

A Framework for the Adaptive Churn Management in Telecommunications

Mohammad Syibli

Diponegoro University, Semarang, Indonesia | Wholesale Services Division, Telkom Indonesia, Jakarta, Indonesia

mohammadsyibli@students.undip.ac.id (corresponding author)

Rahmat Gernowo

Diponegoro University, Semarang, Indonesia

rahmatgernowo@lecturer.undip.ac.id

Bayu Surarso

Diponegoro University, Semarang, Indonesia

bayus@lecturer.undip.ac.id

Aldi Setiawan

Digital Product Division, Telkom Indonesia, Jakarta, Indonesia

aldi.setiawan@telkom.co.id

Nur Andi Setiabudi

Digital Product Division, Telkom Indonesia, Jakarta, Indonesia

nurandi@digitaltelkom.id

Received: 4 March 2026 | Revised: 30 March 2026 and 12 April 2026 | Accepted: 17 April 2026

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | DOI: <https://doi.org/10.48084/etasr.18530>

ABSTRACT

This paper proposes an adaptive churn management paradigm that incorporates feedback-driven retraining, channel suggestion, churn prediction, and churn factor detection into a closed-loop architecture. The framework was assessed by comparing adaptive and non-adaptive setups across six monthly observation periods using actual operational data from a fixed broadband provider in Indonesia. The adaptive approach significantly improved imbalance-sensitive and operational metrics, increasing PR-AUC from 9.32% to 15.02%, recall from 39.44% to 50.70%, and F1-score from 9.57% to 11.01%, even though both configurations achieved comparable discrimination performance in terms of AUC-ROC (77.67% adaptive versus 77.05% non-adaptive). Adaptive learning improved decision-support alignment in the recommendation module, increasing Mean Reciprocal Rank (MRR) from 75.08% to 81.69% and Hit Rate@1 from 51.36% to 64.45%. With churn rate reductions of up to 0.56% during observation periods, these analytical advancements resulted in more reliable business outcomes. The findings demonstrated that churn behavior exhibits temporal drift and that, in dynamic customer contexts, predictive robustness, explanatory relevance, and operational efficacy depend on adaptive system design.

Keywords-adaptive churn management; customer churn; fixed broadband; machine learning; telecommunications industry

I. INTRODUCTION

Customers are one of a business's most precious assets in today's cutthroat marketplaces. Customer churn, which is defined as the decision to stop using a service, is becoming more common since switching barriers have been greatly reduced by the expanding number of options [1]. Especially in sectors like telecommunications and cable services, where

long-term client retention directly supports revenue sustainability and corporate viability, this difficulty is crucial. Unmanaged churn damages a brand's reputation, raises the cost of acquiring new customers, and erodes recurring revenue sources. The seriousness of this problem is demonstrated by recent industry data. Specifically, in 2022, churn rates in the US were over 25% in cable and financial services and 21% in retail and telecoms, meaning that almost one in five telecom

consumers changed providers in a single year [2]. There is heterogeneity across countries regarding churn rates in the fixed broadband market. While Indonesia registered a rate of 15.56% (similar to Turkey), indicating high exposure to churn risk, markets like Brazil and Mexico have churn levels surpassing 25%. In contrast, nations like Singapore, Italy, and Japan often keep their turnover rates under 10% thanks to sophisticated, tailored strategies and highly developed customer management techniques [3]. The urgency of the churn issue in Indonesia's broadband industry is further explained by operator-level data [4-10]. With a turnover rate of 38.73% in 2022, Link Net outperformed regional competitors like América Móvil, which exhibited a rate of 30.62%. In comparison to operators in more developed markets, such as BT, KDDI, and StarHub, other Indonesian broadband providers, including MyRepublic, Biznet, and IndiHome, also pointed to significantly higher churn rates. These differences highlight the need for more efficient churn control strategies in the Indonesian telecom sector and reveal systemic issues with customer retention.

Organizations may now proactively identify customers who are at risk of leaving thanks to the advancements in analytics and Machine Learning (ML). Effective attrition management, however, goes beyond simple prediction. In addition to addressing when churn occurs, a comprehensive strategy should also focus on the reasons for leaving and which consumers are most prone to disengage [11]. Furthermore, customer behavior is dynamic by nature and is influenced by changing market conditions, service experiences, and usage patterns. Therefore, rather than depending on static, one-time models, churn management solutions need to be able to adjust to ongoing changes in customer data [12, 13].

Certain common limitations are found in earlier studies. While providing little connection with commercial decision-making processes, many current methods place an emphasis on forecasting performance on historical datasets [14-16]. Because of this, a significant amount of research has concentrated on increasing forecast accuracy, frequently at the price of interpretability and the production of useful insights for commercial use [17-19]. Additionally, most proposed models are static and lack feedback mechanisms that record user interactions or post-prediction business outcomes, which restricts their capacity to quickly adjust to changing customer behavior [20]. Evaluation is typically based on historical datasets rather than real-world operational environments, which limits the results' relevance for changing business circumstances [21-25]. This problem is getting worse due to privacy laws that sometimes restrict access to real consumer data, which makes validation in practical situations more difficult [26]. Furthermore, a lot of models remain rigid and non-adaptive, with little focus on lifecycle-aware or time-sensitive strategies that could capture client changes over time [27, 28]. Although personalization techniques can improve the results, stakeholders frequently do not understand the underlying reasoning behind automated forecasts, leading to more general interpretability issues [29]. A heatmap showing the prevalence of these restrictions across industries is illustrated in Figure 1. The companies with the most frequency and variety of issues are telecommunications, finance, cross-industry instances, and e-commerce. Manufacturing, energy retail, and smart environments, on the other hand, demonstrate the fewest incidents and the most limited spectrum of problems. This indicates how crucial it is to customize churn solutions for particular business contexts.

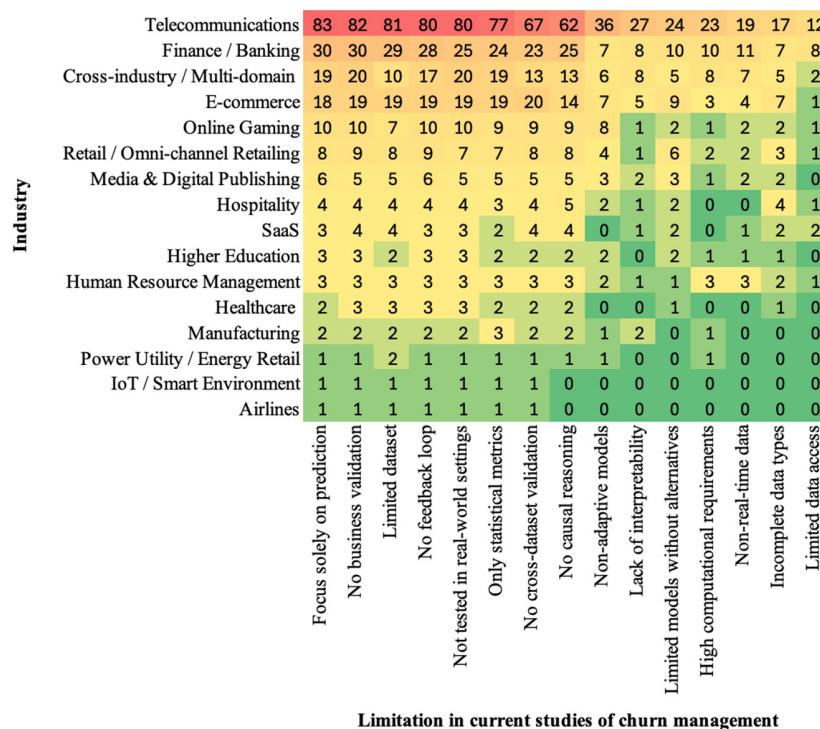


Fig. 1. Heatmap of limitations of current studies across industries.

In this study, an adaptive churn management approach is introduced, designed for the telecom sector. In order to overcome the static and prediction-centric methods, it creates a closed-loop adaptive churn management framework that combines channel recommendation, feedback-driven retraining, churn prediction, and churn factor detection into a single architecture. Additionally, it uses longitudinal evaluation and SHAP-based interpretability to show that churn behavior exhibits temporal drift, offering empirical proof that customer churn drivers are not stationary over time. Real-world operational data are also utilized from a fixed broadband provider over several observation periods to validate the developed framework.

II. METHODOLOGY

The approach used in this study is described in this section, with an emphasis on the proposed adaptive churn management framework as the main technique. In the domain of telecoms, it explains how the framework is operationalized and structured to allow end-to-end churn management. The data sources,

analytical procedures, adaptive learning mechanism, and assessment standards utilized to apply and evaluate the framework are further described. When combined, these components offer a methodical and repeatable explanation of the proposed approach's practical application.

A. Adaptive Churn Management Framework

In order to combat churn in the telecom sector, this paper introduces an adaptive churn management framework as the primary methodological approach. Customer data, analytical modeling, operational decision support, and feedback-driven learning are all integrated into a single system by the framework's end-to-end design. The proposed methodology accounts for data evolution over time, in contrast to traditional churn management techniques that rely on static historical data. This enables churn management to continuously adapt based on freshly observed customer behavior and the results of implemented retention efforts. Figure 2 depicts the framework's general structure and flow.

