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AI Driven Analysis of Customer Behavior in Mobile Telecommunications: Cultural Dynamics, Financial Insights, and Sustainable Development Perspectives

Nidhal Ziadi[1], Eya Ihkaf[2*], Nihel Ziadi[3], Ichrak Ben Slimane[4]

[1] *Associate Professor of Finance and Accounting, University of Tunis El Manar, Faculty of Sciences of Tunis, LARIMRAF Laboratory, Campus Universitaire Farhat Hached, Tunis B.P. n 94 - ROMMANA 1068, Tunisia, Email: nidhal.ziadiellouze@fst.utm.tn*
[2] *Institute of Management of Tunis, Tunisia, Email: ihkafeya123@gmail.com*
[3] *Associate Professor of Marketing, Faculty of Sciences of Tunis, University of Tunis El Manar, ERMA Laboratory, Campus Universitaire Farhat Hached, Tunis B.P. n 94 - ROMMANA 1068, Tunisia, Email: nihel.ziadi@fst.utm.tn*
[4] *Assistant Professor of Marketing, Higher Institute of Applied Science and Technology of Sousse, University of Sousse, Rue Tahar Ben Achour, Sousse 4003, Tunisia, Email: ichrakbs@yahoo.fr*

***Corresponding Author:** ihkafeya123@gmail.com

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ABSTRACT

This study explores the application of predictive data science techniques to anticipate customer behavior in the mobile telecommunications sector, integrating insights from finance and marketing. Leveraging advanced predictive models, including a multitask learning approach, the research is supported by an interactive web interface featuring a home- page, a Power BI dashboard, and a prediction page. The aim is to transform raw historical customer data into action- able insights for marketing teams, enabling accurate forecasts of mobile internet package activation and customers' potential future value. Findings indicate that customer satisfaction and perceived sustainable value significantly influence subscription and recharge decisions, thereby enhancing loyalty and revenue generation. By emphasizing the synergy be- tween business needs, technological tools, and methodological frameworks, this work offers an innovative combination of theoretical and empirical approaches to advance practices within the telecommunications industry. Future research directions include incorporating real-time data streams and developing automated marketing recommendations to further optimize strategic effectiveness.

Keywords: Customer behavior, predictive models, Power BI, sustainable value, multitask learning approach, Financial insights.
JEL Codes: C45, C55, M31, L96, O33, G17, Q01

INTRODUCTION

The rapid evolution of mobile services and subscription plat- forms now requires companies to understand, predict, and support their customers' behavior with greater precision. In an environment where interactions are continuous and expectations are constantly changing, the ability to anticipate churn, detect changes in behavior, and respond in real time is becoming a major strategic asset. Advances in artificial intelligence, particularly multi-task learning, offer new possibilities for simultaneously analyzing multiple dimensions of customer behavior and producing instant predictions that can be used by operational teams.

However, the performance of a predictive model is not enough to guarantee retention or loyalty. User behavior remains strongly influenced by how they perceive the overall value of the service: usefulness, perceived quality, experience, personalization, and cost-benefit ratio. This perceived value shapes their expectations, conditions, their engagement, and influences their intention to renew. It also affects trust, attitudes, and satisfaction, which are essential levers for maintaining customer relationships.

Satisfaction also plays a central role in subscription continuity. When satisfaction is high, it significantly reduces the risk of disengagement and encourages the adoption of complementary services. It results from consistent, transparent, and high-quality interactions, and becomes a key indicator for anticipating changes in customer behavior.

Considering these challenges, this work is part of a strategy to integrate artificial intelligence, behavioral analysis, and technological deployment. The goal is both to develop a multitasking model capable of predicting key behaviors in real time and to examine how a full-stack web architecture can leverage these predictions in an operational decision- making environment.

LITERATURE REVIEW

Recent studies (Poudel et al., 2024; Miao et al., 2024) con- verge on the development of integrated, explainable, and operational models for churn prediction in the telecommunications sector. These models leverage heterogeneous data sources and incorporate advanced explain ability techniques such as LIME, SHAP, and GAT-CNN to ensure predictions are both accurate and actionable. The adoption of multitask learning and deep learning architecture has significantly improved real-time prediction capabilities, enabling telecom operators to anticipate customer behavior patterns and re- duce churn rates.

Beyond technical advancements, a growing body of re- search emphasizes the decisive role of consumers perception of sustainable value encompassing functional, emotional, and social benefits in shaping engagement with subscription services. Empirical evidence (Salim et al., 2021; Akroush &Mahadin, 2019; Molinillo et al., 2021; Chen, 2012) demonstrates that perceived value, influenced by service quality, content relevance, user experience, and cost-benefit ratio, directly affects both initial subscription decisions and retention. Trust, satisfaction, and positive attitudes are frequently mediated by value perception (Zietsman, Mostert, and Svensson 2020), reinforcing its centrality in consumer behavior. Recent literature consistently highlights perceived value as a key determinant of purchase intention, loyalty, and retention across diverse contexts such as streaming plat- forms, e-commerce, and digital services (Kim & Kim, 2020; Guo, 2022; Mntymki et al., 2019). For instance, content superiority, service differentiation, and personalization have been shown to enhance perceived value, which acts as a critical mediator between service characteristics and subscription or renewal intention (Kim et al., 2022; Mntymki et al., 2019).

