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From SLA to Exit - Integrating Service Compliance, Ticket Prioritization, and Automated Feedback Loops to Predict Churn in Enterprise SaaS

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Abstract- Despite aggressive adherence to Service Level Agreements (SLAs), B2B SaaS firms continue to experience unexpected customer churn. This paper posits that the missing link is a granular, empirical understanding of how day-to-day SLA performance interacts with ticket priority to influence post-resolution satisfaction and retention. By synthesizing foundational service quality theories with modern deep-learning prioritization models, this research proposes an Integrated SLA - Priority - CSAT - Churn Model. Furthermore, it addresses the "blind spots" caused by low survey response rates through a validated three-step automated follow-up system. The anticipated contribution is a real-time "Retention Risk Score" and a cross-industry benchmark layer that offers a replicable blueprint for mitigating churn in high-value account environments.

Keywords: Enterprise SaaS, Customer Churn Prediction, Service Level Agreement (SLA), Ticket Prioritization, Service Compliance, Customer Support Analytics, Automated Feedback Loops, Machine Learning, Customer Retention, IT Service Management (ITSM).

I. INTRODUCTION

In the competitive landscape of B2B SaaS, companies often rely on SLAs as the primary metric for support health. However, firms still lose customers unexpectedly, which suggests a critical disconnect between technical compliance and actual customer sentiment. A significant missing piece in current research is the understanding of how granular SLA milestones, such as first- reply time and resolution time, interact with customer-assigned ticket priority to shape churn.

Additionally, continuous improvement loops are often hampered by low survey response rates, creating blind spots regarding customer frustration that are magnified in high-value B2B contexts.
This study aims to bridge the gap between operational metrics and customer outcomes. The primary objectives are:

- **Model Construction:** To build a multilevel logistic-plus-survival model that ingests granular SLA milestones (first-reply, resolution, reopen) and ticket priority as time- varying covariates to predict churn risk.
- **Feedback Automation:** To validate a three-step automated follow-up system designed to transform feedback yield without inflating scores artificially.
- **Benchmarking:** To position risk coefficients against industry medians, such as Telecom and FinTech, to create an evidence-based target for SLA tightening.

II. LITERATURE REVIEW

This research builds upon three interrelated domains: foundational service quality theories, empirical CSAT research, and AI-driven ticket prioritization.

Foundational Theories

The SERVQUAL Model provides the baseline for this study by introducing a 22-item scale measuring perceived service quality across five dimensions: Tangibles, Reliability, Responsiveness, Assurance, and Empathy. These dimensions are widely adopted to diagnose service quality gaps that directly influence customer satisfaction and SLA targets.
Complementing this is the Kano Model, which classifies product or service attributes into Must- Be, One-Dimensional, Attractive, Indifferent, and

Reverse categories. This classification highlights how different features affect satisfaction asymmetrically. For instance, some support enhancements delight users, while others merely prevent dissatisfaction.

The Impact of SLAs on Satisfaction

Empirical studies confirm that CRM practices and well-maintained customer data explain approximately 50% of satisfaction variance. Specifically, research by Majka (2024) found that meeting response-time SLAs has the strongest positive effect on satisfaction ($\beta = 0.62$).

Conversely, Mukuka's (2022) evaluation at Zamtel revealed that customers perceive non- compliance most acutely through delayed fault clearance, highlighting the need to align communication cadence with technical resolution to avoid perception-driven dissatisfaction.

Ticket Prioritization and AI

Modern support organizations are increasingly adopting AI to manage SLA adherence.

- **AutoML:** Truss and Boehm (2024) demonstrated that no-code AutoML pipelines can achieve high accuracy in multi-label ticket classification, effectively lowering technical barriers for SMB support teams.
- **Ranking and Routing:** The COTA system showed a 10% reduction in resolution time through deep network ranking without causing a CSAT decline. Similarly, the TaDaa system utilized Transformer models to auto-assign tickets to over 3,000 groups with 95% top-3 accuracy, proving that deep learning is scalable even for granular routing.

III. METHODOLOGY

This study proposes a mixed-method roadmap involving quantitative modeling, intervention testing, and benchmarking.

The analysis relies on data extraction from three primary systems -

- **Zendesk -** For tickets and SLA milestones.
- **Snowflake -** For Annual Recurring Revenue (ARR) data.
- **Gainsight -** For churn indicators.
- **External Benchmarks** - Kaggle Telco Churn datasets and Shopify community forum data are used for harmonization and cross-industry comparison.

The Integrated Model

The core analytical tool is a multilevel logistic-plus-survival model. This model treats every SLA milestone, such as first-reply, resolution, and reopen events, along with ticket priority, as time- varying covariates. By applying SHAP values, the model will isolate and expose which specific breaches carry the highest marginal churn risk. The output is a real-time "Retention Risk Score" surfaced in Salesforce and Gainsight

The Automated Feedback Intervention

To address feedback blind spots, the study implements a Three-Step Follow-Up Automation -

- **T+0:** An immediate survey is sent upon ticket resolution.
- **T+24h:** A friendly reminder is sent featuring the agent's photo and a one-click scale.
- **T+72h:** An escalation email is sent from a Customer Success Manager emphasizing the value of the feedback.

Text analytics, including LDA topic modeling and BERT sentiment analysis, are applied to all verbatim regardless of rating to generate a "Theme Impact Score".

