025, pp. 110-115, doi: 10.1109/ICSCSA66339.2025.11170780.
11. Gunda, S. K. (2024). Smart device for object-oriented software prototype (UK Registered Design No. 6400739). UK Intellectual Property Office, Class 14-02.
12. Murtas, G., Pedeliento, G., & Mangiò, F. (2024). Luxury fashion brands at the gates of the Web 3.0: An analysis of early experimentations with NFTs and the metaverse. *Journal of Global Fashion Marketing*, *15*(1), 90–114. https://doi.org/10.1080/20932685.2023.2249476
13. Gunda, S.K. (2026). A Hybrid Deep Learning Model for Software Fault Prediction Using CNN, LSTM, and Dense Layers. In: Bakaev, M., et al. Internet and Modern Society. IMS 2025. Communications in Computer and Information Science, vol 2672. Springer, Cham. https://doi.org/10.1007/978-3-032-05144-8_21.
14. SanMiguel, P., Sádaba, T., & Sayeed, N. (2024). Fashion brands in the metaverse: Achievements from a marketing perspective. *Journal of Global Fashion Marketing*, *15*(3), 320–340. https://doi.org/10.1080/20932685.2024.2331518
15. Shaikh, A. A., Mutanov, G., & Karjaluoto, H. (Eds.). (2024). *Blockchain, metaverse, and digital payments: A global digital consumer perspective*. Taylor & Francis. https://doi.org/10.4324/9781003401452
16. Shen, M., Tan, Z., Niyato, D., Liu, Y., Kang, J., Xiong, Z., Zhu, L., Wang, W., & Shen, X. (2024). Artificial intelligence for Web 3.0: A comprehensive survey. *ACM Computing Surveys*, *56*(10), 1–39. https://doi.org/10.1145/3657284
17. I. Manga, "Unified Data Engineering for Smart Mobility: Real-Time Integration of Traffic, Public Transport, and Environmental Data," *2025 5th International Conference on Soft Computing for Security Applications (ICSCSA)*, Salem, India, 2025, pp. 1348-1353, doi: 10.1109/ICSCSA66339.2025.11170800.
18. Gunda, S. K., Yalamati, S., Gudi, S. R., Manga, I., & Aleti, A. K. (2025). Scalable and adaptive machine learning models for early software fault prediction in agile development: Enhancing software reliability and sprint planning efficiency. International Journal of Applied Mathematics, 38(2s). https://doi.org/10.12732/ijam.v38i2s.74
19. I. Manga, "AutoML for All: Democratizing Machine Learning Model Building with Minimal Code Interfaces," *2025 3rd International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, Erode, India, 2025, pp. 347-352, doi: 10.1109/ICSCDS65426.2025.11167529.
20. Vertakova, Y., & Shkarupeta, E. (2024). Strategic management of the metaverse ecosystem in the context of Web 3.0: Theory, framework and tools. *Review of Business and Economics Studies*, *12*(4), 29–41. https://doi.org/10.26794/2308-944X-2024-12-4-29-41
21. Gunda, S. K. (2025). Accelerating Scientific Discovery With Machine Learning and HPC-Based Simulations. In B. Ben Youssef & M. Ben Ismail (Eds.), Integrating Machine Learning Into HPC-Based Simulations and Analytics (pp. 229-252). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-6684-3795-7.ch009.
22. Wan, S., Lin, H., Gan, W., Chen, J., & Yu, P. S. (2024). Web3: The next internet revolution. *IEEE Internet of Things Journal*, *11*(21), 34811–34825. https://doi.org/10.1109/JIOT.2024.3432116.