Similarly, customer satisfaction emerges as a pivotal driver of contract renewals and the adoption of additional services within subscription-based industries. Evidence from banking, insurance, telecommunications, and e-commerce indicates that higher satisfaction levels are strongly associated with increased loyalty, renewal intentions, and cross-buying behaviors (Moon et al., 2025; Hai et al., 2024; Tjahjaningsih et al., 2020; Williams et al., 2023). Satisfaction, shaped by service quality, communication, and trust, consistently predicts whether customers will renew contracts or maintain engagement over time. In multi- service contexts, satisfied customers are not only more likely to renew but also to explore additional offerings, with satisfaction mediating the link between service experience and future purchasing decisions (Verhoef et al., 2001; Lima et al., 2024; Van Der Borgh et al., 2023). These insights underscore the strategic importance of investing in customer experience, transparent communication, and consistent service quality to foster satisfaction and, consequently, long- term retention and growth.

Despite significant progress in predictive modeling and consumer behavior research, few studies have integrated advanced AI-based churn prediction models with behavioral constructs such as perceived value and customer satisfaction in a unified framework for the telecommunications sec- tor. Existing research tends to focus either on technical optimization (accuracy, explain ability) or on marketing dimensions (value perception, loyalty) but rarely examines how predictive insights can inform strategic decisions related to customer experience and retention. Moreover, the operationalization of real-time predictive analytics into actionable financial and marketing strategies remains underexplored, particularly in emerging markets such as Tunisia. This gap underscores the need for a holistic approach that combines multitask learning models with behavioral drivers to enhance both predictive accuracy and strategic impact.

Multitask Learning Models for Real-Time Prediction of Mobile Customer Behavior: State of the Art

Predicting mobile customer behavior in real time is a complex challenge due to the dynamic and multifaceted nature of user interactions with mobile services. Recent advances in machine learning, particularly multitask

learning (MTL), have shown promise in addressing this complexity by enabling simultaneous learning of related tasks, such as behavior classification and prediction, within a unified frame- work. MTL architectures leverage shared representations to improve predictive accuracy and computational efficiency, making them well-suited for resource-constrained mobile environments (Rago et al. 2020; El-Sherief, Khafagy, and Sweidan 2025; Morel et al. 2022; Alberi-Morel et al. 2019; Isgder and Incel 2025).
For example, MTL models have been successfully applied to predict sequential user actions, such as clicks and con- versions, by capturing dependencies between behaviors and utilizing attention mechanisms to enhance feature extraction and context awareness (El-Sherief, Khafagy, and Swei- dan 2025; Wang, Zhang, and Wulamu 2021). In mobile net- work scenarios, MTL approaches deployed at the network edge have demonstrated superior performance over single- task models, reducing computational overhead and enabling timely predictions of user activity and resource needs (Rago et al. 2020; Morel et al. 2022). Furthermore, integrating multimodal data such as application usage, mobility patterns, and contextual information into MTL frameworks has led to more robust and accurate predictions of user behavior, supporting applications in targeted marketing, resource al- location, and personalized service delivery (Lee et al., 2025; (Lin 2025; Huang et al. 2024; Isgder and Incel 2025)). How- ever, challenges remain in ensuring real-time generalizability, handling data sparsity, and adapting to rapidly changing user patterns, which are active areas of ongoing research (Lee et al., 2025; (Lin 2025; Arefeen and Ghasemzadeh 2025)). We concluded:

Hypothesis 1: The multitask learning model enables real-time prediction of mobile customer behavior patterns

The real-time integration of predictions from multitask learning (MTL) into financial and marketing strategies re- lies on full-stack web architectures capable of managing, processing, and visualizing large volumes of heterogeneous data. Recent advances show that modern web platforms, combining robust backend frameworks (Python/Django, Flask, Spark) and interactive frontend interfaces, facilitate the automation of the collection, analysis, and reporting of predictions from MTL models, while enabling rapid and in- formed decision-making (G et al. 2025; Tuarob et al. 2021; Munthe 2024; Ismaeel and Zeebaree 2025; Vennamaneni 2025).

These systems leverage real-time data streams (financial APIs, social networks, news) and integrate machine learning modules for forecasting, portfolio management, sentiment analysis, and anomaly detection (Tuarob et al. 2021; G et al. 2025; Munthe 2024) (Emmanuel et al., 2024). The use of real-time data pipelines (Kafka, Spark) and cloud solutions ensures elasticity, security, and regulatory compliance, while reducing latency between the generation of predictions and their strategic exploitation (Vennamaneni 2025; Ismaeel and Zeebaree 2025) (Vijayan, 2024). Finally, the seamless integration of these tools into web applications enables decision-makers to develop data-driven financial and marketing strategies, relying on interactive visualizations and automated alerts to optimize responsiveness and performance (Tuarob et al. 2021; G et al. 2025; Munthe 2024; Is- maeel and Zeebaree 2025). We concluded:

Hypothesis 2: The full-stack web stack enables seam- less real-time integration of multitask learning predictions, facilitating data-driven financial and marketing strategies development.

