Smart Synergies: Open Innovation and Predictive Models in the Telecom-Insurance Ecosystem

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Abstract. *This study examines the convergence of the telecommunications and insurance industries through the lens of open innovation and digital transformation, using predictive analytics to uncover customer behavior patterns. The aim is to understand how integrating telecom services with financial and insurance products impacts customer churn, revenue generation, and market segmentation. We employ a quantitative methodology on a real-world convergent telecom dataset, applying logistic regression to predict customer churn, multiple linear regression to identify revenue drivers, and cluster analysis to segment customers, all implemented in Microsoft Power BI. The findings reveal that customer churn is significantly influenced by service bundling depth, acquisition channels, and use of value-added services, while monthly revenue is driven primarily by base service pricing, multi-service adoption, and customer tenure. Unsupervised clustering uncovered three distinct customer segments with varying risk profiles: a segment of high-value yet high-churning customers expecting greater value, a segment of minimally engaged customers with extreme churn rates, and a segment of long-tenured, mid-/high-tier customers lacking cross-service engagement. These results highlight critical implications for industry convergence strategy: multi-service bundles and open innovation partnerships can enhance value but must be aligned with customer expectations to improve retention and lifetime value. The study contributes to literature by providing an empirical, data-driven perspective on cross-industry digital ecosystem strategies. It offers actionable insights for practitioners on tailoring retention efforts and product offerings in an era of blurring industry boundaries.*

Keywords. industry convergence, telecommunications, insurance services, open innovation, predictive analytics.

1 Introduction

The telecommunications and insurance sectors are increasingly intertwining as firms extend beyond traditional industry boundaries. Spurred by digital transformation, financial services are now delivered through broad ecosystems of diverse players co-evolving via collaboration and competition (Baumann et. al., 2023). Telecom operators and banks, for example, have been converging services for years, leveraging technological advancements and regulatory trends (e.g. open banking) that lower barriers to cross-industry offerings. This phenomenon of industry convergence is characterized by telecom companies offering financial and insurance products, and conversely, banks and insurers embracing telecom-style digital platforms. The drivers include shared technological trends (cloud, mobile, data analytics) and common challenges around data privacy and customer experience (Research and Markets, 2024). In essence, digital transformation has blurred industry lines, pushing firms to form new partnerships and value networks.

Open innovation provides a strategic framework for this convergence. Coined by Chesbrough (2006), open innovation involves leveraging purposive inflows and outflows of knowledge to accelerate internal innovation and expand markets. In practice, this means companies partner with external organizations to co-create services and access new capabilities. In the telecom and finance context, open innovation manifests as telecoms collaborating with fintech or insurtech startups, and banks opening their APIs to third-party developers. Industry analysts argue that banks must adopt an *open innovation model with third parties*, analogous to how telecoms innovated with over-the-top (OTT) partners (Kazmi, 2021). By teaming up, each sector can remain innovative and relevant in the digital era. Indeed, much of the recent innovation in telecom is introduced via partnerships rather than in-house development (Kazmi, 2021). This shift is exemplified by initiatives like open banking and open insurance, where sharing data and services across firm boundaries is encouraged to spur innovation and new business models (Baumann et. al., 2023). Such cross-sector collaboration is rapidly becoming imperative rather than optional.

Market trends underscore the momentum of convergence. Telecom operators are expanding their digital portfolios to include financial and insurance services, via both proprietary platforms and strategic partnerships (Research and Markets, 2024). Banks and insurers seek telecom partners to enhance digital distribution and access real-time data streams (for example, telecom data used in credit scoring or pricing insurance). Convergence offers mutual benefits: telcos gain new revenue streams, and banks/insurers gain innovative channels and customer insights. However, it also introduces strategic challenges, telecoms must manage services outside their core expertise, and financial institutions must ensure regulatory compliance and customer trust when partnering with non-bank actors (Kazmi, 2021).

Despite the growing prevalence of such partnerships, academic research has only begun to explore their implications. Prior studies have extensively examined customer analytics within individual industries, for instance, churn prediction in telecom or customer segmentation in banking, but integrated analyses across telecom and insurance remain scarce. The convergence of these industries raises new questions: *How do bundled cross-industry services affect customer loyalty (churn) and revenue? Can data analytics identify distinct customer segments in a combined service ecosystem?* Addressing these questions is important for both scholars (to understand emerging business ecosystem dynamics) and practitioners (to optimize convergence strategies).