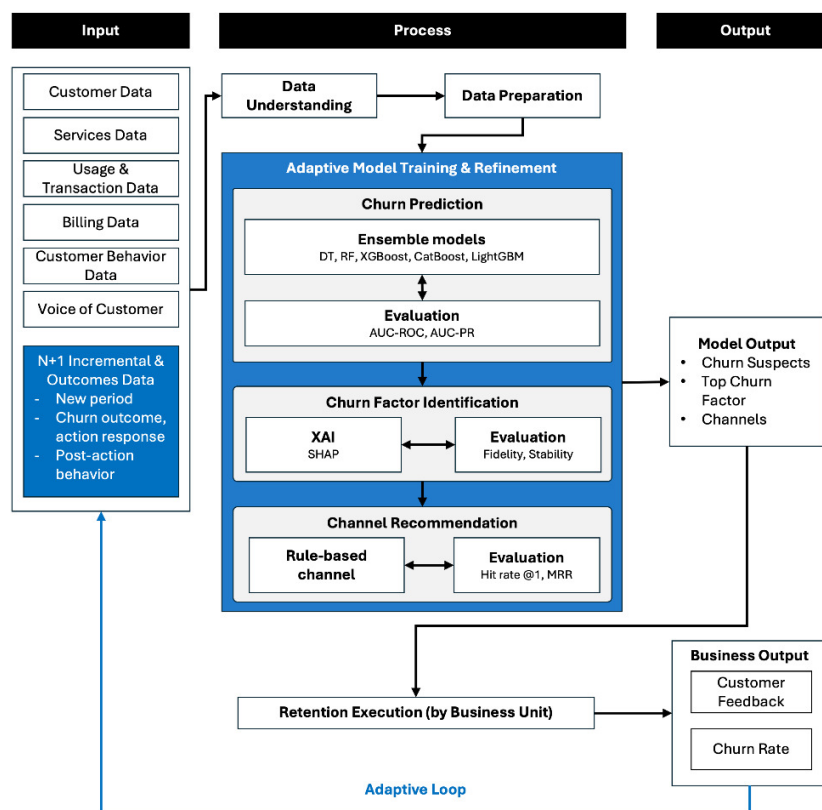


Fig. 2. Adaptive churn management framework.

The framework follows a closed-loop process that starts with input, moves through analytical processing, and ends with action and feedback. This structure illustrates how customer-related data are not only converted into insights that can be put into practice, but also how business activities' outcomes provide fresh data that feed into further cycles of analysis. As a result, churn is viewed as a continuous learning process rather than a one-time prediction activity.

As frequently used in churn management research, the framework integrates diverse customer-related data from the input perspective, representing consumer context, engagement, and interaction history [30, 31]. These inputs usually consist of customer profile information, service and subscription data, usage and transaction records, billing data, behavioral indicators, and voice-of-customer information [32, 33]. To guarantee data consistency and analytical readiness across

various systems and observation periods, multi-source customer data should be integrated and preprocessed.

The system specifically supports incremental and outcome-driven data produced in later operational periods, such as freshly observed customer behavior, churn realization, action reactions, and post-intervention outcomes, in addition to static historical inputs. According to recent research on feedback-driven learning systems, incorporating such developing inputs allows the framework to reflect temporal changes in customer behavior and supports adaptive churn management over time [30, 31].

The framework's analytical core is represented by the process viewpoint, which converts customer-related inputs into insights that aid in decision-making. Data comprehension, which focuses on examining data features and behavioral patterns pertinent to churn analysis, was the first step in this process [34-37]. The next step was feature engineering, which created informative attributes to improve model performance and explanatory power [34, 36-38].

The probability of client attrition was then estimated using churn prediction models, which operated as early warning systems for proactive retention [18, 30, 39-41]. Churn factor identification models were incorporated to improve interpretability and well-informed decision-making by explaining the factors underpinning churn risk in addition to prediction accuracy [12, 34, 27, 39, 41]. As proposed by modern decision-oriented churn management strategies, the framework also included channel recommendation models, which convert explanatory and predictive outputs into practical retention advice [42, 43].

The procedure comprised model evaluation to gauge operational and predictive performance in order to guarantee analytical soundness [30, 32, 38, 44], as well as model interpretability evaluation to promote openness and confidence in analytical results [35, 36]. Additionally, the methodology combined adaptive model retraining and feedback loop integration, allowing them to change as new result data become available and overcoming the drawbacks of static churn prediction techniques [31, 44-45]. Longitudinal performance evaluation and adaptive improvement were further supported by ongoing churn rate monitoring [31, 35, 39].

From an output standpoint, the framework generated business-level indicators that facilitate operational decision-making in addition to analytical outputs. Identification of possible churners was one of the analytical outputs that allowed for focused intervention tactics [32, 39, 42, 46]. Furthermore, the approach provided explanatory expertise that facilitates tailored and context-aware retention activities by generating insights into important churn-driving elements [12, 35-37].

The framework also generated churn rate indicators at an aggregate level, which are frequently used to assess overall churn management performance and retention efficacy [44]. Collectively, these outputs help business units execute retention strategies and provide quantifiable inputs for later feedback cycles, promoting adaptive learning and continuous improvement throughout operational periods.

B. Data Description and Sources

The proposed adaptive churn control strategy was empirically evaluated using customer-level data from a fixed broadband telecommunications service run by a major Indonesian provider. There are roughly 561,000 active subscribers to this service overall. The study focused on service locations in Jakarta that were chosen because of their high customer density and comparatively consistent service attributes, which allowed for controlled and comparable experimentation while preserving operational reality.

Two observation periods with similar temporal features were established for a fair comparison between adaptive and non-adaptive techniques. The adaptive configuration used data from June to December 2025, whereas the non-adaptive setup employed data from June to December 2024. In order to minimize bias caused by temporal variance and ensure comparability between configurations, these periods were purposefully aligned to account for similar seasonal patterns, billing cycles, and client behavior dynamics.

The individual consumer, as observed on a monthly basis, served as the study's unit of analysis. During the specified observation periods, between 13,000 and 15,000 active customer records were examined each month for experimental evaluation. This monthly subset ensured consistency and a controlled comparison between adaptive and non-adaptive configurations while offering enough analytical coverage to assess churn-related phenomena under actual operating situations.

Customer context, service interaction, behavioral patterns, and feedback were all captured by the varying customer-related data. This section describes the kinds of data that the developed framework employs, rather than going into detail about preprocessing or feature generation. The primary data categories and representative characteristics utilized throughout the framework are summarized in Table I.

TABLE I. OVERVIEW OF CUSTOMER-RELATED DATA CATEGORIES

Category	Description
Customer data	Customer profile and classification attributes, including customer segment, high-value customer indicators, geographic region, subscription tenure, and contact validity flags.
Service data	Information related to subscribed services, including service type, package characteristics, and subscription details.
Usage data	Internet usage and consumption patterns reflecting service utilization behavior.
Transaction data	Payment and transaction history associated with subscribed services.
Billing data	Billing-related information such as billing amounts, billing regularity, and payment status.
Customer behavior data	Behavioral indicators reflecting customer interaction, engagement, and service usage trends.
Voice of customer data	Customer complaints, feedback, and reported service issues captured through service channels.

The integration of these data categories enabled the framework to support action-oriented, explanatory, and predictive modules in a unified manner. In addition to baseline historical data, the system incorporated incremental and

outcome-driven data from subsequent periods, including updated customer behavior, churn realization, and post-action responses. This addition was utilized within the adaptive learning mechanism to capture temporal dynamics in customer behavior. All data were anonymized and processed in accordance with applicable confidentiality and data protection regulations. No personal identifiable information was involved at any stage of model development, evaluation, or analysis. Due to company data protection policies, the dataset cannot be publicly shared; however, it may be made available upon reasonable request, subject to organizational approval and compliance requirements.

C. Data Understanding and Preparation

Through data understanding and preparation, customer-related data from various sources are transformed into a consistent and analytically relevant format prior to being processed by the downstream modules. This step focuses on examining data structure, completeness, and temporal aspects to facilitate reliable churn analysis.

Aligning customer identities, standardizing attribute formats, and integrating data across operational systems are all part of the data preparation process. While categorical attributes are converted into suitable analytical representations, missing values and discrepancies are handled appropriately. To ensure comparability between experimental setups, certain procedures are regularly followed.

The approach makes a distinction between baseline and incremental ($N + 1$) data in order to facilitate adaptive learning. While incremental data records freshly observed customer behavior, churn consequences, and post-action responses in later periods, baseline data established the first analytical cycle. Because both data types go through the same preparation process, adaptivity is guaranteed to reflect behavioral change rather than variance in preprocessing.

D. Stacking Ensemble Learning

Stacking is a meta-modeling technique that improves the prediction accuracy by combining multiple classification models. It operates on a two-level hierarchy: Level-0 (Base Learners) generates predictions which serve as input features for a Level-1 (Meta-Learner) model to produce the final output [38, 47]. If the base learners L_1, \dots, L_k produce predictions $\hat{y}_1, \dots, \hat{y}_k$, the meta-learner M learns the optimal combination function f :

$$\hat{y}_{final} = f(\hat{y}_1, \hat{y}_2, \dots, \hat{y}_k) \quad (1)$$

This approach leverages the strengths of heterogeneous algorithms to capture diverse patterns in the data [48].