EMPIRICAL METHODOLOGY

The study is based on a dataset of 14,246 observations and 68 variables, covering marketing and financial dimensions such as customer characteristics, offers, revenues, consumption, and recharge behaviors. Two binary targets were de- fined: the probability of recharge and the activation of a data package for the following month. To address these objectives, we employed advanced predictive models, with a particular focus on the multitask MMOE (Multi-gate Mixture- of-Experts) model, designed to learn both tasks simultaneously by leveraging correlations between them. The architecture includes three shared experts, softmax gates for each task, and sigmoid output layers, optimized through a weighted combined loss function. Training was conducted over 100 epochs using the Adam optimizer. Performance was assessed using standard metrics (accuracy, precision, re- call, F1-score) and ROC curves. Results show an accuracy of 0.86 for data package prediction and satisfactory performance for recharge, confirming the relevance of the multitask approach in capturing weak signals. Alternative models, such as the Bayesian Neural Network (BNN) and Neural Additive Models (NAMS), were also tested for comparison, highlighting the superiority of multitask learning in terms of consistency and its ability to integrate multiple behavioral dimensions.

Evaluation Metrics

To evaluate the performance of the proposed models, we employ a comprehensive set of metrics designed to capture both predictive accuracy and the quality of classification across classes. In addition to overall accuracy, we report class-wise metrics derived from the confusion matrix, including Sensitivity (Recall for positive class), Specificity (Recall for negative class), and per-class F1-scores. These metrics provide a detailed understanding of model behavior, especially in the presence of class imbalance.

We also analyze the Area Under the Receiver Operating Characteristic Curve (ROC AUC) to assess the discriminative ability of the models between the positive and negative classes. Together, these metrics offer a holistic view of model performance, combining measures of correctness, robustness, and ability to separate classes effectively.

EXPERIMENTS AND RESULTS

Dataset

The database contains 14,246 observations and 68 variables. Each observation represents a unique customer, identified by a customer ID. The available variables describe several key dimensions:

- **Customer characteristics:** customer status, tenure, geo- graphical region, and sales channel.
- **Offers and segmentation:** offer type, data segment, and network status.
- **Revenues:** total revenue and service-level revenues, including voice, data, SMS, roaming, and bundled plans.
- **Consumption:** data session volume, number of SMS sent, and USSD usage.
- **Packages and subscriptions:** number and monetary value of subscribed packages, including voice, data, and weekend plans.
- **Recharges and payments:** recharge frequency, number of recharges, and total recharge amounts.
- **Behavioral indicators:** evaporation status, binary recharge indicator, and average revenue per user (ARPU).

The study focuses on two binary target variables:

- **Recharge:** a binary variable indicating whether the customer recharged during the period.
- **MNT FORFAIT DATA next month:** a binary indicator capturing the activation of a data package in the following month.

The variables in Table 1 are classified into marketing and financial categories:

Table I: Marketing and Financial Variables

Marketing Variables	Financial Variables
Customer characteristics	Revenues
Offers and segmentation	Recharges and payments
Packages and subscriptions	-
Behavioral indicators	-

In order to examine the linear relationships between the explanatory variables in the dataset, we calculated and visualized the correlation matrix shown below.

This lower triangular matrix, as shown in Figure I, high- lights the positive (red) and negative (blue) correlations be- tween the main behavioral, financial, and marketing variables of mobile customers. Specifically, we observe:

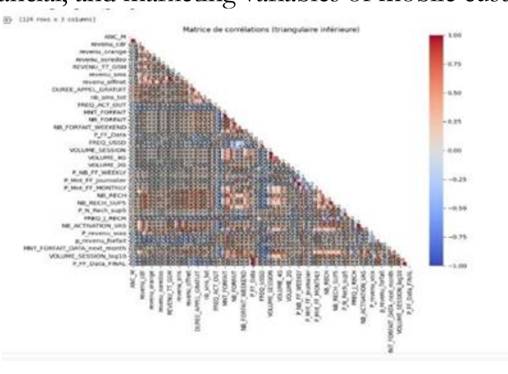

Figure I: Correlation matrix

- A high positive correlation between data volumes (VOLUME4G, VOLUMESESSION) and package amounts (MNT FORFAIT DATA next month).

- A moderate correlation between recharge indicators (NBRECH, FREQJRECH) and revenue (revenu cdr, ARPU).
- A negative correlation between customer seniority (ANCM) and the frequency of new package activations, indicating that loyal customers have more stable behavior.

This visualization helped guide the selection of relevant variables for training predictive models.

Experimental setup

MMOE (Multi-gate Mixture-of-Experts) Model

Objective: Simultaneously predict recharge and MNT FORFAIT DATA next month.