This paper aims to fill this gap by studying a real-world case of industry convergence through a data-driven approach. We leverage customer data from a telecom operator in North Macedonia that has incorporated financial/insurance offerings into its service bundle, a prime example of open innovation in action. Using predictive modeling techniques (logistic regression, linear regression, and clustering) within a business intelligence platform (Power BI), we analyze customer churn drivers, revenue factors, and segmentation in this converged-service context.

The contributions of this paper are threefold: 1) Conceptual: we bridge the literature on open innovation and digital transformation with industry convergence, proposing a framework in which telecom and insurance form a collaborative ecosystem to co-create value. We highlight how predictive analytics serves as a linking mechanism between strategic convergence initiatives and customer-level outcomes; 2) Methodological: we demonstrate an integrated application of predictive modeling in an *open innovation ecosystem context*. Specifically, we show how logistic regression (for churn prediction), multiple linear regression (for revenue estimation), and cluster analysis (for customer segmentation) can be applied using Power BI's AI-powered tools. This approach illustrates the feasibility of advanced analytics in accessible BI software, which is valuable for practitioners outside traditional data science environments; 3) Empirical: we provide insights based on a unique dataset spanning telecom services and insurance add-ons. The analysis identifies key factors that influence churn and revenue in a converged setting (e.g. product bundling, service tenure, channel of acquisition, regional differences), and uncovers distinct customer segments that inform targeted retention and marketing strategies. These findings offer actionable guidance for companies pursuing convergence strategies, such as the importance of aligning new services with customer needs to truly realize retention benefits.

In the following sections, we first review relevant literature on industry convergence, open innovation, and predictive analytics in telecom/finance (Section 2). We then describe our data and methodology (Section 3), followed by the results of the predictive models and clustering (Section 4). Section 5 discusses the implications of the findings for theory and practice, and Section 6 concludes the paper with recommendations and future research directions.

2 Literature Review

2.1 Industry Convergence and Open Innovation

Industry convergence refers to the blurring of boundaries between formerly distinct industries, often driven by technological innovation and changing consumer demands. Scholars note that digital technologies create common platforms enabling firms from different sectors to offer overlapping services, leading to *"competitive encroachment"* and collaboration across industries (Research and Markets, 2024). In the context of telecom and insurance, convergence is evident in examples such as telecommunication companies offering mobile payment and insurance products, or insurers leveraging telecom data (e.g., telematics for auto insurance). The convergence trend is underpinned by the rise of digital ecosystems: networks of firms that co-evolve their capabilities around a shared platform or customer base. Deloitte and the Institute of International Finance observe that financial services are extending into broad ecosystems with new actors, where value is co-created through complex collaboration and competition (Baumann et. al., 2023). In these ecosystems, roles are fluid, and firms integrate via API and data sharing agreements, going beyond traditional industry silos (Kazmi, 2021).

Open innovation theory provides a lens to understand how and why firms engage in such cross-industry integration. Open innovation is defined by Chesbrough as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation" (Chesbrough et al., 2006). Rather than relying solely on internal R&D, companies embrace external ideas and paths to the market. In telecom and

financial services, this might involve joint ventures, platform sharing, or enabling third-party developers. By adopting open innovation, incumbent firms can respond to digital disruption more rapidly, for example, banks partnering with fintech startups to offer innovative services, or telecoms co-developing products with insurance companies. A 2019 industry report noted that organizations across sectors, including telecom operators, have widely accepted the open innovation paradigm to harness external expertise and technology. This approach has proven effective in many cases (with oft-cited examples like P&G's connect-and-develop, or LEGO's user co-creation) and is increasingly seen in telecom and finance. Open banking (the regulatory-driven opening of bank APIs) and emerging "open insurance" initiatives are concrete manifestations of this trend, intended to spur service convergence through shared data and collaborative product offerings (Kazmi, 2021). However, convergence via open innovation is not without challenges. Regulatory and security concerns arise when sharing sensitive financial data across industries (Kazmi, 2021). Differences in organizational culture between, say, a telecom and a bank can hinder seamless collaboration. Moreover, delivering an integrated customer experience requires significant IT integration and coordinated innovation. When executed well, convergence can create win-win scenarios, e.g., telecoms can leverage their customer reach to distribute banking services in underserved markets, improving financial inclusion, while banks gain new customers and data sources (Baumann et. al., 2023). The convergence of telecom and insurance can be viewed as part of a broader shift toward open data ecosystems, wherein data flows enable new business models, partnerships, and customer value propositions (Baumann et. al., 2023).

