From CLV to Action: A Lightweight Framework for Omnichannel Automation and Budget Allocation in SaaS

Zohra Nourhane CHEBAB[1*] and Yahia BOUKERCH[2]

[1] Laboratory of Economic Reforms, Strategy and Integration into the Global Economy, École Supérieure de Commerce, Kolea University hub, Tipaza, Algeria.
z_chebab@esc-alger.dz

[2] Laboratory of Economic Reforms, Strategy and Integration into the Global Economy, École Supérieure de Commerce, Kolea University hub, Tipaza, Algeria.
y_boukerch@esc-alger.dz

Abstract. The increasing use of artificial intelligence (AI) in customer relationship management has enabled firms to automate interactions across multiple channels. However, many software-as-a-service (SaaS) companies struggle to align omnichannel automation and budget allocation with customer value, particularly in emerging market contexts where data and analytical resources are constrained. This study proposes an AI-enabled, yet non–machine-learning, framework that integrates short-horizon customer value estimation with operational risk signals to guide automation governance and resource allocation. Using an 18-month customer–month panel from a B2B SaaS company, the analysis examines cohort-based churn heterogeneity, validates the economic relevance of forward-looking value tiers, and evaluates journey-level outcomes in terms of churn, realized revenue, and automation spend. The results show that churn probabilities vary systematically by customer tenure and subscription tier, that short-horizon value tiers align closely with realized six-month revenue and retention outcomes, and that aggregating value and risk at the journey level provides a transparent basis for allocating automation budgets. Rather than prioritizing predictive complexity, the proposed framework emphasizes interpretability, managerial relevance, and feasibility. The findings demonstrate how explainable AI principles can be operationalized to improve omnichannel automation governance in SaaS firms, offering practical insights for organizations operating under data, budgetary, and capability constraints.

Keywords: Customer Lifetime Value, SaaS, Omnichannel Automation, Explainable AI, Churn Management, Budget Allocation.

1 Introduction

In software-as-a-service (SaaS) firms, the diffusion of AI and data-driven technologies has driven the adoption of omnichannel automation systems to coordinate customer interactions across digital and human-led channels. These systems are increasingly positioned as AI-enabled decision-support tools for customer management.

D. Agti et al. (eds.), *Proceedings of the International Conference on Artificial Intelligence Applications in Business Administration in MENA Region (ICAIABA 2026)*, Advances in Economics, Business and Management Research 393,
https://doi.org/10.2991/978-94-6239-711-8_18

Despite these advances, many SaaS firms, particularly in emerging markets such as the Middle East and North Africa (MENA), struggle to translate automation into sustained economic value. Automation is often deployed as a volume-driven mechanism, with customer journeys triggered by simple behavioral rules and limited consideration of customer value-at-risk. This misalignment leads to inefficient resource allocation, including overinvestment in low-value customers and insufficient attention to high-value customers exhibiting early signs of churn.

A key reason for this gap is the limited integration of customer lifetime value (CLV) into operational decision-making. While CLV is central to customer-centric strategy, many AI-driven CRM applications rely on complex machine learning models requiring advanced data infrastructures and organizational trust, conditions that remain unevenly developed in North Africa. Against this backdrop, this paper proposes a transparent AI-enabled decision-support framework that combines short-horizon customer value estimation with operational risk signals to guide omnichannel automation and budget allocation, emphasizing interpretability and managerial feasibility.

2 Literature Review

2.1 Customer Lifetime Value in Subscription and SaaS Contexts

Customer Lifetime Value (CLV) is a central construct in marketing analytics and customer-centric management, commonly defined as the present value of future cash flows generated by a customer relationship [1-2]. Over time, CLV has evolved from a financial metric into a strategic tool guiding customer selection, targeting, and resource allocation decisions [3].

In subscription-based and contractual models such as telecommunications and SaaS, CLV is particularly important because revenues are recurring and customer defection directly truncates future value streams [4]. Unlike transactional settings, subscription contexts place greater emphasis on relationship duration and retention dynamics, making CLV closely intertwined with churn behavior and survival probabilities.