Architecture:

- 3 shared experts (Dense 64, ReLU)
- 2 softmax gates for each task
- Sigmoid output layers (binary)

Training:

- Combined loss (binary cross-entropy) weighted at 0.5 per task
- Adam optimizer (learning rate *lr* = 0.001), 100 epochs, batch size 32

Mathematical formula:

$$\hat{\boldsymbol{y}} = \boldsymbol{\sigma}\left(\frac{\mathbf{1}}{\boldsymbol{S}}\sum_{\boldsymbol{s}=\mathbf{1}}^{\boldsymbol{S}}\left[\boldsymbol{W}_{\boldsymbol{out}}^{(\boldsymbol{s})}\boldsymbol{\sigma}\left(\sum_{\boldsymbol{l}=\mathbf{1}}^{\boldsymbol{L}}\boldsymbol{W}^{(\boldsymbol{L},\boldsymbol{S})}\boldsymbol{h}^{(\boldsymbol{l}-\mathbf{1},\boldsymbol{S})} + \boldsymbol{b}^{(\boldsymbol{l},\boldsymbol{s})}\right) + \boldsymbol{b}_{\boldsymbol{out}}^{(\boldsymbol{s})}\right]\right)$$

Where:

- $\hat{Y}$ represents the predicted probability of the target event (recharge or data package subscription).
- $\sigma(\cdot)$ denotes the sigmoid activation function, used to map outputs into probabilities between 0 and 1.
- S is the number of experts in the MMOE architecture.
- s indexes each expert contributing to the final prediction.
- $W^{(l,s)}$ and $b^{(l,s)}$ are the weights and biases of layer l for expert s.
- $h^{(l-1,s)}$ represents the hidden representation from the previous layer of expert s.
- W_{out}^{S} and b^{S} correspond to the output layer parameters of experts S^{out}.
- The averaging term $\frac{1}{S}\sum_{s=1}^{S}$ combines the outputs of all experts, allowing the model to capture shared and task- specific patterns.

RESULTS

Table II: Performance Metrics for Task 1

Metric	Value
Weighted Precision	0.86
Weighted Recall	0.86
Weighted F1-score	0.85
Accuracy	0.86

Task 1: Prediction of MNT FORFAIT DATA next month. As shown in Table II, the multitask MMOE model demon- strates strong and balanced performance in predicting MNT FORFAIT DATA next month, with high weighted precision, recall, and accuracy, confirming its ability to reliably capture customers data subscription behavior.

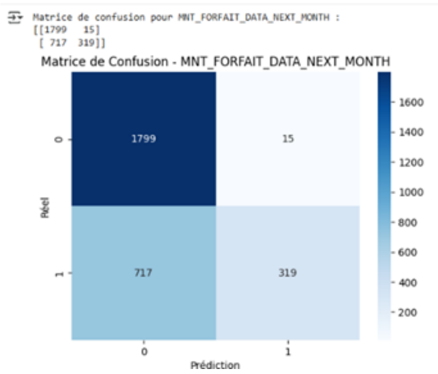

Figure II: Confusion Matrix for Task 1

The confusion matrix presented in Figure II highlights the model's classification performance, with 1,799 correctly classified negative cases and 319 correctly classified positive cases, demonstrating effective discrimination between subscription and non-subscription behaviors.

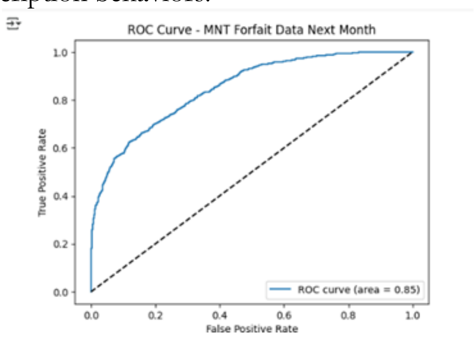

Figure III: ROC Curve for

The ROC curve presented in Figure III shows that the model has good discrimination ability between classes, with an area under the curve (AUC) of 0.85, indicating overall satisfactory performance for binary classification.

Task 2: Prediction of Recharge.

Table III: Performance Metrics for Task 2

Metric	**Value**
Precision	0.66
Recall	0.75
F1-score	0.64
Accuracy	0.75

As shown in Table III, the multitask MMOE model achieves satisfactory performance in predicting customer recharge behavior, with a higher recall than precision, indicating an effective ability to identify customers likely to recharge while maintaining acceptable overall accuracy.

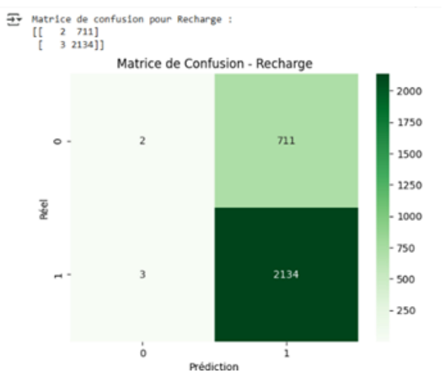

Figure IV: Confusion Matrix for Task

The confusion matrix presented in Figure IV shows that the model correctly predicted 2,134 positive cases (class 1) and only 2 negative cases (class 0), indicating a strong ability to identify customers likely to recharge.