2.2 Digital Transformation and Customer Analytics

Digital transformation in all three industries has elevated the importance of data-driven decision making. In telecommunications, firms have long used analytics for network optimization and customer relationship management. Banking and insurance, too, increasingly relies on big data and AI for risk assessment, personalized marketing, and operational efficiency. A notable area of analytics application is customer churn prediction, identifying customers likely to leave (churn) so that preventative retention actions can be taken. The telecom industry has a rich history of research in churn modeling due to the high competitiveness of the market and the substantial cost of customer acquisition. Early studies applied statistical methods and decision trees, while more recent approaches leverage machine learning ensembles and feature selection techniques to improve predictive accuracy. For example, Idris et al. (2012) used an ensemble (RotBoost) with maximum relevance feature selection to achieve high churn prediction performance. Likewise, Lemmens and Croux (2006) demonstrated that bagging and boosting decision trees can significantly enhance churn classification accuracy. These advances have made churn prediction a well-established practice in telecom management.

Insurance companies use predictive models to identify policyholder lapses or cross-selling opportunities. What is novel in a convergence context is analyzing customer behavior across service types, for instance, how usage of an add-on insurance product might correlate with telecom service churn. Bundling of services is a related concept: telecom providers often bundle services (e.g. phone, internet, TV) to increase customer stickiness. Research indeed shows that multi-service bundles can reduce churn; Prince and Greenstein (2011) found that offering *"triple-play"* telecom bundles significantly lowered churn rates for all included services. By analogy, one might expect that bundling financial or insurance services with core telecom offerings could also improve retention by increasing the overall value proposition and switching costs. At the same time, poorly executed bundling could have the opposite effect if customers do not perceive added value.

Another pertinent area is customer segmentation. Clustering techniques are widely used to segment a customer base into homogeneous groups for targeted marketing. In telecommunications, clustering can reveal profiles such as "high-usage business users" vs. "low-ARPU prepaid users," enabling differentiated retention strategies. In a converged setting, segmentation might separate customers by their adoption of cross-industry services (e.g., those who embrace the full bundle vs. those who only use core services). Prior work has applied clustering in telecom for usage-based segmentation, often using k-means or hierarchical clustering on usage metrics (Ren et al., 2009, Edwine et al., 2022, Sharaf Addin et al., 2022). With the addition of financial product variables, new hybrid segments may emerge (for example, a cluster of tech-savvy users who buy device insurance and use mobile payments heavily, versus a cluster of traditionalists who only use basic telecom services).

Despite notable advances in analytics within individual sectors, a significant gap remains in the literature regarding integrated analytics across the telecom and insurance industries. Most existing studies focus either on two-sector convergence (e.g., telecom-fintech) or remain conceptual in their approach to digital ecosystem strategies. A SCOPUS database search using the keywords "telecom," "insurance," and "prediction" confirms this gap, revealing an absence of empirical research that integrates all three service sectors using predictive analytics, a foundational pillar of modern business intelligence.

Several studies have explored predictive modeling within single industries. For instance, Deepthu and Raju Ramakrishna (2021) investigate various data mining and machine learning techniques to forecast

customer switching behavior between insurance companies. Their models include logistic regression, decision trees, and artificial neural networks. Similarly, Mukhopadhyay et al. (2021) apply machine learning algorithms to reduce churn risk within service industries, emphasizing the strategic importance of early detection. More recently, Wagh et al. (2024) conducted a comprehensive evaluation of classification algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) for predicting customer churn in the telecom sector. Their findings highlight the superior performance of the Random Forest model (92.31% accuracy and 91.57% precision) and the importance of demographic data, usage behavior, and customer feedback in enhancing prediction outcomes.

Building on these insights, our study addresses the identified research gap by applying multiple predictive analytics techniques to an integrated dataset that spans telecom and insurance services. Specifically, we investigate customer churn and segmentation within a cross-sector context, evaluating the influence of bundled service offerings (e.g., telecom + insurance) on customer behavior and lifetime value. In doing so, we extend previous research and contribute to both academic discourse on digital ecosystem management and the practical design of open-innovation strategies aimed at maximizing customer value through convergence.