E. Base Learners

1) Decision Tree (DT) Classifier

DT is a non-parametric supervised learning technique that divides data into feature-value-based subgroups. The Gini index is commonly used to assess a split's quality in order to reduce impurity. For a dataset D with K classes, the Gini index is defined as [49]:

$$Gini(D) = \sum_{k=1}^K \frac{|c_k|}{|D|} \left(1 - \frac{|c_k|}{|D|} \right) \quad (2)$$

Even though they are interpretable, single trees are susceptible to overfitting, which ensemble approaches assist in reducing.

2) Random Forest (RF) Classifier

During training, an ensemble bagging technique builds a large number of DTs. Compared to individual DTs, RF lowers both the variance and danger of overfitting by training each tree on a random selection of data and features [50]. Usually, the mode of the classes that each tree produces is the final forecast [51].

3) XGBoost (XGB) Classifier

A scalable version of Gradient-Boosted Decision Trees (GBDT) is called eXtreme Gradient Boosting (XGBoost). In order to fix the residual mistakes of earlier models, XGBoost builds trees one after the other. Its objective function is a combination of a loss function ($L(\theta)$) and a regularization term $\Omega(\theta)$, which controls the model complexity [52]:

$$Obj(\theta) = L(\theta) + \Omega(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (3)$$

XGBoost is an expert in managing sparse data and avoiding overfitting as it employs a level-wise tree growth technique [53].

4) LightGBM (LGBM) Classifier

A histogram-based approach is used by the Light Gradient Boosting Machine (LGBM) to improve training speed and memory economy. In contrast to XGBoost, it uses a leaf-wise (best-first) growth method, which may require depth limits to avoid overfitting on smaller datasets but can lead to lower loss [53].

5) CatBoost Classifier

CatBoost, which was created to efficiently handle categorical data, uses oblivious DTs (symmetric trees) as base predictors and ordered boosting to reduce target leakage. Without requiring a lot of data preprocessing, this structure serves as a regularizer, strengthening and stabilizing the model [53].

F. Meta-Learner: Logistic Regression

The probabilistic outputs of the base learners are linearly combined using Logistic Regression as the meta-classifier. It uses the sigmoid function to transfer predictions to a probability value between 0 and 1:

$$P(y = 1|x) = \frac{1}{1 + e^{-(w^T x + b)}} \quad (4)$$

This layer provides a calibrated ultimate churn probability by mitigating the biases of the intricate base models [50].

G. SHAP (SHapley Additive exPlanations)

By determining each feature's marginal contribution to the prediction using the cooperative game theory, SHAP offers interpretability. The SHAP value ϕ_i for feature i is calculated by [54]:

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (5)$$

This method explains individual customer risk profiles and pinpoints important churn causes, such as contract type and monthly fees [55].

H. RandomizedSearchCV

RandomizedSearchCV is a method for hyperparameter optimization that draws samples from predetermined distributions for a specific number of parameter configurations. It successfully finds near-optimal hyperparameters for high-dimensional models while being computationally more efficient than exhaustive grid search [50].

I. Evaluation Metrics

The multi-layer structure of the proposed framework is captured by the chosen metrics taken together. Discrimination and imbalance sensitivity were evaluated by predictive metrics, whereas interpretability consistency was assessed by explanation metrics. Additionally, operational alignment with customer reactions was measured by recommendation metrics, and overall business impact was reflected by the churn rate. This integrated assessment methodology guaranteed that performance was evaluated at the decision-support and business levels in addition to the modeling level.

Table II summarizes the formula and purpose of each evaluation metric that was utilized in this study.

TABLE II. SUMMARY OF EVALUATION METRICS

Metric	Formula	Purpose
Churn prediction module		
AUC-ROC	$\int_0^1 TPR(FPR^{-1}(x))dx$	Measures overall discrimination capability
PR-AUC	$\int \text{Precision}(\text{Recall}) d(\text{Recall})$	Evaluates performance under class imbalance
Precision	$\frac{TP}{TP + FP}$	Proportion of correctly predicted churners
Recall	$\frac{TP}{TP + FN}$	Ability to capture actual churners
Churn factor identification module		
AUC-ROC	$\int_0^1 TPR(FPR^{-1}(x))dx$	Measures overall discrimination capability
PR-AUC	$\int \text{Precision}(\text{Recall}) d(\text{Recall})$	Evaluates performance under class imbalance
Channel recommendation		
Hit rate	$HR@K = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(\text{rank}_i \leq k)$	Whether recommended channel matches response
MRR	$MRR = \frac{1}{N} \sum_{i=1}^N \frac{1}{\text{rank}_i}$	Evaluates ranking quality of recommendations
Business level outcome		
Churn rate	$\frac{N_{churn}}{N_{total}}$	Measures aggregate service discontinuation

To make sure that the assessment encapsulated both technical efficacy and operational significance, the selection of the evaluative metrics was meticulously aligned with the attributes of churn data and the strategic objectives within the telecommunications domain. Specifically, churn datasets exhibited a pronounced imbalance, wherein churners constitute merely a minor segment of the overall customer population. In this case, ROC-AUC is a robust evaluation metric for ranking

classifiers as it is mathematically invariant to class imbalance [56]. However, PR-AUC is often considered a more authentic evaluation since its precision component explicitly penalizes false positive errors, more accurately reflecting the balance between precision and recall [57]. To account for the limitations of any single metric, researchers propose adopting a multi-metric evaluation framework [57].

Precision, Recall, and F1-score were incorporated to elucidate the operational trade-offs inherent in churn prediction. Precision indicates the effectiveness of directing retention initiatives, successfully minimizing costly false positive errors. Conversely, Recall guarantees the accurate identification of genuine churners, ensuring that false negatives are minimized. The F1-score harmonizes these two dimensions by calculating the harmonic mean of both precision and recall [58]. In the context of the recommendation module, Hit Rate@K and Mean Reciprocal Rank (MRR) serve as metrics for assessing the precision and ranking efficacy of advised intervention channels [59]. Ultimately, churn rate was incorporated as a business-oriented outcome metric to evaluate the practical implications of the framework in mitigating customer attrition.

III. IMPLEMENTATION AND RESULTS

The application of the proposed adaptive churn management framework and the empirical findings from practical testing are presented in this part. The framework's efficacy in terms of prediction accuracy, explanatory capacity, recommendation quality, and business-level outcomes is assessed in two experimental settings: non-adaptive and adaptive configurations.

A. Experimental Setup and Implementation Overview

Customer-level data from a fixed broadband service in Jakarta were used to implement and assess the introduced adaptive churn control approach. Every month, between 13,000 and 15,000 active clients were covered by the implementation, guaranteeing a large enough population for accurate assessment. There were two defined experimental configurations. While the adaptive configuration utilized data from June to December 2025 and incorporated incremental customer behavior and outcome data at each period to enable feedback-driven learning, the non-adaptive configuration employed models trained on data from June to December 2024 without incorporating post-action feedback.

The same evaluation metrics and data preparation techniques were used in both settings. The stacking ensemble architecture was employed to implement the churn prediction module in both setups. DT, RF, XGBoost, LightGBM, and CatBoost were used as base learners, and Logistic Regression was deployed as the meta-learner to combine probabilistic outputs. RandomizedSearchCV was operated for hyperparameter optimization using the same parameters for both configurations. In order to ensure that observed performance differences were due to the adaptive learning mechanism rather than differences in model structure, preprocessing approach, or optimization design, the analytical workflow, model architecture, and execution environment were maintained consistently between tests.

B. Churn Prediction Module Performance and Evaluation

Over the course of six monthly observation periods, the evaluation compared adaptive versus non-adaptive designs. The temporal performance comparison for all evaluation metrics is illustrated in Figure 3. Over time, the adaptive setup demonstrated more consistent and stable performance, especially for AUC-ROC and PR-AUC, which are crucial under class imbalance. The non-adaptive arrangement, on the other hand, presented greater variations over time, indicating a lack of reactivity to changing churn patterns.