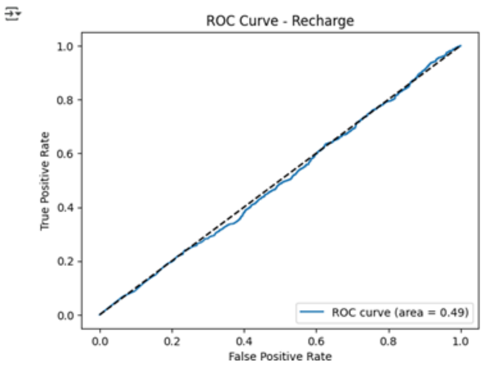

Figure V: ROC Curve for Task2

The ROC curve presented in Figure V indicates that the model is unable to effectively distinguish between recharge and non-recharge classes, as the curve remains close to the diagonal, suggesting limited discriminative power for this task.

Bayesian Neural Network (BNN) Model

Objective: The Bayesian Neural Network (BNN) is employed to predict MNT FORFAIT DATA next month while explicitly modeling predictive uncertainty through Bayesian inference.

Architecture: The Bayesian Neural Network (BNN) is defined as follows:

- Three fully connected dense layers with 128, 64, and 32 neurons, using ReLU activation functions.
- Monte Carlo Dropout with a rate of 0.3 applied during training and inference to capture Bayesian uncertainty.
- A sigmoid output layer for binary classification.

This architecture enables the model to jointly capture non- linear relationships while providing uncertainty-aware pre- dictions.

Training

The Bayesian Neural Network (BNN) is trained as fol- lows:

- Binary cross-entropy loss function optimized using the Adam optimizer with a learning rate of 0.001.
- Monte Carlo Dropout with a rate of 0.3 applied during training to approximate Bayesian inference.
- Training conducted over 100 epochs with a batch size of 32, ensuring stable convergence and uncertainty-aware predictions.

Mathematical formula

$$\hat{y} = \sigma\left(\frac{1}{S}\sum_{s=1}^{S}\left[W_{out}^{(s)}\sigma\left(\sum_{l=1}^{L} W^{(L,S)} h^{(l-1,S)} + b^{(l,s)}\right) + b_{out}^{(s)}\right]\right)$$

Where:

- $\widehat{Y}$ is the predicted output (binary prediction).
- S is the number of Monte Carlo samples or experts.
- L is the number of hidden layers.

- $W^{(l,s)}$ and $b^{(l,s)}$ are the weights and biases of layer l for sample s.

- $W^{(s)}$ and $b^{(s)}$ are the weights and bias of the output layer.

- $h^{(l-1,s)}$ is the output of the previous layer for sample s.

- $\sigma(\cdot)$ denotes the activation function (e.g., ReLU for hid- den layers and sigmoid for the output), introducing non- linearity.

RESULTS

Table IV: Performance Metrics of the BNN Model

Metric	Value
Training Accuracy	94.98%
Validation Accuracy	89.17%
Validation Loss	0.2573

As shown in Table IV, the BNN model achieves very high training accuracy and maintains strong validation performance, with a decreasing validation loss, indicating effective learning and good generalization capability.

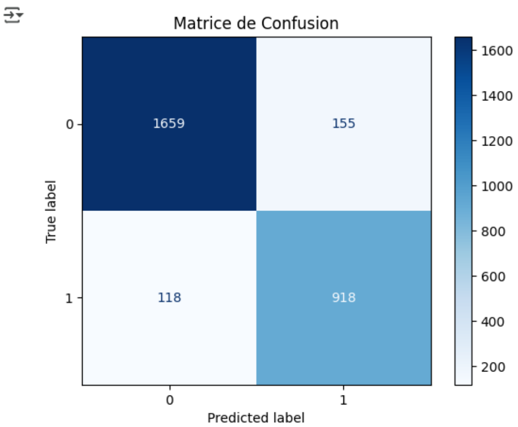

Figure VI: Confusion Matrix for the BNN model

The confusion matrix presented in Figure VI shows that the model correctly distinguished the majority of classes with 1,659 true negatives and 918 true positives, indicating reliable classification performance.

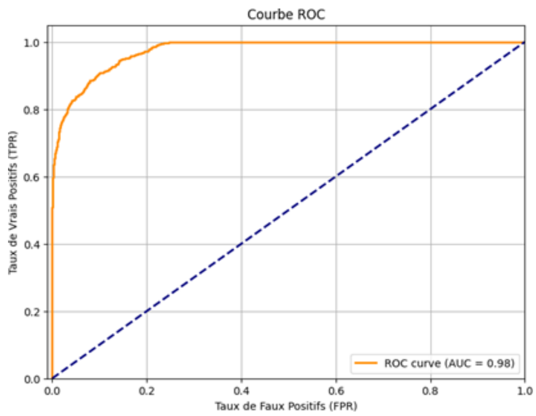

Figure VII: ROC Curve for the BNN model

Figure VII shows that the BNN achieves excellent dis- crimination between classes, with an AUC of 0.98, confirm- ing its strong predictive capability.

Neural Additive Models (NAMS)

Objective: Neural Additive Models (NAMS) are employed to predict the probability of customer recharge by modeling the additive contribution of each explanatory variable, while preserving model interpretability.