3. Methodology and Data

3.1. Data Source and Description

To investigate the convergence of telecom and insurance services, we utilized an anonymized customer dataset from a telecommunications operator that has diversified its portfolio by offering insurance products (and/or related financial services) to its subscribers. This dataset represents a *converged service environment*, capturing information on customers' telecom usage as well as their uptake of optional services like device insurance and travel insurance. The data can be seen as a manifestation of open innovation strategy, the telecom partnered with insurance providers to bundle insurance with its core offerings, and the resulting customer data reflects behaviors across these combined services.

The dataset contains customer-level records with a variety of attributes, totaling 20+ variables. Key variables include:

- Customer demographics: age, and region (city). For instance, AGE (in years) and City (which we encoded via a marketing region code, e.g., BAN_City_Marketing for billing city) (*Lemmens & Croux, 2006; Idris et al., 2012*).
- Telecom service tenure: how long the customer has been with the provider, measured in months on both the mobile subscription level (Months_in_onevip_MSISDN) and account level (Months_in_onevip_BAN).
- Account/service features: number of mobile lines on the account (NUMBER_OF_MOBILE_LINES), account type (ACCOUNT_TYPE, e.g., prepaid vs postpaid), and the primary product or tariff plan (ProductName and associated base fee).
- Financial metrics: the monthly subscription fee, including any discounts (Monthly_fee_incl_dsc_tariff), and the base tariff fee without discounts (Monthly_fee_tariff). The difference indicates promotional discounts applied.
- Insurance and value-added service flags: binary indicators for whether the customer has certain add-on services, such as device insurance (DEVICE_INSURANCE_FLAG), screen insurance, an internet security service (A1_NET_PROTECT_CURRENT_FLAG and a flag if they ever had it, A1_NET_PROTECT_EVER_FLAG), and travel assistance insurance (TRAVEL_ASSISTENCE_CURRENT_FLAG and ..._EVER_FLAG). These variables link to the insurance industry and represent cross-selling within the telecom's open-innovation ecosystem.
- Acquisition channel: how the customer was acquired or purchased services, denoted by CHANNEL (e.g., retail store, online, or D2D – door-to-door sales) (*Neslin et al., 2006*).
- Contract timing: variables like TIME_OF_ACTIVATION (possibly the time of day or a code for when service was activated) and SAME_DAY_CONVERGENCY_FLAG (which might indicate if multiple services were adopted on the same day, a proxy for bundle purchase behavior).

The dependent variables for our analysis are derived as follows:

- Churn: We define a binary churn outcome indicating whether the customer has churned (i.e., discontinued service). Due to data limitations (no direct churn label), churn was operationalized from the service expiration date. Specifically, we created a field Churn such that Churn = 1 if the customer's subscription expiration date precedes the analysis date (meaning the service would have expired or not renewed), and Churn = 0 if the expiration date is in the future or the service is still active. In practice, this was implemented with a formula in Power BI:

Churn = IF([EXPIRATION_DATE] < TODAY(), 1, 0). This proxy aligns with common telecom churn definitions (non-renewal of service by a certain date) and was necessary in the absence of an explicit churn field. We also created a more readable categorical variable Churn_Status (values "Yes" for churned and "No" for active) for use in analysis and visualization.

- Monthly Revenue: As a continuous outcome, we use the net monthly fee paid by the customer (Monthly_fee_incl_dsc_tariff). This is effectively the customer's average monthly revenue to the company after any discounts, and reflects the financial value of that customer. It incorporates the effect of any cross-sold products if their fees are included in the billing, thus serving as a holistic revenue measure.
- Customer Segments: For clustering analysis, there is no single target variable; instead, we use a set of key features to discover natural groupings. The clustering will consider variables that reflect customer profile and behaviors, such as churn status, number of lines, tenure, spending level, and use of insurance services, to form segments.