In operational CRM settings, CLV is often used for customer prioritization rather than precise lifetime valuation, serving as a relative indicator of economic importance to guide differentiated service and retention strategies [5-6]. This is especially relevant in digital and SaaS environments, where rapid changes in customer behavior and offerings limit the reliability of long-horizon forecasts.

Recent research suggests that shorter planning horizons better align with managerial decision cycles, as near-term value approximations can provide actionable guidance without the complexity of full discounted cash-flow models [1-6]. This reflects a broader shift toward pragmatic and explainable CLV formulations that balance economic relevance with operational feasibility.

2.2 Customer Lifetime Value in Subscription and SaaS Contexts

Customer churn is a key driver of profitability in subscription-based businesses, motivating extensive research on retention and churn prediction. Early work challenged the assumption that longer customer relationships are inherently more profitable, highlighting the need for selective and value-aware retention strategies [7].

Churn risk is heterogeneous and time-varying. In contractual settings, defection rates are typically higher during early tenure and stabilize among longer-tenured customers [4-8].

Beyond structural factors, behavioral and operational signals act as early indicators of churn. Usage decline, increased customer support interactions, and payment irregularities have all been linked to higher defection likelihood [9-10]. These indicators are particularly valuable as they are observable in real time and can trigger timely interventions.

However, a trade-off exists between predictive accuracy and organizational adoption. While complex models can improve forecasting performance, their opacity and data requirements may limit practical use. As a result, there is growing interest in interpretable, action-oriented churn indicators that support decision-making without excessive complexity [11-12], emphasizing that effectiveness depends not only on statistical performance but also on transparency, trust, and ease of integration.

2.3 CRM, Omnichannel Automation, and Decision Governance

Customer Relationship Management (CRM) systems have evolved from transactional databases into strategic platforms that integrate customer data across organizational functions and interaction channels [13]. Advances in digital technologies have enabled firms to automate interactions across multiple touchpoints, giving rise to omnichannel engagement strategies aimed at delivering consistent and personalized experiences [14].

The marketing analytics literature highlights that omnichannel environments generate rich data and new opportunities for personalization, but also increase decision complexity [15]. While automation platforms enable sophisticated customer journeys, these are often governed by heuristic rules related to timing or behavior rather than explicit economic or value-based logic. Consequently, automation intensity may not align with customer importance or risk exposure.

Existing research has focused primarily on executional aspects of omnichannel management, such as channel coordination, sequencing, and customer experience outcomes [14-16]. Far less attention has been paid to resource governance, particularly how marketing and customer success budgets should be allocated across automated journeys and channels. This gap is especially salient in SaaS contexts, where resources are constrained and must be continuously reallocated across evolving customer portfolios.

2.4 Artificial Intelligence, Explainability, and Adoption Constraints

Artificial intelligence has emerged as a key enabler of digital transformation in business administration, with applications spanning marketing, CRM, and customer service. Rather than fully replacing human decision-makers, most organizational AI applications function as decision-support systems that assist managers in prioritizing actions and allocating resources [17].

Recent research emphasizes that the success of AI systems in managerial contexts depends heavily on explainability and trust. Black-box models may offer superior predictive accuracy, but their opacity can hinder adoption, accountability, and governance, particularly in high-stakes decision environments [18]. As a result, explainable AI approaches are increasingly advocated in business applications where transparency and managerial oversight are critical. Prior research shows that, beyond technical performance, the adoption of AI in organizations is strongly influenced by transparency, explainability, trust, ethical governance, and accountability considerations [19].

These concerns are particularly relevant in emerging and developing digital ecosystems, where data infrastructures, analytical expertise, and governance mechanisms may be unevenly developed. In such contexts, AI solutions that emphasize interpretability, economic relevance, and ease of deployment may offer greater practical value than highly complex modeling approaches.

2.5 Conceptual Framework

The literature highlights the importance of customer lifetime value (CLV) for prioritization, the role of churn risk in value erosion, and the increasing use of CRM and omnichannel automation systems. However, important gaps remain. CLV and churn risk are often examined separately, automation is primarily studied from an executional rather than a governance perspective, and limited guidance exists on transparent budgeting and resource allocation mechanisms in subscription-based and SaaS contexts.