Architecture. The NAMS framework consists of an individual neural sub-network for each input variable. Each sub-network learns a non-linear transformation of its corresponding feature, and the outputs are combined through an attention mechanism to capture variable importance and interactions in an additive manner.

Training

The NAMS model is trained as follows:

- Binary cross-entropy loss function optimized using the Adam optimizer.
- Training conducted over 100 epochs with a batch size of 32.
- Early stopping applied to prevent overfitting and ensure stable convergence.

Mathematical formula

$$\hat{Y} = \sigma\left(\sum_{j=1}^{d} \left[W_j^{(2)} . \sigma\left(W_j^{(1)} x_j + b_j^{(1)}\right) + b_j^{(2)}\right]\right)$$

Where:

- x_j is the input feature j,
- $W^{(1)}$, $b^{(1)}$ are the weights and biases of the first layer for feature j.
- $W^{(2)}$, $b^{(2)}$ are the weights and biases of the second layer for feature j.
- d is the total number of input features.
- σ is the activation function (e.g., ReLU or sigmoid) in- troducing non-linearity.
- The summation reflects the additive contribution of all input features to the output.

RESULTS

Table V: Performance Metrics for the NAMS Model

Metric	Value
Accuracy	0.76
Precision	0.74
Recall	0.75
F1-score	0.74

As shown in Table V, the NAMS model achieves an ac- curacy of 76.02%, meaning it correctly predicts the label in just over three out of four cases on the test data. This performance highlights the model's reasonable classification capability while maintaining interpretability.

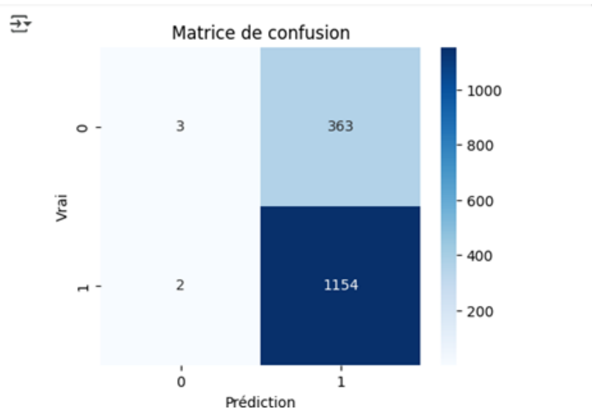

Figure VIII: Confusion Matrix for the NAMS model

The confusion matrix presented in Figure VIII shows that the NAMS model predicts class 1 almost systematically. It successfully identifies 1,154 true positives but fails to detect most true negatives, indicating a bias toward the positive class.

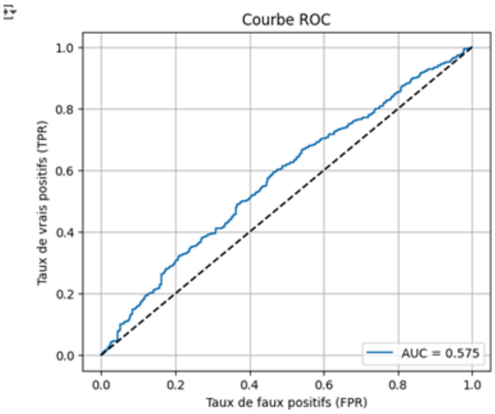

Figure IX: ROC Curve for the NAMS model

The ROC curve presented in Figure IX shows that the NAMS model has limited discriminative ability between classes, with an area under the curve (AUC) of 0.575. This suggests that the model struggles to capture meaningful pat- terns in the data for binary classification.

Results

Hypothesis 1: The multitask learning model enables real-time prediction of mobile customer behavior patterns.

The MMOE multitask learning architecture delivered robust predictive performance, particularly for the data package activation task, achieving an accuracy of 0.86, precision and recall of 0.86, and an F1-score of 0.85, with an AUC of

0.85. These metrics confirm the models ability to capture latent behavioral signals and exploit cross-task correlations, which is critical in telecom marketing where bundle activation and recharge frequency are interdependent drivers of Average Revenue Per User (ARPU). From a marketing perspective, this capability supports dynamic segmentation and personalized offer targeting, reducing churn risk and in- creasing Customer Lifetime Value (CLV). From a data science standpoint, the multitask approach outperforms single- task models by leveraging shared representations, improving sensitivity to weak predictors such as usage patterns and frequency of micro-recharges. Financially, accurate prediction of data package adoption enables forecasting incremental revenue streams, optimizing pricing strategies, and aligning with profitability objectives. The moderate performance on recharge prediction (accuracy = 0.75, AUC = 0.49) suggests that recharge behavior is influenced by contextual variables (e.g., liquidity constraints, promotional timing), which could be addressed by integrating real-time transactional data in future models.

Hypothesis 2: The full-stack web stack enables seamless real-time integration of multitask learning predictions, facilitating data-driven financial and marketing strategies development.