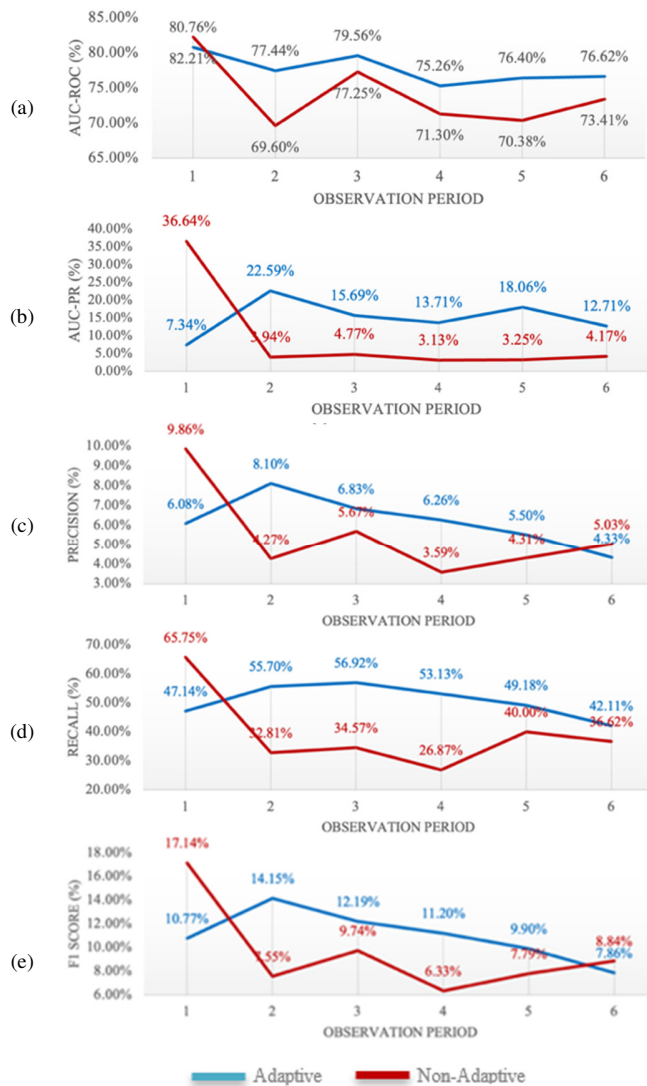


Fig. 3. Churn prediction performance over time for adaptive and non-adaptive configuration: (a) AUC-ROC, (b) PR-AUC, (c) precision, (d) recall, (e) F1-score.

The adaptive model maintained AUC-ROC values between 75.26% and 80.76%, with comparatively little variation over time. The non-adaptive model, on the other hand, exhibited greater volatility; it fell to 69.60% in period 2 and only partially recovered to 73.41% in period 6. This disparity suggests that

the adaptive approach's capacity for discrimination has grown over time.

PR-AUC demonstrated a more noticeable difference, which is especially important for unbalanced churn data. The non-adaptive configuration's performance drastically dropped after Period 1 (36.64%), and it stayed below 5% for most of the following periods. Conversely, the adaptive configuration maintained values above 12% throughout subsequent periods, demonstrating a significant improvement from 7.34% in Period 1 to a peak of 22.59% in Period 2. The adaptive model's enhanced capacity to rank real churn cases under imbalanced circumstances was supported by this persistent separation.

Metrics that are dependent on thresholds indicated similar trends. The adaptive configuration for precision stayed above the non-adaptive configuration in five of the six periods, reaching a maximum of 8.10% in Period 2. From 9.86% in Period 1 to 4.27% in Period 2, the non-adaptive precision dropped dramatically and then varied between 3.59% and 5.67%. In terms of recall, the non-adaptive configuration decreased to as low as 26.87% in Period 4 and stayed below 40.00% in subsequent periods, whereas the adaptive model continuously reached a higher percentage of churn cases, peaking at 56.92% in Period 3.

Similarly, the F1-score, which strikes a balance between recall and precision, reflected these patterns. The adaptive configuration's F1-score peaked in Period 2 at 14.15% and remained above 9% through Period 5 before declining to 7.86% in Period 6. The non-adaptive arrangement exhibited a steep drop from 17.14% in Period 1 to 7.55% in Period 2, followed by poorer and more erratic performance throughout subsequent periods.

The structural distinctions between non-adaptive and adaptive designs were further demonstrated by the confusion matrix comparison depicted in Figure 4. There were many more false positives (1,469) in the non-adaptive model, which suggests an aggressive categorization propensity that flags many non-churn consumers as churn. This method produced significant misclassification noise and operational inefficiencies, even though it captured a few more churn cases.

The adaptive setup maintained a similar degree of genuine positive detection while significantly reducing false positives (498). A more consistent and precise decision boundary is shown in the rise of true negatives (3,954 versus 2,514). The adaptive model exhibited a more balanced categorization behavior, despite the moderate recall disparities between the two setups. The adaptive configuration's better and more stable AUC-ROC was consistent with these important gains in classification consistency. Thus, the confusion matrix comparison confirms that adaptive learning improved discrimination robustness while decreasing needless churn flagging, even beyond threshold-specific behavior.

The observed decline in class "1" accuracy was linked to a trade-off between lowering false positives and preserving sensitivity in a highly imbalanced scenario, according to a deeper look at the confusion matrix. By significantly lowering false positives, the adaptive setup enhances class "0" classification performance and minimizes needless retention

interventions. This improvement is made possible by a more cautious decision boundary that more effectively distinguishes probable churn cases from non-churn consumers.

Consequently, some occurrences of borderline churn might no longer be categorized as positive, which would result in a minor decrease in class "1" accuracy. This behavior, however, does not point to a decline in the model's efficacy. Rather, it represents a more equitable and practical classification approach. The adaptive model continues to show a significant improvement in Recall and PR-AUC, suggesting a greater overall capacity to detect real churn cases. The goal of optimizing churn detection under class imbalance is thus aligned with the observed pattern, which constitutes a controlled and advantageous trade-off.

the adaptive configuration's average AUC-ROC of 77.67% was marginally greater than the non-adaptive configuration's 77.05%, suggesting that the two methods' overall discriminative power was equivalent.

TABLE III. AVERAGE CHURN PREDICTION PERFORMANCE ACROSS OBSERVATION PERIODS

Metric	Adaptive	Non-adaptive
AUC-ROC	77.67%	77.05%
PR-AUC	15.02%	9.32%
Precision	6.18%	5.45%
Recall	50.70%	39.44%
F1-score	11.01%	9.57%

Metrics that are sensitive to class imbalance revealed more significant differences. With an average PR-AUC of 15.02% as opposed to 9.32% for the non-adaptive setup, the adaptive configuration demonstrated a significantly better capacity to rank real churn cases in a highly unbalanced environment. Metrics that depend on thresholds presented similar trends. In addition to retaining a significantly better recall of 50.70% as opposed to 39.44% for the non-adaptive configuration, the adaptive model achieved greater average precision (6.18%) than the non-adaptive model (5.45%).

Together, these gains are pointed in the F1-score, where the adaptive setup achieved an average value of 11.01%, higher than the non-adaptive approach's 9.57%. Overall, the combined findings in Table III support the temporal analysis by demonstrating that the adaptive design consistently produces higher average performance across a variety of evaluation dimensions without masking the previously noted period-specific variances.

Predictive measures confirmed the adaptive configuration's performance benefit, while the SHAP-based temporal analysis further revealed the dynamic nature of churn drivers across observation periods. Figure 5 illustrates the heatmap of average mean absolute SHAP values for the top 15 churn-driving features across observation periods. The relative importance of features varied over time, with payment-related variables consistently appearing among the most influential, while usage and network-related factors exhibited fluctuating contributions across different periods. This pattern highlighted the non-stationary nature of customer behavior, where the drivers of churn are not constant but evolve over time.

Such variation suggests that a static model trained on historical patterns may progressively lose both explanatory and predictive alignment as underlying behavior shifts. In contrast, the adaptive learning mechanism incorporated in the proposed framework continuously updates its understanding by integrating incremental behavioral and outcome data, thereby maintaining relevance in both prediction and explanation. These findings empirically support the necessity of adaptive learning in dynamic churn environments.

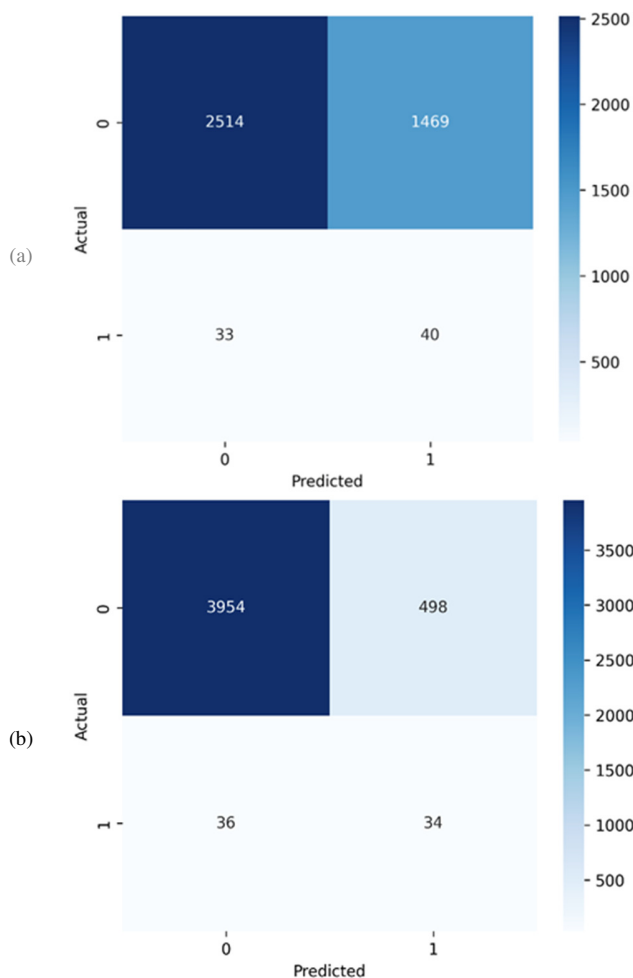


Fig. 4. Confusion matrix comparison between (a) non-adaptive and (b) adaptive configurations.