3.2 Analytical Approach

We adopted a quantitative analytical methodology comprising three complementary techniques: logistic regression, multiple linear regression, and cluster analysis. Each technique addresses a specific aspect of the research questions: churn prediction, revenue estimation, and customer segmentation, respectively. All analyses were conducted in *Microsoft Power BI Desktop*, leveraging its data modeling capabilities and AI-enhanced visuals (Key Influencers and segmentation tools, i.e., Top Segments). Power BI provides a user-friendly environment to perform advanced analytics on business data; in particular, the Key Influencers visual uses machine learning (logistic/linear regression) to identify and rank the impact of variables on a chosen outcome, and a built-in clustering tool (via the "Top Segments" feature) to automatically segment data. Using Power BI allowed us to integrate data preparation, modeling, and visualization in one platform, exemplifying how practitioners can apply predictive modeling in a BI setting.

The overall workflow was as follows:

- Data Preparation: We imported the raw data into Power BI and performed cleaning and transformation. Categorical variables (like Channel or City) were encoded as needed (Power BI typically handles categories internally). We ensured that the Churn field was correctly derived as described, and filtered the data to exclude any obviously irrelevant or erroneous records (for example, customers with missing key data fields). We also created any necessary calculated fields (such as Churn_Status). Descriptive statistics were reviewed to understand distributions (e.g., churn rate was about 25.9% overall, as gleaned from the data, and various service adoption rates for add-ons).
- Logistic Regression (Churn Prediction): We set Churn_Status (Yes/No) as the target and used Power BI's Key Influencers visual to run a logistic regression model. The independent variables provided to the model included all relevant customer attributes: age, tenure, number of lines, account type, base tariff, actual fee, presence or absence of each insurance/add-on service, channel, city/region, etc. The Key Influencers analysis then evaluated which factors had the most significant influence on the probability of churn, outputting the top influencers and an approximate odds ratio or impact magnitude for each. This approach identifies both increasing factors (features whose presence or range raise churn likelihood) and decreasing factors (features associated with retention). We paid special attention to factors reflecting convergence (e.g., the insurance flags, multi-line subscriptions, etc.) to see how they correlate with churn in this cross-industry context.
- Multiple Linear Regression (Revenue Modeling): We next examined drivers of Monthly Revenue (Monthly_fee_incl_dsc_tariff) using a multiple linear regression approach. Again, we used the Key Influencers visual but for a continuous outcome, which in Power BI uses linear regression and decision tree analysis to find key factors that increase or decrease the value. The independent variables considered were similar to the churn model (customer tenure, number of lines, product type, region, insurance flags, etc.), excluding any that were redundant or highly collinear with revenue (for instance, the base tariff Monthly_fee_tariff is naturally a strong determinant of net fee, but we included it to quantify its effect). The model provides insight into how much each factor contributes to changes in monthly revenue. We treat the results as a linear approximation of revenue drivers, recognizing that some relationships might be non-linear or interacting (Power BI's tool can capture simple interactions by segmenting the data as well).
- Cluster Analysis (Customer Segmentation): Finally, we performed an unsupervised clustering to identify homogeneous customer segments. We used Power BI's built-in

clustering on the dataset, instructing it to find an optimal segmentation based on features like churn status, number of lines, tenure, age, monthly fee, and presence of add-on services. The algorithm behind this is akin to k-means clustering (partitioning customers into k clusters by maximizing similarity within clusters and differences between clusters). We experimented with different numbers of clusters and found that three clusters provided a meaningful and interpretable segmentation of the customer base. The "Top Segments" feature in Power BI was then used to profile each cluster, revealing which attributes most distinguish each segment. This helped relate the clusters back to business characteristics (e.g., high churn group vs low churn group, etc.). Each cluster's profile (in terms of average attributes and churn rate) was documented for analysis.

Throughout the modeling, we took care to avoid overfitting and to validate results. Given that Power BI's visuals do not output traditional statistical metrics (like R-squared or p-values) directly to the user, we interpreted the results primarily in terms of practical significance. For logistic regression, we note which factors have the strongest influence on churn probability and cross-check that they align with domain expectations or patterns observed in the data. For linear regression, we consider the directional effects and relative magnitudes to ensure they make sense (for example, higher base tariff should correspond to higher revenue a sanity check that the model is logical). The clustering was validated by examining cluster statistics (size of each cluster, churn rate within cluster, etc.) and ensuring they were distinct. We also reviewed a sample of data points in each cluster to ensure no obvious miscoding.