The implemented full-stack architecture, combining Python/Django backend, Flask APIs, and Power BI dashboards, successfully operationalized predictive out- puts into visual analytics for marketing and financial decision-making. This integration allowed conversion of historical behavioral data into actionable KPIs, such as propensity-to-buy scores, expected ARPU uplift, and churn risk indicators, supporting campaign optimization and budget allocation. Although real-time streaming remains a future enhancement, the current system demonstrates the feasibility of embedding predictive intelligence into marketing workflows, enabling data-driven pricing, targeted promotions, and ROI-focused segmentation strategies. From a finance perspective, this architecture provides a foundation for predictive revenue modeling, cash flow forecasting, and risk-adjusted investment in customer acquisition.

CONCLUSION

The analysis conducted in this study demonstrates that understanding and predicting mobile customer behavior re- quires an integrated approach combining the strategic in- sights of marketing with the methodological rigor of artificial intelligence and the financial dimension of customer value creation. From a theoretical perspective, the research underscores the pivotal role of perceived value, customer satisfaction, and attitudinal drivers in shaping decisions related to subscription renewal, recharge frequency, and loyalty programs. These behavioral levers act as key determinants of Customer Lifetime Value (CLV), churn risk, and overall financial performance, structuring the customer relationship and explaining variability in usage intensity and engagement levels, consistent with prior studies, including Ziadi et al 2025., which emphasize their impact on retention strategies, brand equity, and revenue optimization. On the empirical side, the experimentation validates these conceptual foundations while demonstrating the added value of predictive analytics and multitask learning for telecom operators. The MMOE multitask model, trained concurrently on predicting the next-month data package activation and recharge probability, achieved an accuracy of 0.86 for the data package task and satisfactory performance for recharge prediction. This confirms that shared representations enhance sensitivity to weak behavioral signals, enabling propensity modeling and micro-segmentation for targeted campaigns. Such predictive capability supports agile marketing strategies, personalized offer design, ARPU optimization, and financial forecasting, aligning with the principles of data-driven marketing and sustainable economic growth. Comparison with alternative models (BNN, NAMS) reinforces this conclusion. While BNN delivered strong dis- criminative power for a single task and NAMS provided interpretable outputs, only the multitask model integrated multiple behavioral dimensions within a coherent framework, reflecting the omnichannel reality of customer interactions. This synergy between statistical robustness, shared learning, and business relevance positions multitask learning as a strategic enabler for predictive CRM and financial planning, consistent with trends in AI-driven marketing automation and digital transformation. By embedding these predictions into a full-stack architecture with interactive dashboards, the study illustrates how historical data can be converted into actionable KPIs such as propensity-to-buy scores, expected ARPU uplift, churn probability, and projected revenue streams, supporting budget allocation, campaign ROI analysis, and pricing optimization. This opens avenues for dynamic segmentation, early churn detection, and promotion optimization, leveraging AI-powered personalization to maximize customer equity, profitability, and long-term financial sustainability. Ultimately, the major contribution of this research lies in the successful articulation between behavioral determinants and intelligent predictive models, enabling a data-driven strategy that strengthens loyalty, enhances customer experience, and creates new growth opportunities. This approach provides a robust foundation for future developments in real-time analytics, automated recommendation engines, and predictive financial planning, in line with recent advances in AI for digital marketing and customer relationship management. Despite its significant contributions, this study has certain limitations. First, the analysis relies on historical and static data, which restricts the ability to capture real-time behavioral dynamics and sudden shifts in customer preferences. Second, the scope is limited to the mobile telecommunications sector, reducing the generalizability of findings to other industries. Additionally, some behavioral and contextual variables such as social influence or macroeconomic factors were not incorporated, which could enhance predictive accuracy. From a technical standpoint, scalability and data security challenges in cloud-based environments were not explored. Future research should address these gaps by integrating real- time data streams, developing reinforcement learning-based recommendation engines, and extending multitask learning to omnichannel contexts. Moreover, incorporating ESG indicators and financial performance metrics into segmentation models could strengthen the link between sustainability and profitability. Finally, advancing predictive CRM to- ward automated marketing recommendations and real-time analytics will enable telecom operators to optimize customer equity and long-term economic value. This research lies in the successful articulation between behavioral determinants and intelligent predictive models, enabling a data- driven strategy that strengthens loyalty, enhances customer experience, and creates new growth opportunities. This approach provides a robust foundation for future developments in real-time analytics, automated recommendation engines, and predictive financial planning, in line with recent advances in AI for digital marketing and customer relation- ship management. Despite its significant contributions, this study has certain limitations. First, the analysis relies on historical and static data, which restricts the ability to capture real-time behavioral dynamics and sudden shifts in cus- tomer preferences. Second, the scope is limited to the mo- bile telecommunications sector, reducing the generalizabil- ity of findings to other industries. Additionally, some be- havioral and contextual variables such as social influence or macroeconomic factors were not incorporated, which could enhance predictive accuracy. From a technical standpoint, scalability and data security challenges in cloud-based en- vironments were not explored. Future research should ad- dress these gaps by integrating real-time data streams, de- veloping reinforcement learning-based recommendation en- gines, and extending multitask learning to omnichannel con- texts. Moreover, incorporating ESG indicators and finan- cial performance metrics into segmentation models could strengthen the link between sustainability and profitability. Finally, advancing predictive CRM toward automated mar- keting recommendations and real-time analytics will enable telecom operators to optimize customer equity and long- term economic value.