Table III offers a succinct numerical supplement to the temporal trends displayed in Figure 3 and highlights the average performance of the churn prediction module throughout all observation periods. When combined over time,

Churn Driving Features	Observation Period						Avg
	M1	M2	M3	M4	M5	M6	
payment date (2 months lag)	0.000064	0.000582	0.000326	0.000864451	0.000162	0.000373747	0.000395
payment date (4 months lag)	0.000033	0.000347	0.000080	0.000937773	0.000037	0.000320262	0.000292
payment date variability range	0.000123	0.000503	0.000178	0.00050244	0.000123	0.000168933	0.000266
last internet usage (dossier)	0.000041	0.000375	0.000074	0.000800201	0.000115	0.000109879	0.000253
payment date (3 months lag)	0.000040	0.000464	0.000251	0.000234478	0.000096	0.000262897	0.000225
internet usage (1 month lag)	0.000060	0.000222	0.000042	0.000776027	0.000052	0.000148587	0.000217
payment date (1 month lag)	0.000090	0.000565	0.000143	0	0.000050	0.000220384	0.000178
payment date (5 months lag)	0.000025	0.000074	0.000202	0.000496736	0.000092	0.000127906	0.000169
days since last on-time payment	0.000062	0.000260	0.000026	0.000363088	0.000124	0.000137085	0.000162
customer tenure	0.000101	0.000282	0.000068	0.000341004	0.000039	0.000130316	0.000160
voice service tenure	0.000101	0.000420	0.000059	9.95529E-05	0.000019	0.000114602	0.000136
internet usage (2 months lag)	0.000025	0.000128	0.000130	0.000242988	0.000103	0.000114173	0.000124
internet speed	0.000077	0.000261	0.000078	5.19775E-05	0.000020	0.00016463	0.000109
payment frequency (day 16-20)	0.000013	0.000120	0.000050	0.000369524	0.000023	7.45432E-05	0.000108
internet usage (5 months lag)	0.000018	0.000081	0.000076	0.000380618	0.000037	5.45675E-05	0.000108

Fig. 5. Heatmap of average mean absolute SHAP values for the top 15 churn-driving features across observation periods (M1-M6).

C. Churn Factor Identification Module Performance and Evaluation

AUC-ROC and PR-AUC were utilized to compare the adaptive and non-adaptive setups in order to assess the robustness of churn factor detection over observation periods. When explanatory factors were added to the analytical pipeline, these metrics evaluated the model's capacity to distinguish churn-related signals.

The adaptive arrangement exhibited more consistent discrimination performance over time, as depicted in Figure 6. The adaptive model maintained AUC-ROC values between 56.10% and 64.37% over the course of the six periods, with comparatively little change. The non-adaptive configuration showed greater volatility, peaking at 69.61% in Period 2, then abruptly declined to 46.64% in Period 4, and finally remained below 50% in future periods. When factor identification depends on static patterns, this variation indicates decreased explanatory alignment.

PR-AUC, which is especially instructive under class imbalance, revealed a similar tendency. Although the non-adaptive setup momentarily reached a higher number in Period 2 (68.95%), its performance significantly deteriorated in the following periods, stabilizing at 39-42%. In contrast, the adaptive configuration, ranging from 44.45% to 61.83%, kept more constant values. This consistent performance suggests that, as consumer behavior changes, adaptive retraining helps maintain the significance of identified churn-driving elements.

After Period 2, the gap between configurations became more noticeable. While the adaptive arrangement exhibited resistance to temporal drift, the non-adaptive setup had indications of explanatory degeneration. These results implied that static factor identification progressively loses discriminatory alignment and that churn drivers are not constant over time. The findings demonstrated the importance of adaptive learning in keeping consistent and context-sensitive identification of churn-driving elements as well as prediction resilience. The adaptive framework improved the stability of factor relevance over operational cycles by updating explanatory patterns in response to changing data.

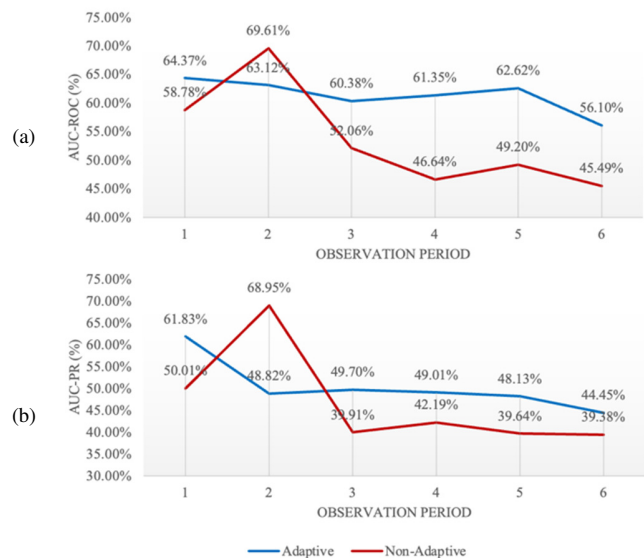


Fig. 6. Churn identification factor performance over time for adaptive and non-adaptive configuration: (a) AUC-ROC, (b) PR-AUC.

D. Channel Recommendation Module Performance and Evaluation

MRR and Hit Rate@K were used to assess the channel suggestion module's performance. Specifically, this study set $K = 1$ (Hit Rate@1) to isolate the precision of the primary recommendation. These measures evaluate the ranking quality of suggestions throughout six observation periods as well as the accuracy of the proposed channels.

The temporal comparison of Hit Rate@1 between adaptive and non-adaptive configurations is displayed in Figure 7. Throughout all time periods, the adaptive configuration consistently exhibited greater hit rates, indicating a better fit between the proposed channels and actual customer reactions. In particular, the adaptive Hit Rate@1 peaked at 68.59% in Period 3 and ranged from 61.69% to 68.59%. The non-adaptive configuration presented a significant deterioration following Period 1, falling from 63.72% to 45.07% in Period 3 and only marginally rebounding to 51.10% by Period 6. This divergence

demonstrated the adaptive model's enhanced capacity to sustain recommendation relevance over time.

consumers who stopped using the service during each observation period.



Fig. 7. Channel recommendation performance over time for adaptive and non-adaptive configuration: (a) Hit Rate @1, (b) MRR.

Ranking quality for MRR demonstrated a similar trend. With the highest value of 83.79% recorded in Period 3, the adaptive configuration maintained high and steady MRR values, varying within a comparatively small range between 80.09% and 83.79%. In contrast, the ranking performance of the non-adaptive configuration declined more sharply, falling from 81.40% in Period 1 to 71.71% in Period 3 before leveling off at 72.69%-75.00% in subsequent periods. These findings imply that adaptive learning helps produce channel recommendations that are consistently ranked highly.

The average recommendation performance over all observation periods is presented in Table IV. The Hit Rate@1 for the adaptive setup was 64.45%, whereas the non-adaptive configuration's was 51.36%. The adaptive technique achieved an average MRR of 81.69%, which is higher than the non-adaptive setup's 75.08%. By demonstrating that the adaptive configuration produces greater overall recommendation accuracy and ranking quality when evaluated over periods, this aggregated perspective validates the temporal trends captured in Figure 7.

TABLE IV. AVERAGE CHURN PREDICTION PERFORMANCE ACROSS OBSERVATION PERIODS

Metric	Adaptive	Non-adaptive
Hit Rate @1	64.45%	51.36%
MRR	81.69%	75.08%

E. Business-Level Churn Outcomes

Churn rate was used to assess the proposed framework's business-level impact. This statistic gave an overall indicator of retention performance by reflecting the percentage of

The monthly churn rate comparison between the adaptive and non-adaptive configurations over the course of six observation periods is displayed in Figure 8. The adaptive design recorded a churn rate of 1.74% for the first period, which is marginally less than the 1.81% recorded under the non-adaptive arrangement. In later periods, this gap became more noticeable, suggesting persistent variations in churn outcomes.

The adaptive setup kept churn rates within a more constrained range of 1.23% to 1.74%, during the observation frame. Period 5 exhibited the lowest churn rate for the adaptive configuration, at 1.23%, and Period 6 had a slight increase to 1.28%. The non-adaptive setup, on the other hand, presented greater volatility, with churn rates between 1.29% and 1.97%. Period 3 had the greatest non-adaptive configuration churn rate of 1.97%, which was much higher than the equivalent adaptive churn rate of 1.41%.

For the majority of the time, there was a constant difference between the two arrangements. In Period 3, for instance, the adaptive design reduced the churn rate by 0.56% compared to the non-adaptive setup (1.41% versus 1.97%). Comparably, in Period 6, the adaptive churn rate was still lower at 1.28% as opposed to 1.65% in the non-adaptive setup. These variations indicate that, at the overall company level, the adaptable setup is linked to better churn results.