To address these gaps, the proposed framework is grounded in the principle that customer management decisions should be guided jointly by expected economic value and near-term retention risk. In SaaS business models, subscription revenues unfold over time and are continuously exposed to churn, making it insufficient to rely on value or risk indicators in isolation. The framework therefore integrates short-horizon, forward-looking value assessments with observable operational risk signals available at the customer–month level.

By intersecting these two dimensions, customers are assigned to distinct automation journeys that differ in objective and intensity, including retention-focused escalation, cost-efficient retention, growth-oriented engagement, and baseline maintenance. Beyond guiding individual customer treatment, the framework supports portfolio-level governance by aggregating value and risk across journeys to inform prioritization and budget allocation. In doing so, it links customer analytics, automation design, and managerial control within a transparent and explainable AI-enabled decision structure.

In this study, AI-enabled refers to a transparent, data-driven decision-support approach rather than reliance on machine learning or black-box models. The framework combines cohort-based probabilistic forecasting, rule-based logic, and operational signals to generate forward-looking value and risk assessments at scale. Customer prioritization, journey assignment, and budget allocation are governed by explicit, auditable rules, ensuring that all decisions are interpretable and reproducible. Explainability is therefore achieved by design through transparent assumptions and decision logic, rather than through post-hoc explanations of opaque models, aligning the framework with principles of explainable and responsible AI in business administration. For example, a high-value customer exhibiting declining usage and increased support interactions would be classified as high-risk and assigned to a high-touch retention journey. In contrast, a low-risk, high-value customer may be directed toward growth-oriented engagement, while low-value, low-risk customers are maintained through baseline automated interactions.

3 Methodology

3.1 Empirical Setting & Data

The empirical analysis is based on data from a single B2B software-as-a-service (SaaS) company operating in the business intelligence and data analytics sector. The firm provides a cloud-based analytics platform with tiered subscription pricing and serves customers ranging from small businesses to large enterprises across multiple industries. Customer engagement combines product-led growth, marketing automation, and selective human-led interventions, making this setting well suited to the study of omnichannel automation and retention governance.

The dataset consists of a customer–month panel covering 18 consecutive months, with approximately 1,200 customers, including both active and churned accounts. Each observation corresponds to a customer in a given month, enabling longitudinal analysis of customer value dynamics, churn outcomes, and automation activity. The panel integrates data from subscription billing systems, product usage logs, customer support records, and marketing automation platforms.

3.2 Measures

All metrics are defined at the customer–month level unless otherwise stated. Revenue reflects realized subscription revenue over a six-month horizon (USD per customer), while automation spend represents estimated cost per customer-month aggregated at the journey level. Churn is measured as both next-month and six-month probabilities. These definitions are applied consistently across all analyses.

The analysis uses four categories of measures: subscription and revenue variables (monthly recurring revenue, subscription tier, account status); retention outcomes (next-month and six-month churn); operational signals (usage activity, support interactions, billing events); and omnichannel automation measures capturing exposure to automated and human-led interactions and their associated costs.

3.3 Research Questions

Guided by the conceptual framework, the study addresses the following research questions:

RQ1: Do churn probabilities vary systematically by customer tenure and subscription tier, supporting the use of cohort-based retention logic?

RQ2: Do customer value tiers meaningfully correspond to realized revenue and churn outcomes over a six-month forward horizon?

RQ3: Can a combined value-and-risk framework be translated into actionable automation journeys and a transparent rule for budget allocation?

These questions are intentionally descriptive and evaluative, reflecting the applied orientation of the study and its emphasis on managerial relevance rather than algorithmic optimization.

3.4 Empirical Strategy

The empirical analysis proceeds in three steps. First, descriptive cohort analysis examines churn heterogeneity across tenure and subscription tiers, establishing the basis for cohort-based retention inputs. Second, customers are grouped into value tiers, and realized revenue and churn over a six-month horizon are compared to assess prioritization effectiveness. Third, customer-month observations are aggregated into automation journeys, with outcomes analyzed in terms of value at risk, automation spend, churn, and realized revenue. This aggregation supports portfolio-level evaluation of automation governance and budget allocation. Overall, the methodology combines longitudinal customer data with transparent, explainable analytics to evaluate a practical framework for omnichannel automation governance in a SaaS context.