REFERENCES

Alberi-Morel, M.; Saffar, I.; Singh, K.; and Viho, C. 2019. Multi-task Deep Learning based Environment and Mobility Detection for User Behavior Modeling. In 2019 Interna- tional Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOPT), 1–7.

Arefeen, A.; and Ghasemzadeh, H. 2025. Cost-Effective Multitask Active Learning in Wearable Sensor Systems. Sensors (Basel, Switzerland), 25.

El-Sherief, M.; Khafagy, M.; and Sweidan, A. 2025. Multi- task Model with an Attention Mechanism for Sequentially Dependent Online User Behaviors to Enhance Audience Targeting. International Journal of Advanced Computer Sci- ence and Applications.

Ellouze, N. Z. 2025. Credit risk prediction using behavioral features in an AI chatbot interface. International Journal of Innovative Research and Scientific Studies, 8(6): 2099– 2120.

G, A.; K, A.; R, A.; and R, . 2025. Stock market Price Pre- diction Using Machine Learning and Deep learning. Inter- national Journal of Scientific Research in Engineering and Management.

Huang, T.; Pan, X.; Cai, X.; Zhang, Y.; and Yuan, X. 2024. Learning Time Slot Preferences via Mobility Tree for Next POI Recommendation. ArXiv, abs/2403.12100.

Isgder, E.; and Incel, . 2025. FedOpenHAR: Federated Mul- titask Transfer Learning for Sensor-Based Human Activity Recognition. Journal of Computational Biology.

Ismaeel, A.; and Zeebaree, S. 2025. Optimizing Digital Marketing through Machine Learning in Cloud-Based En- terprise Systems: The Role of Web Technologies. Asian Journal of Research in Computer Science.

Lin, J. 2025. Application of machine learning in predicting consumer behavior and precision marketing. PLOS One, 20.

Morel, M.; Saffar, I.; Singh, K.; Hamideche, S.; and Viho,

C. 2022. Improving User Environment Detection Using Context-Aware Multi-Task Deep Learning in Mobile Net- works. IEEE Transactions on Cognitive Communications and Networking, 8: 1665–1676.

Munthe, I. 2024. Implementation of Stacking Technique Combining Machine Learning and Deep Learning Algo- rithms Using SMOTE to Improve Stock Market Prediction Accuracy. Journal of Applied Data Sciences.

Rago, A.; Piro, G.; Boggia, G.; and Dini, P. 2020. Multi- Task Learning at the Mobile Edge: An Effective Way to Combine Traffic Classification and Prediction. IEEE Trans- actions on Vehicular Technology, 69: 10362–10374.

Tuarob, S.; Wettayakorn, P.; Phetchai, P.; Traivijitkhun, S.; Lim, S.; Noraset, T.; and Thaipisutikul, T. 2021. DAViS: a unified solution for data collection, analyzation, and vi- sualization in real-time stock market prediction. Financial Innovation, 7: 1–32.

Vennamaneni, P. 2025. Real-Time Financial Data Process- ing Using Apache Spark and Kafka. International Journal of Data Science and Machine Learning.

Wang, Y.; Zhang, D.; and Wulamu, A. 2021. A Multitask Learning Model with Multiperspective Attention and Its Ap- plication in Recommendation. Computational Intelligence and Neuroscience.

Wu, T.; Jiang, N.; Kumar, T.; and Chen, M. 2024. The role of cognitive factors in consumers perceived value and subscrip- tion intention of video streaming platforms: A systematic literature review. Cogent Business & Management, 11(1): 2329247.

Zhang, T.; Moro, S.; and Ramos, R. 2022. A data-driven ap- proach to improve customer churn prediction based on tele- com customer segmentation. Future Internet, 14(3): 94.

Ziadi, N. 2013. The effectiveness of Internet advertising through memorization and click on a banner. International Journal of Marketing Studies, 5(2): 93–103.

Ziadi, N.; and Gafsi, N. 2025. Leveraging AI to uncover the effects of pivotal moments in the LIBOR framework and its evolution on the banking industry. Revue Internationale de Recherche Innovante et d'tudes Scientifiques, 8(2): 886– 896.

Ziadi, N.; and ZIADI, N. 2025. Determinants of Fin- tech Product Adoption by Tunisian Customers: A Predic- tive Model Study. Journal of Cultural Analysis and Social Change, 10(2): 12–21.

ZIADI, N.; ZIADI, N.; and Yazid, B. A. 2025. Credit De-
fault Risk and Client Segmentation in Agricultural Lending.
Journal of Posthumanism, 5(12): 225–239.

Ziadi Ben Fadhel, N. 2025. Leveraging predictive intelli- gence to understand banking customer behavior. Interna- tional Journal of Innovative Research and Scientific Studies, 8(5): 1771–1788.

Zietsman, M.; Mostert, P.; and Svensson, G. 2020. A mul- tidimensional approach to the outcomes of perceived value in business relationships. European Business Review, 32(5): 759–777.