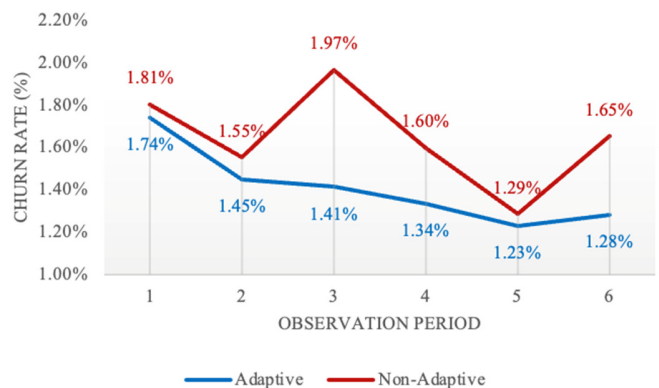


Fig. 8. Churn rate performance over time for adaptive and non-adaptive configurations.

IV. DISCUSSION

The actual findings indicated that the utilization of adaptive learning in churn control consistently outperformed static modeling techniques. While the average AUC-ROC values for both setups were similar (77.67% for the adaptive model and 77.05% for the non-adaptive model), imbalance-sensitive and operationally relevant metrics revealed more significant variations. In extremely imbalanced settings where churn rates varied from 1% to 2%, the adaptive setup significantly improved PR-AUC from 9.32% to 15.02% and raised recall from 39.44% to 50.70%, indicating a higher ability to prioritize minority churn events. Accurately identifying real churners is

more important in these telecom situations than just maximizing overall discrimination effectiveness.

Both configurations presented comparatively poor precision and, as a result, small F1-scores despite these notable gains. The high class imbalance exhibited in turnover statistics, where the positive class only made up a small portion of the overall customer population, was the main cause of this result. Because the number of actual churn cases was intrinsically limited in comparison to the large non-churn base, even models with excellent discriminative capability may yield poor absolute precision values. Therefore, when compared to a rare positive class, a moderate frequency of false positives might significantly lower precision. The adaptive configuration run under a threshold that prioritizes sensitivity over rigorous positive certainty since it was purposefully intended to enhance recall and minority-class priority. Consequently, rather than being a sign of analytical weakness, the comparatively low accuracy and F1-scores reflected structural features of the data distribution. The comparison of the confusion matrix showed that the adaptive setup significantly improved classification efficiency by reducing false positives from 1,469 to 498. False positives are consumers who are unnecessarily targeted for retention interventions in operational contexts. This could result in unnecessary marketing expenditures, promotional incentives, and communication campaigns. The practical utility of adaptive learning in reducing ineffective intervention activities while preserving strong recall performance was demonstrated by the elimination of almost a thousand misclassified non-churn clients within a single evaluation window.

Additionally, temporal analysis confirmed that while the adaptive configuration remained more stable, the non-adaptive configuration had discernible performance loss over observation periods. A SHAP-based analysis revealed that the main causes of churn changed over time, with payment-related issues dominating in certain months and service or network-related factors becoming more significant in others. These findings demonstrated non-stationary churn behavior empirically. While the adaptive retraining mechanism used incremental behavioral and outcome data to recalibrate predictive and explanatory patterns, static models trained on past patterns progressively lost alignment with changing customer dynamics. Throughout operating cycles, this ongoing modification improved robustness in both explanatory relevance and forecast accuracy.

The alignment between the training data and the initial test distribution, where customer behavior stayed consistent with historical patterns, is the main factor driving the relatively strong performance of the non-adaptive configuration at the start of the observation period, according to a closer look at the temporal performance pattern. As a result, during this first stage, the static model could still identify pertinent churn signals. A brief stability or partial reappearance of behavioral patterns, possibly impacted by cyclical factors like billing cycles, promotional efforts, or seasonal usage trends, could be the cause of the observed performance rebound at a later time. The distribution mismatch between the current data and the static model is temporarily lessened under these circumstances.

This trend was not maintained, though. The non-adaptive setup, also known as temporal drift, provided observable performance loss and fluctuation during intermediate periods, demonstrating its incapacity to adjust to changing customer behavior. Conversely, through feedback-driven retraining, the adaptive design continuously incorporated incremental behavioral and outcome data to maintain more stable and consistent performance. This means that static models were not durable in dynamic situations where consumer behavior is intrinsically non-stationary, even when they might function well under transient alignment conditions.

Adaptivity had benefits for corporate outcomes and decision support as well. Stronger alignment between the proposed intervention channels and the actual customer responses was demonstrated by the adaptive configuration's higher Hit Rate@1 of 64.45% compared to 51.36% for the non-adaptive model and higher MRR of 81.69% compared to 75.08%. With a maximum observed reduction of 0.56%, these analytical improvements resulted in lower and more consistent churn rates ranging from 1.23% to 1.74%, as opposed to 1.29% to 1.97% under the non-adaptive arrangement. Even small percentage variations had a direct impact on recurring income and customer lifetime value in subscription-based telecom services. Overall, the results lent credence to the idea that churn management should be viewed as a dynamic, feedback-driven system instead of a static prediction task, with adaptive learning being essential to maintaining operational efficacy and predictive robustness.

Over the course of the six-month observation period, the presented adaptive framework had significant economic ramifications in addition to predictive accuracy. Promotional offers, outbound calls, and customer engagement initiatives are examples of needless retention interventions that have significantly decreased, as evidenced by the notable drop in false positives. By allocating fewer resources to clients who are not at risk of churning, this reduction directly results in operational cost savings.

Additionally, better revenue retention is a result of the observed decline and stabilization of churn rates. Even modest percentage increases in churn rates can have a cumulative effect on recurring income and customer lifetime value in subscription-based telecom services. The adaptive configuration's capacity to sustain lower and more stable churn rates pointed to a more effective distribution of retention tactics, guaranteeing that interventions are more precisely targeted and financially sound.

Higher Hit Rate@1 and MRR indicated improved suggestion quality, which also improved economic outcomes by raising the probability that the chosen intervention channels correspond with real consumer replies. This alignment maximized the return on retention efforts while decreasing ineffective engagement. When combined, these results indicated that the adaptive framework not only enhanced predictive performance but also produced observable financial gains by maximizing revenue preservation and cost effectiveness in practical operating settings.

The proposed framework enhanced churn management by moving beyond traditional static prediction models and partially integrated methods, unlike previous research. Standard churn prediction models usually prioritize maximizing predictive accuracy with historical data, without including feedback loops or linking outcomes to operational decisions. Although some studies have presented integrated churn management frameworks that merge prediction with segmentation or recommendation features, these methods frequently stay static and cannot adjust to evolving customer behavior over time. Thus, their effectiveness often diminishes when underlying churn patterns change.

However, the introduced adaptive closed-loop system overcame these issues by incorporating prediction, churn factor identification, and channel recommendation into a feedback-driven learning process. Instead of static models, this system regularly updated its analytical parts with new behavioral and outcome data, ensuring that its predictions remained relevant and explanations consistent over time. Compared to existing integrated frameworks, the inclusion of adaptive retraining and longitudinal evaluation allows the system not only to generate insights but also to sustain its operational effectiveness over time. This positions the framework as a more comprehensive and practically deployable solution, bridging the gap between predictive modeling and real-world churn management execution.

V. CONCLUSION

In this study, an adaptive churn management framework for the telecom sector was proposed and empirically assessed. It incorporated feedback-driven retraining, channel suggestion, churn prediction, and churn factor detection into a closed-loop system. The findings demonstrated that adaptive learning improved both analytical robustness and business-level effectiveness by comparing adaptive and non-adaptive configurations over six observation periods using actual operational data from a fixed broadband provider in Indonesia.

The adaptive framework performed significantly better on imbalance-sensitive and operationally relevant metrics, despite the fact that both configurations yielded similar average AUC-ROC values (77.67% adaptive versus 77.05% non-adaptive). In particular, the adaptive setup raised recall from 39.44% to 50.70%, improved PR-AUC from 9.32% to 15.02%, and enhanced the F1-score (11.01% versus 9.57%). With Hit Rate@1 rising from 51.36% to 64.45% and Mean Reciprocal Rank (MRR) from 75.08% to 81.69%, adaptive learning significantly enhanced decision-support quality in the recommendation module. These progresses revealed that adaptivity can improve both prediction discrimination and the correspondence between analytical results and implemented retention strategies.

The adaptive arrangement regularly resulted in lower and more stable churn rates at the overall business level, ranging from 1.23% to 1.74%, as opposed to 1.29% to 1.97% under the non-adaptive structure. In a single observation period, the greatest decline was 0.56%. These results demonstrated that feedback-driven retraining reduces temporal drift in churn

behavior and converts analytical improvements into quantifiable retention benefits.

Overall, churn management should be seen as a dynamic, adaptive system. The proposed paradigm expanded previous churn research beyond prediction-centric techniques toward a business-aligned, operationally sustainable solution by combining predictive modeling, explanatory analysis, actionable advice, and continuous learning inside a single architecture.