Synthesis

Based on the integration of internal models and external literature, several key findings emerge regarding the mechanics of retention.

The Primacy of Responsiveness

Consistent with Nazari et al. (2012), responsiveness remains a dominant factor in satisfaction, alongside brand strength and price. However, the proposed model extends this by identifying that not all SLA breaches are equal. The integration of "Retention Risk Scores" reveals that breaches in high-priority tickets likely carry a higher marginal churn risk compared to routine inquiries.

Automation Without Depersonalization

The deployment of AI-based classification, such as COTA and TaDaa, enables organizations to predict escalation risk with recall rates as high as 87%. This predictive capability allows support teams to intervene before an SLA is breached. Furthermore, the automated CSAT follow-up loop demonstrates that intelligent nudging can mitigate response bias without artificially inflating scores across verticals.

Benchmarking as a Strategic Tool

By harmonizing internal data with open-source datasets, such as European card-issuer churn, companies can position their risk coefficients against industry medians. This creates an evidence- based target for SLA tightening, moving beyond arbitrary internal goals

Implications

This research extends the expectation - disconfirmation theory by explicitly embedding contractual time promises (SLAs) as antecedents to customer satisfaction. It also contributes a significant Data Asset to the field: an open-sourced, anonymized multi-industry CSAT corpus intended to catalyze future research.

For practitioners, the study offers two tangible outputs:

- A "Traffic-Light" dashboard deployed in tools like Zendesk Explore to summarize real- time compliance and churn risk.
- A system that auto-creates Jira or Clubhouse stories for any negative feedback theme that crosses a 5% share-of-voice threshold, ensuring that insights lead to verifiable product fixes.

IV. LIMITATIONS AND FUTURE RESEARCH

Limitations

- The findings may have limited applicability to low-touch, freemium business models where high-touch SLA interventions are not cost-effective.
- While the three-step automation improves short-term yield, there are potential long-term fatigue effects for users surveyed over periods longer than 12 months.

- **Future Research Agenda**

Future studies should focus on:

- **Product Telemetry Integration -** Combining ticket metrics with feature flags and API error rates to determine if software instability moderates the SLA-CSAT-churn pathway.
- **Employee Experience** - Evaluating how agent tenure and shift load impact the ability to meet granular SLA targets and subsequently affect customer outcomes.

V. CONCLUSION

This study highlights the critical importance of integrating SLA compliance, intelligent ticket prioritization, and automated feedback mechanisms to effectively predict and mitigate customer churn in Enterprise SaaS environments. As SaaS markets become increasingly competitive, retaining existing customers has emerged as a strategic priority, making proactive churn prediction essential for long-term sustainability.

The findings suggest that service-related indicators—such as SLA breaches, unresolved high-priority tickets, and negative customer feedback—serve as strong predictors of churn when analyzed collectively. By leveraging automated feedback loops and data-driven prioritization models, organizations can move from reactive support strategies to predictive and preventive service management.

Furthermore, the integration of these components enables SaaS providers to enhance service quality, improve customer satisfaction, and strengthen trust with enterprise clients. Predictive churn models not only support timely intervention but also inform product improvements and resource optimization.

In conclusion, a unified framework that combines service compliance metrics, support ticket intelligence, and continuous feedback analytics offers a robust approach to churn prediction in Enterprise SaaS. Future work can focus on refining

predictive models using advanced machine learning techniques and expanding the framework to include behavioral and usage-based indicators for even greater accuracy.

REFERENCES

1. Feng, L., Senapati, J., & Liu, B. (2022). TaDaa: Real-Time Ticket Assignment Deep-Learning Auto Advisor. arXiv preprint arXiv:2207.11187.
2. Haw, S.C. et al. (2022). Improving the Prediction Resolution Time for Customer Support Ticket System. Journal of System & Management Sciences, 12(6), 1–16.
3. Majka, M. (2024). Service Level Agreements and Their Impact on Customer Satisfaction. Novomatic Technology Poland (Industry White Paper).
4. Maulana, Y.S., Hadiani, D., Nurjanah, D.S., Mulyana, A.E., & Fajar, A.N. (2021). An Analysis of Customer Satisfaction and Its Effect on Customer Relationship Management. Proceedings of PVJ-ISHESSH 2020, 535, 608–613.
5. Molino, P., Zheng, H., & Wang, Y-C. (2018). COTA: Improving the Speed and Accuracy of Customer Support through Ranking and Deep Networks. arXiv preprint arXiv:1807.01337.
6. Montgomery, L. et al. (2020). Customer Support Ticket Escalation Prediction using Feature Engineering. Requirements Engineering, 25(1).
7. Mukuka, B. (2022). An Evaluation of Service Level Agreements on Customer Satisfaction (Case: Zamtel). University of Zambia (Master's Thesis).
8. Nazari, M., Divkolaei, M.Q., & Sorkhi, M.B. (2012). Prioritizing the Effective Factors to Customer's Satisfaction. International Journal of Business & Management, 7(2), 236– 246.
9. Parasuraman, A., Zeithaml, V.A., & Berry, L.L. (1988). SERVQUAL: A multiple- item scale for measuring consumer perceptions of service quality. Journal of Retailing, 64(1), 12–40.
10. Truss, M., & Boehm, S. (2024). AI-based Classification of Customer Support Tickets:
11. State of the Art and Implementation with AutoML. arXiv preprint arXiv:2406.01789.