4 Analysis, Results & Discussion

4.1 Dataset Characteristics and Business Stability

The customer–month panel exhibits stable and economically meaningful dynamics over the observation period. The active customer base grows steadily from approximately 800 to more than 1,000 customers, indicating sustained acquisition and platform adoption. Over the same period, monthly recurring revenue increases from about 317,000 to over 411,000, reflecting stable monetization alongside growth.

Next-month churn rates remain consistently low, fluctuating around 1%, with no evidence of extreme volatility. This pattern suggests a relatively mature SaaS environment rather than a volatile early-stage context, while the persistence of churn underscores the continued relevance of retention-focused decision-making.

Portfolio total forecasted six-month customer value increases steadily, rising from approximately USD 1.85 million to USD 2.43 million. This progression closely tracks growth in both customer base and revenue, indicating that the value forecasting approach behaves coherently at scale without generating erratic aggregate dynamics.

Overall, these patterns confirm that the dataset is temporally stable, economically substantial, and well suited for analyzing customer value prioritization and omnichannel automation governance without relying on transient fluctuations.

4.2 Cohort-Based Churn Heterogeneity

Table 1 reports monthly churn probabilities and cohort benchmark churn rates. Monthly churn reflects the observed likelihood of churn in the subsequent month for customers within a given tenure and plan cohort, while the benchmark rate represents the historical average for that cohort. Their close alignment indicates stable retention dynamics and supports the use of cohort-based estimates for forward-looking value calculations.

The results show systematic heterogeneity in churn across tenure and plan type, confirming that churn risk evolves over the customer lifecycle.

Across all plan tiers, churn probabilities are lowest in the earliest tenure bucket (0–3 months), rise during intermediate stages (4–6 and 7–12 months), and peak around 13–24 months, before declining and stabilizing at very low levels for customers with tenure exceeding 25 months. This non-monotonic pattern reflects increasing churn risk after onboarding followed by greater stability among long-tenured customers.

Churn also varies systematically across subscription tiers, with higher-tier plans generally exhibiting lower or more stable churn than entry-level plans at comparable tenure stages, particularly beyond the onboarding period. These differences are consistent with higher switching costs and deeper product integration.

Observed monthly churn probabilities closely align with cohort-level benchmark rates across tenure and plan combinations, indicating that cohort-based estimates reliably capture underlying retention behavior. Together, these findings address RQ1, confirming that churn is heterogeneous over time and across customer segments and that cohort-based retention logic is appropriate for forward-looking value estimation and prioritization.

Table 1. Cohort Retention.

	plan_tier	Values						
	Business		Enterprise		Professional		Starter	
tenure_bucket	Monthly churn probability	Cohort monthly churn rate (benchmark)	Monthly churn probability	Cohort monthly churn rate (benchmark)	Monthly churn probability	Cohort monthly churn rate (benchmark)	Monthly churn probability	Cohort monthly churn rate (benchmark)
0-3	0.005	0.004	0.000	0.000	0.005	0.005	0.005	0.005
4-6	0.010	0.008	0.011	0.017	0.017	0.015	0.017	0.014
7-12	0.013	0.012	0.011	0.012	0.018	0.016	0.025	0.021
13-24	0.015	0.013	0.019	0.016	0.016	0.016	0.019	0.016
25+	0.001	0.001	0.001	0.001	0.004	0.004	0.004	0.003

Notes: Monthly churn probability refers to the observed probability of churn in the subsequent month for customers within a given tenure and plan cohort. Cohort benchmark churn rate represents the historical average churn rate for the same cohort over the observation window. Both metrics are expressed as monthly probabilities.

4.3 Validation of Customer Value Tiers

Table 2 evaluates whether customer value tiers correspond to realized economic outcomes over a six-month forward horizon using customer-month observations as the unit of analysis. The results show clear and systematic differentiation across value tiers in both realized revenue and retention outcomes.

Customer-months in the high-value tier generate substantially higher realized revenue over the subsequent six months and exhibit lower churn than mid- and low-value tiers, with churn increasing monotonically as value decreases. This ordered relationship shows that higher expected value is associated with both greater profitability and higher retention.