Future work should focus on examining economic impact modeling at the revenue level, statistical significance testing across time periods, and scalability assessment in multi-regional or multi-service settings. Furthermore, adaptive processes in other relationship-intensive businesses should be assessed in order to confirm the introduced framework's generalizability.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGMENT

The authors would like to thank Diponegoro University (www.undip.ac.id), Semarang, Indonesia, for its support in the present work. The authors also acknowledge all parties who contributed to data provision, domain insights, and validation of the proposed framework. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

DATA AVAILABILITY

The data that support the findings of this study are derived from internal company data and are not publicly available due to confidentiality agreements and data protection policies. However, aggregated or anonymized data may be made available from the corresponding author upon reasonable request and with permission from the respective organization.

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the authors used generative AI tools to support language refinement and improve the clarity of the manuscript. The authors reviewed and edited all generated content as needed and take full responsibility for the content of the publication.

REFERENCES

- [1] S. Ouf, K. T. Mahmoud, and M. A. Abdel-Fattah, "A proposed hybrid framework to improve the accuracy of customer churn prediction in telecom industry," *Journal of Big Data*, vol. 11, no. 1, May 2024, Art. no. 70, <https://doi.org/10.1186/s40537-024-00922-9>.
- [2] R. Bohne, "Customer churn rate in the United States in 2020, by industry," Statista, <https://www.statista.com/statistics/816735/customer-churn-rate-by-industry-us/>.
- [3] A. Mason, "Company Financial Report and Web Search, NPS Survey," 2022.
- [4] S&P Global, "Industry Credit Outlook 2025 Contacts Telecoms What's changed?," Jan. 2025.

- [5] "Unifiqu'e quarterly and annual economic data." Teleco: Intelligence in Telecommunications. https://teleco.com.br/en/en_operadoras/unifiqu'e.asp.
- [6] "Sustainability at Converge." Converge, <https://corporate.convergeict.com/sustainability>.
- [7] AVN, "Asia Vision Network-Investment Presentation." July 2021, https://www.sec.gov/Archives/edgar/data/1807594/000121390021036713/ea144144ex99-1_malacca.htm.
- [8] BT Group, "BT Group plc Annual Report 2023." 2023, <https://www.bt.com/bt-plc/assets/documents/investors/financial-reporting-and-news/annual-reports/2023/2023-bt-group-plc-annual-report.pdf>.
- [9] KDDI Corporation, "Performance Highlights and Q&A for the Financial Results for the Fiscal Year Ended March 2023." 2023, https://www.kddi.com/extlib/files/english/corporate/ir/library/presentation/2023/pdf/kddi_2023_4_e_qa.pdf.
- [10] Starhub, "Starhub Ltd Annual Report 2022." https://ir.starhub.com/newsroom/20230413_StarHub_AR22_For_SGX.pdf.
- [11] T. Zhang, S. Moro, and R. F. Ramos, "A Data-Driven Approach to Improve Customer Churn Prediction Based on Telecom Customer Segmentation," *Future Internet*, vol. 14, no. 3, pp. 1-19, Mar. 2022, <https://doi.org/10.3390/fi14030094>.
- [12] X. Wen, Y. Wang, X. Ji, and M. K. Traoré, "Three-stage churn management framework based on DCN with asymmetric loss," *Expert Systems with Applications*, vol. 207, Nov. 2022, Art. no. 117998, <https://doi.org/10.1016/j.eswa.2022.117998>.
- [13] N.-T. Lee, H.-C. Lee, J. Hsin, and S.-H. Fang, "Prediction of Customer Behavior Changing via a Hybrid Approach," *IEEE Open Journal of the Computer Society*, vol. 5, pp. 27-38, Nov. 2023, <https://doi.org/10.1109/OJCS.2023.3336904>.
- [14] P. Sulikowski and T. Zdziebko, "Churn factors identification from real-world data in the telecommunications industry: case study," *Procedia Computer Science*, vol. 192, pp. 4800-4809, 2021, <https://doi.org/10.1016/j.procs.2021.09.258>.
- [15] Y. Islem Adnane and M. Zerari, "Optimizing Business Intelligence Classification Rule Mining Using Quantum-Inspired Genetic Algorithm," *IEEE Access*, vol. 12, pp. 137041-137053, Sept. 2024, <https://doi.org/10.1109/ACCESS.2024.3463506>.
- [16] R. A. Moral *et al.*, "Profiling Television Watching Behavior Using Bayesian Hierarchical Joint Models for Time-to-Event and Count Data," *IEEE Access*, vol. 10, pp. 113018-113027, Oct. 2022, <https://doi.org/10.1109/ACCESS.2022.3215682>.
- [17] F. Wu *et al.*, "Characterizing Internet Card User Portraits for Efficient Churn Prediction Model Design," *IEEE Transactions on Mobile Computing*, vol. 23, no. 2, pp. 1735-1752, Feb. 2024, <https://doi.org/10.1109/TMC.2023.3241206>.
- [18] M. Seufert and I. Orsolich, "Improving the Transfer of Machine Learning-Based Video QoE Estimation Across Diverse Networks," *IEEE Transactions on Network and Service Management*, vol. 21, no. 3, pp. 2824-2836, June 2024, <https://doi.org/10.1109/TNSM.2023.3326664>.
- [19] J. Tao *et al.*, "Explainable AI for Cheating Detection and Churn Prediction in Online Games," *IEEE Transactions on Games*, vol. 15, no. 2, pp. 242-251, June 2023, <https://doi.org/10.1109/TG.2022.3173399>.
- [20] N. Ahmad, M. J. Awan, H. Nobanee, A. M. Zain, A. Naseem, and A. Mahmoud, "Customer Personality Analysis for Churn Prediction Using Hybrid Ensemble Models and Class Balancing Techniques," *IEEE Access*, vol. 12, pp. 1865-1879, 2024, <https://doi.org/10.1109/ACCESS.2023.3334641>.
- [21] M. Afzal, S. Rahman, D. Singh, and A. Imran, "Cross-Sector Application of Machine Learning in Telecommunications: Enhancing Customer Retention Through Comparative Analysis of Ensemble Methods," *IEEE Access*, vol. 12, pp. 115256-115267, Aug. 2024, <https://doi.org/10.1109/ACCESS.2024.3445281>.
- [22] M. Alizadeh, D. S. Zadeh, B. Moshiri, and A. Montazeri, "Development of a Customer Churn Model for Banking Industry Based on Hard and Soft Data Fusion," *IEEE Access*, vol. 11, pp. 29759-29768, Mar. 2023, <https://doi.org/10.1109/ACCESS.2023.3257352>.
- [23] K. Rothmeier, N. Pflanzl, J. A. Hüllmann, and M. Preuss, "Prediction of a Player Churn and Disengagement Based on User Activity Data of a Freemium Online Strategy Game," *IEEE Transactions on Games*, vol. 13, no. 1, pp. 78-88, Mar. 2021, <https://doi.org/10.1109/TG.2020.2992282>.
- [24] A. Perišić and M. Pahor, "RFM-LIR Feature Framework for Churn Prediction in the Mobile Games Market," *IEEE Transactions on Games*, vol. 14, no. 2, pp. 126-137, June 2022, <https://doi.org/10.1109/TG.2021.3067114>.
- [25] B. Amiri and S. Hasan Hosseini, "Unveiling the Power of Social Influence: A Machine Learning Framework for Churn Prediction With Network Analysis," *IEEE Access*, vol. 12, pp. 71271-71285, May 2024, <https://doi.org/10.1109/ACCESS.2024.3402684>.
- [26] V. Harihasan, K. Muthukumar, and K. Hariharanath, "Arithmetic Optimization with Deep Learning Enabled Churn Prediction Model for Telecommunication Industries," *Intelligent Automation & Soft Computing*, vol. 35, no. 3, 2023, Art. no. 3532, <https://doi.org/10.32604/iasec.2023.030628>.
- [27] D. Freire, D. Santos Mauricio Sanchez, J. L. Castillo Sequera, and D. Fiallo Moncayo, "Factors, Predictability, and Explainability of Mobile Telephony Customer Departure in Telecommunications Companies: A Systematic Review of the Literature," *IEEE Access*, vol. 12, pp. 118968-118980, Aug. 2024, <https://doi.org/10.1109/ACCESS.2024.3443318>.
- [28] Y. Zhao, T. Lai, Z. Wang, K. Chen, H. Li, and K. Zheng, "Worker-Churn-Based Task Assignment With Context-LSTM in Spatial Crowdsourcing," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 9, pp. 9783-9796, Sept. 2023, <https://doi.org/10.1109/TKDE.2023.3249828>.
- [29] D. Seo and Y. Yoo, "Improving Shopping Mall Revenue by Real-Time Customized Digital Coupon Issuance," *IEEE Access*, vol. 11, pp. 7924-7932, Jan. 2023, <https://doi.org/10.1109/ACCESS.2023.3239425>.
- [30] F. E. Usman-Hamza *et al.*, "Sampling-based novel heterogeneous multi-layer stacking ensemble method for telecom customer churn prediction," *Scientific African*, vol. 24, June 2024, Art. no. e02223, <https://doi.org/10.1016/j.sciaf.2024.e02223>.
- [31] I. Pereira *et al.*, "A Machine Learning as a Service (MLaaS) Approach to Improve Marketing Success," *Informatics*, vol. 11, no. 2, p. 19, Apr. 2024, <https://doi.org/10.3390/informatics11020019>.
- [32] S. F. Bilal, A. A. Almazroi, S. Bashir, F. H. Khan, and A. A. Almazroi, "An ensemble based approach using a combination of clustering and classification algorithms to enhance customer churn prediction in telecom industry," *PeerJ Computer Science*, vol. 8, Feb. 2022, Art. no. e854, <https://doi.org/10.7717/peerj-cs.854>.
- [33] H. D. Tran, N. Le, and N. Van-Ho, "Customer Churn Prediction in the Banking Sector Using Machine Learning-Based Classification Models," *Interdisciplinary Journal of Information, Knowledge, and Management*, vol. 18, pp. 87-105, 2023, <https://doi.org/10.28945/5086>.
- [34] S.-H. Park, M.-Y. Kim, Y.-J. Kim, and Y.-H. Park, "A Deep Learning Approach to Analyze Airline Customer Propensities: The Case of South Korea," *Applied Sciences*, vol. 12, no. 4, Feb. 2022, Art. no. 1916, <https://doi.org/10.3390/app12041916>.
- [35] U. Gani Joy, K. E. Hoque, M. Nazim Uddin, L. Chowdhury, and S.-B. Park, "A Big Data-Driven Hybrid Model for Enhancing Streaming Service Customer Retention Through Churn Prediction Integrated With Explainable AI," *IEEE Access*, vol. 12, pp. 69130-69150, May 2024, <https://doi.org/10.1109/ACCESS.2024.3401247>.
- [36] A.-G. Văduva, S.-V. Oprea, A.-M. Niculae, A. Băra, and A.-I. Andreescu, "Improving Churn Detection in the Banking Sector: A Machine Learning Approach with Probability Calibration Techniques," *Electronics*, vol. 13, no. 22, Nov. 2024, Art. no. 4527, <https://doi.org/10.3390/electronics13224527>.
- [37] S. M. Kostić, M. I. Simić, and M. V. Kostić, "Social Network Analysis and Churn Prediction in Telecommunications Using Graph Theory," *Entropy*, vol. 22, no. 7, July 2020, Art. no. 753, <https://doi.org/10.3390/e22070753>.
- [38] R. Rofik, J. Unjung, and B. Prasetyo, "Enhancing customer churn prediction with stacking ensemble and stratified k-fold," *Bulletin of Electrical Engineering and Informatics*, vol. 14, no. 1, pp. 398-408, 2025, <https://doi.org/10.11591/eei.v14i1.8112>.