By using three different techniques on the same dataset, we triangulate our understanding of the converged customer base. The logistic model answers "who is likely to leave and why," the linear model answers "what drives more revenue per customer," and the clustering answers "what distinct groups of customers exist and what characterizes them." The integration of these results provides a comprehensive view that can inform strategic decisions in an open innovation context, such as which segment to target with a new bundled offering or which factor to improve to reduce churn.

4 Results and Analysis

4.1 Logistic Regression: Churn Prediction

The logistic regression analysis for churn yielded clear insights into the factors that increase or decrease the likelihood of customer attrition in the converged telecom-financial service context (Fig. 1). The most influential factor was the channel of acquisition: customers acquired through the door-to-door sales channel ("D2D") showed a dramatically higher propensity to churn. In fact, the model indicates that being acquired via D2D is associated with about 3.10 times greater odds of churning compared to customers acquired through other channels. This suggests that aggressively acquired customers (e.g., through direct sales campaigns) may be less loyal or of lower long-term fit, possibly because they were attracted by a short-term promotion or had less intrinsic interest in the service. It underscores the risk of certain customer acquisition tactics without strong ongoing engagement; these customers tend to disconnect early.

The analysis also found that customers with minimal service engagement are much more likely to churn. Subscribers who have zero mobile lines on their account (for instance, perhaps only using a fixed service or having an account structure with no active line) were highly prone to churn. This intuitively aligns with the idea that the more services a customer has (and the more entrenched they are), the less likely they are to leave. A customer with no mobile lines (or essentially very low usage) is likely to have weak attachment to the provider. This result reinforces the strategy of service bundling to increase stickiness with each additional service (e.g., adding a mobile line, or an insurance product) can deepen the customer's commitment.

Interestingly, the presence of certain insurance add-on services correlated with higher churn likelihood. Customers who had purchased device insurance were more likely to churn than those who hadn't, all else being equal. At first glance, this is counter-intuitive: one might expect that if a customer bought device insurance (an indicator of engagement and an additional service), they would be more loyal. Two possible explanations are: (1) Timing effect, customers may tend to buy device insurance near the end of a device contract or when concerns about device damage rise, which might coincide with the end of their service contract as well. Thus, the insurance purchase could be a last act before churn (for instance, they insure a device but then churn when their contract term is up). (2) Satisfaction issues it's conceivable that some customers who filed a claim or interacted with the insurance service became dissatisfied (perhaps due to claim process hassles or coverage limitations) and that contributed to their decision to leave the telecom provider entirely. While our data cannot pinpoint the reason, the association is a valuable insight: simply selling an add-on service does not guarantee retention, and in some cases might cluster with higher churn, meaning companies should monitor customer satisfaction with those add-ons closely.

Price and tariff factors also emerged as significant. The model highlighted that customers in a certain mid-range of monthly fee were more likely to churn: specifically, those paying a monthly fee (after discount) in the range of about 635 to 677 MKD had

an elevated churn probability. This segment of upper-mid-tier spenders might feel they are not getting sufficient value for the cost, as they are not the lowest budget customers, yet not the absolute top-tier who might receive premium perks. Additionally, the analysis flagged low base tariff levels (≤ 592) as another churn-prone category, these could be low-paying customers who are always hunting for cheaper deals and thus have low loyalty. Taken together, it seems both ends of the spectrum need attention: low-value customers churn perhaps due to price sensitivity, whereas mid-value customers churn possibly due to value perception issues (feeling "for what I pay, I deserve better").

Another demographic insight was that senior customers (age above 67) showed higher churn probability. Older customers might be churning due to different reasons (e.g., less need for service, moving to family plans, or even age-related factors). It's a reminder that different age segments have different churn drivers; retention approaches must be tailored (for example, tech-savvy youth might churn if services are not digitally advanced, whereas seniors might churn due to complexity or life stage changes).

Crucially, the analysis unveiled some regional patterns in churn. Customers residing in particular cities: Gostivar, Kochani, Prilep, and Tetovo were more likely to churn than those in the capital or other regions. For instance, being in one of those medium-sized cities correlated with higher churn risk. This could reflect local competitive dynamics (perhaps a strong competitor presence or network issues in those areas), or economic factors unique to those regions. It signals that the company may need targeted retention efforts or market research in those cities to address the root causes (be it service quality, localized marketing, or distribution issues).