These patterns validate the value stratification as an effective prioritization mechanism rather than a descriptive segmentation. By consistently distinguishing customer-months with different economic trajectories, the value tiers align with future revenue and retention outcomes, directly addressing RQ2.

Table 2. CLV Tier Validation.

Clv_tier	Customer-months	Avg realized revenue next 6m	Churn within 6m rate
High	3376	7108.821	0.043
Mid	5049	2008.594	0.055
Low	8436	504.753	0.074
Total	*16861*	*2277.378*	*0.062*

Notes: Customer-months indicate the number of customer–month observations in each value tier. Average realized revenue next 6 months is measured as total subscription revenue per customer over the subsequent six months (monetary units). Churn within 6 months is the probability of customer churn occurring within the six-month forward horizon.

4.4 Automation Journeys and Budget Allocation Logic

Over the 18-month panel (N = 16,861 customer-months), the framework assigns customers to four automation journeys: J1 High-Touch Retention (n = 2,669; 15.8%), J2 Growth (n = 707; 4.2%), J3 Low-Cost Retention (n = 6,010; 35.7%), and J4 Maintenance (n = 7,475; 44.3%). This distribution highlights a strong divergence between customer volume and retention relevance.

Aggregated value-at-risk is highly concentrated in retention journeys. High-Touch Retention accounts for approximately 71.3% of total value-at-risk, while Low-Cost Retention captures the remaining 28.7%. By construction, Growth and Maintenance journeys exhibit near-zero value-at-risk, as customers in these groups fall below the operational risk threshold (Risk$i,t< \tau$) at the time of classification.

Automation spend broadly follows this risk exposure. High-Touch Retention receives 42.0% of total spend, Low-Cost Retention 25.9%, Growth 8.5%, and Maintenance 23.7%, indicating selective escalation toward journeys with higher economic exposure rather than proportional allocation by customer volume.

Observed six-month churn differs across journeys, with lower churn in High-Touch Retention (3.6%) and Low-Cost Retention (4.3%) relative to Growth (6.9%) and Maintenance (8.7%). While some churn persists in low-risk journeys, these patterns support the governance logic of prioritizing retention investment based on ex ante value-at-risk, while acknowledging residual churn arising from conservative thresholds and imperfect operational signals.

These journey-level comparisons are descriptive and do not identify the causal impact of automation intensity on churn.

4.5 Discussion

Taken together, the results show that explainable, rule-based analytics can support effective automation governance in SaaS contexts. Churn heterogeneity across tenure and subscription tiers suggests that retention risk evolves predictably over the customer lifecycle, while the alignment between value tiers and realized outcomes confirms that short-term CLV captures meaningful economic differences across customers. Aggregating value and risk at the journey level, therefore, provides a practical basis for prioritization and budget allocation.

The framework emphasizes managerial control over predictive complexity, enabling firms to allocate resources more efficiently by aligning automation intensity with value-at-risk and differentiating retention, growth, and maintenance strategies across customer segments.

This study contributes by integrating customer value and retention risk into a unified, decision-support framework for customer portfolio management. It extends prior work by linking customer evaluation directly to resource allocation, and differs from machine learning–based approaches by prioritizing transparency, interpretability, and ease of implementation. Its applicability is strongest in subscription settings with stable behavior and reliable data, and more limited in volatile or data-constrained environments.

5 Conclusion

This paper demonstrates how short-horizon customer value estimation and operational risk signals can be combined to govern omnichannel automation and budget allocation in a SaaS context. Using a longitudinal customer–month panel, the results demonstrate that churn behavior varies systematically across tenure and subscription tiers, that forward-looking value tiers align closely with realized revenue and retention outcomes, and that integrating value and risk enables actionable automation journeys and economically grounded budgeting decisions.

The study contributes to AI research in business administration by reframing customer value as a governance instrument rather than a predictive metric. By emphasizing transparency, explainability, and feasibility, the framework shows how AI-enabled decision support can be embedded into CRM and automation systems without complex or opaque models. This perspective is particularly relevant for SaaS firms operating under data, budgetary, and capability constraints in North African and broader emerging-market contexts.