- [39] S. Wu, W.-C. Yau, T.-S. Ong, and S.-C. Chong, "Integrated Churn Prediction and Customer Segmentation Framework for Telco Business," *IEEE Access*, vol. 9, pp. 62118–62136, Apr. 2021, <https://doi.org/10.1109/ACCESS.2021.3073776>.
- [40] A. Dursun-Cengizci and M. Caber, "Using machine learning methods to predict future churners: an analysis of repeat hotel customers," *International Journal of Contemporary Hospitality Management*, vol. 37, no. 1, pp. 36–56, 2025, <https://doi.org/10.1108/IJCHM-06-2023-0844>.
- [41] M. Pejić Bach, J. Pivar, and B. Jaković, "Churn Management in Telecommunications: Hybrid Approach Using Cluster Analysis and Decision Trees," *Journal of Risk and Financial Management*, vol. 14, no. 11, Nov. 2021, Art. no. 544, <https://doi.org/10.3390/jrfm14110544>.
- [42] M. U. Tariq, M. Babar, M. Poulin, and A. S. Khattak, "Distributed model for customer churn prediction using convolutional neural network," *Journal of Modelling in Management*, vol. 17, no. 3, pp. 853–863, May 2021, <https://doi.org/10.1108/JM2-01-2021-0032>.
- [43] Y. Zhou, W. Chen, X. Sun, and D. Yang, "Early warning of telecom enterprise customer churn based on ensemble learning," *PLOS One*, vol. 18, no. 10, Oct. 2023, Art. no. e0292466, <https://doi.org/10.1371/journal.pone.0292466>.
- [44] L. Lucantoni, S. Antomarioni, M. Bevilacqua, and F. E. Ciarapica, "Big data-driven framework for viral churn prevention: a case study," *Management and Production Engineering Review*, vol. 11, no. 3, pp. 38–47, 2020, <https://doi.org/10.24425/mp.2020.134930>.
- [45] B. Steenwinckel *et al.*, "FLAGS: A methodology for adaptive anomaly detection and root cause analysis on sensor data streams by fusing expert knowledge with machine learning," *Future Generation Computer Systems*, vol. 116, pp. 30–48, Mar. 2021, <https://doi.org/10.1016/j.future.2020.10.015>.
- [46] S. Hu and A. Chen, "Data-Driven Customer Retention Strategies in E-Commerce: A Fuzzy Z-Number Approach," *IEEE Access*, vol. 13, pp. 75388–75399, Mar. 2025, <https://doi.org/10.1109/ACCESS.2025.3550190>.
- [47] N. N. bt Adnan and M. K. Awang, "Enhancing Customer Churn Prediction Across Industries: A Comparative Study of Ensemble Stacking and Traditional Classifiers," *International Journal of Advanced Computer Science & Applications*, vol. 16, no. 1, 2025, Art. no. 201, <https://doi.org/10.14569/ijacsa.2025.0160120>.
- [48] M. Z. Alotaibi and M. A. Haq, "Customer Churn Prediction for Telecommunication Companies using Machine Learning and Ensemble Methods," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14572–14578, June 2024, <https://doi.org/10.48084/etasr.7480>.
- [49] Z. Wen, "Feature analysis and model comparison of logistic regression and decision tree for customer churn prediction," *Applied and Computational Engineering*, vol. 20, pp. 55–61, Oct. 2023, <https://doi.org/10.54254/2755-2721/20/20231073>.
- [50] M. Basri, "A Comparative Study: Predicting Customer Churn in Banking Using Logistic Regression & Random Forest," *Ultimatics: Jurnal Teknik Informatika*, vol. 17, no. 1, pp. 72–81, 2025.
- [51] L. N. Wakhidah, A. K. Zyen, and B. B. Wahono, "Evaluation of Telecommunication Customer Churn Classification with SMOTE Using Random Forest and XGBoost Algorithms," *Journal of Applied Informatics and Computing*, vol. 9, no. 1, pp. 89–95, Feb. 2025, <https://doi.org/10.30871/jaic.v9i1.740>.
- [52] N. Khandelwal and V. Sakalle, "TBMOR Customer Churn Prediction using XGBoost Classifier," *Journal of Information Systems Engineering and Management*, vol. 10, pp. 717–736, 2025.
- [53] R. Rivaldo, R. Taufik, I. S. Ilman, and O. D. E. Wulansari, "A Comparative Study of XGBoost, LightGBM, and CatBoost Models for Customer Churn Prediction in the Banking Industry," *Jurnal Pepadun*, vol. 6, no. 2, pp. 178–187, Aug. 2025, <https://doi.org/10.23960/pepadun.v6i2.277>.
- [54] C. Özkurt, "Comparative Analysis of XAI Techniques on Telecom Churn Prediction Using SHAP and Interpreted ML Partial Dependence," *Türk Doğa ve Fen Dergisi*, vol. 14, no. 2, pp. 11–25, June 2025, <https://doi.org/10.46810/tdfd.1529139>.
- [55] A. El Attar and M. El-Hajj, "Explainable AI-driven customer churn prediction: a multi-model ensemble approach with SHAP-based feature analysis," *Frontiers in Artificial Intelligence*, vol. 9, Feb. 2026, Art. no. 1748799, <https://doi.org/10.3389/frai.2026.1748799>.
- [56] E. Richardson, R. Trevizani, J. A. Greenbaum, H. Carter, M. Nielsen, and B. Peters, "The receiver operating characteristic curve accurately assesses imbalanced datasets," *Patterns*, vol. 5, no. 6, June 2024, Art. no. 100944, <https://doi.org/10.1016/j.patter.2024.100944>.
- [57] M. Imani, M. Joudaki, A. Bagheri, and H. R. Arabnia, "Why ROC-AUC Is Misleading for Highly Imbalanced Data: In-Depth Evaluation of MCC, F2-Score, H-Measure, and AUC-Based Metrics Across Diverse Classifiers," *Technologies*, vol. 14, no. 1, Jan. 2026, Art. no. 54, <https://doi.org/10.3390/technologies14010054>.
- [58] P. Thölke *et al.*, "Class imbalance should not throw you off balance: Choosing the right classifiers and performance metrics for brain decoding with imbalanced data," *NeuroImage*, vol. 277, Aug. 2023, Art. no. 120253, <https://doi.org/10.1016/j.neuroimage.2023.120253>.
- [59] R. Miao, Q. Jia, F. Sun, G. Chen, H. Huang, and S. Miao, "Semantic Representation of Robot Manipulation with Knowledge Graph," *Entropy*, vol. 25, no. 4, Apr. 2023, Art. no. 657, <https://doi.org/10.3390/e25040657>.