From a managerial standpoint, retention efforts should be selectively escalated toward customers with both high economic value and elevated risk, while lower-value at-risk customers can be managed through cost-efficient automated interventions. Growth-oriented journeys should prioritize high-value, stable customers, whereas low-value, stable segments can be maintained through baseline automation. At the portfolio level, automation and customer success budgets should be allocated in proportion to the aggregated value at risk across journeys, while monitoring channel costs and observed retention outcomes.

Overall, the findings suggest that meaningful improvements in omnichannel automation governance do not require advanced machine learning or extensive analytical infrastructures. Instead, clear value-based prioritization and explainable decision rules can provide a practical and effective pathway for AI-driven customer management in SaaS firms.

This study is subject to several limitations. The analysis is based on a single-firm dataset, which may limit generalizability across industries and contexts. In addition, the descriptive design does not allow for causal inference regarding the impact of automation strategies on churn or revenue outcomes. The framework's effectiveness may also depend on data quality and the availability of reliable operational signals. Furthermore, its applicability is primarily suited to subscription-based models and may be more limited in non-contractual or highly volatile environments.

References

1. Gupta S, Lehmann DR (2003) Customers as assets. Journal of Interactive Marketing 17(1):9–24. https://doi.org/10.1002/dir.10045
2. Jain D, Singh SS (2002) Customer lifetime value research in marketing: A review and future directions. Journal of Interactive Marketing 16(2):34–46. https://doi.org/10.1002/dir.10032
3. Kumar V, Reinartz W (2016) Creating enduring customer value. Journal of Marketing 80(6):36–68. https://doi.org/10.1509/jm.15.0414
4. Fader PS, Hardie BG, Lee KL (2005) Counting your customers the easy way: An alternative to the Pareto/NBD model. Marketing Science 24(2):275–284
5. Gupta S, Lehmann DR, Stuart JA (2004) Valuing customers. Journal of Marketing Research 41(1):7–18. https://doi.org/10.1509/jmkr.41.1.7.25084
6. Fader PS, Hardie BG (2009) Probability models for customer-base analysis. Journal of Interactive Marketing 23(1):61–69. https://doi.org/10.1016/j.intmar.2008.11.003
7. Reinartz WJ, Kumar V (2000) On the profitability of long-life customers in a noncontractual setting: An empirical investigation and implications for marketing. Journal of Marketing 64(4):17–35. https://doi.org/10.1509/jmkg.64.4.17.18077
8. Van den Poel D, Lariviere B (2004) Customer attrition analysis for financial services using proportional hazard models. European Journal of Operational Research 157(1):196–217. https://doi.org/10.1016/S0377-2217(03)00069-9
9. Neslin SA, Gupta S, Kamakura W, Lu J, Mason CH (2006) Defection detection: Measuring and understanding the predictive accuracy of customer churn models. Journal of Marketing Research 43(2):204–211. https://doi.org/10.1509/jmkr.43.2.204
10. Verbeke W, Martens D, Baesens B (2014) Social network analysis for customer churn prediction. Applied Soft Computing 14:431–446. https://doi.org/10.1016/j.asoc.2013.09.017
11. Ribeiro MT, Singh S, Guestrin C (2016) Why should I trust you? Explaining the predictions of any classifier. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp 1135–1144. https://doi.org/10.1145/2939672.2939778
12. Molnar, C. (2020). Interpretable machine learning. Lulu. com.
13. Payne A, Frow P (2005) A strategic framework for customer relationship management. Journal of Marketing 69(4):167–176. https://doi.org/10.1509/jmkg.2005.69.4.167
14. Lemon KN, Verhoef PC (2016) Understanding customer experience throughout the customer journey. Journal of Marketing 80(6):69–96. https://doi.org/10.1509/jm.15.0420
15. Wedel M, Kannan PK (2016) Marketing analytics for data-rich environments. Journal of Marketing 80(6):97–121. https://doi.org/10.1509/jm.15.0413
16. Chaffey D (2022) Digital marketing excellence: Planning, optimizing and integrating online marketing. Routledge, London
17. Davenport TH, Ronanki R (2018) Artificial intelligence for the real world. Harvard Business Review 96(1):108–116
18. Rai A (2020) Explainable AI: From black box to glass box. Journal of the Academy of Marketing Science 48(1):137–141. https://doi.org/10.1007/s11747-019-00710-5

19. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International journal of information management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002