Service tenure had a nuanced effect. Medium tenure ranges (customers around 1.5-2 years with the company, e.g. 17-23 months) as well as very long tenure (e.g. > 47 months) showed higher churn propensity than the baseline. The medium-tenure spike likely represents contract cycle churn many contracts are 12 or 24 months, so churn often occurs at those renewal points. The higher churn among ultra-long tenured customers might indicate that after many years, some customers eventually do leave possibly due to complacency by the provider or attractive offers elsewhere targeting long-time customers of competitors. It's an important reminder that loyalty is not forever without continued value delivery, and even long-time clients should not be neglected.

The absence of certain cross-service engagements was telling. Customers who never subscribed to the Net Protect service (a cybersecurity/value-added service) were more likely to churn. This could mean that those who engage with such supplementary services end up having more reasons to stay (the service itself providing stickiness), or conversely, those who churn might generally be less engaged and thus never bothered with extra services. In either case, it suggests that encouraging adoption of value-added services (security, insurance, etc.) as part of an open innovation bundle can help reduce churn, but only if those services truly add perceived value.

Churn in this converged service scenario is multifactorial, driven by a combination of how the customer was acquired, how many and what types of services they use, how much they pay relative to perceived value, where they live, and who they are (tenure and age). Notably, no single factor dominates churn risk, instead, it's the interplay: for example, a door-to-door acquired customer with one line, who never took an add-on service and lives in a smaller city, is an archetype of a high-risk churner. In contrast, a customer acquired through a stable channel (store or online), with multiple lines and one or two add-on services, living in the capital and on a fitting plan, would be relatively secure. These insights confirm that in an open innovation ecosystem, retaining customers requires a holistic strategy addressing product bundle value, customer experience across channels, and targeted interventions for specific segments prone to churn.

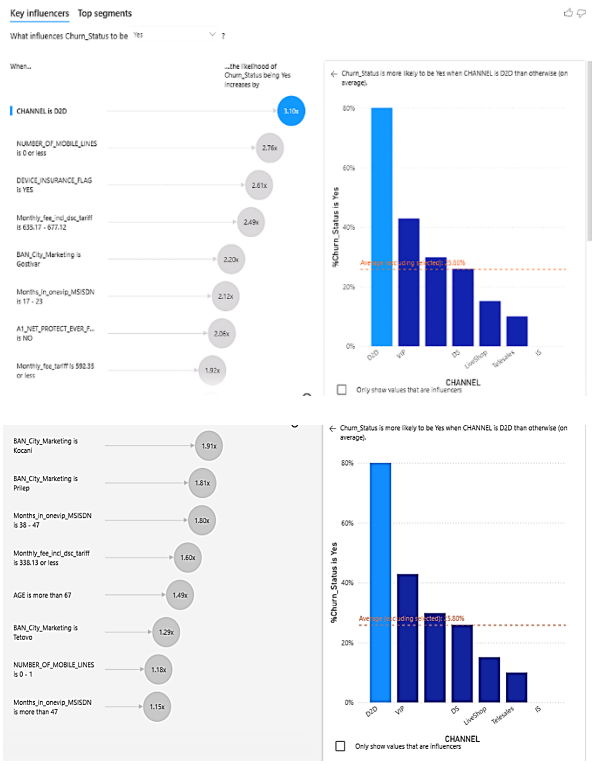

Figure 1. Key influencers of Churn Status to be YES

4.2 Multiple Linear Regression: Revenue Drivers

The multiple linear regression (Key Influencers) analysis on monthly revenue revealed critical insights into the drivers of customer-level revenue contribution, identifying which elements of customer profiles and

service usage behaviors most significantly influence monthly billing outcomes (Fig. 2). As expected, the base service plan price emerged as the strongest predictor. This near-linear relationship confirms that customers on higher-tier plans consistently generate greater revenue, even after discounts or promotional offers are applied. Quantitatively, the model shows an approximate 0.74:1 ratio of net revenue gain for each unit increase in plan tariff, highlighting the enduring value of premium subscribers. In essence, even when adjusted for incentives, higher-paying customers remain substantially more profitable. This underlines the strategic importance of upselling, positioning premium plans as a high-impact lever to increase average revenue per user (ARPU). In addition to plan pricing, the breadth of services subscribed also significantly influenced revenue. Customers with multiple lines (e.g., family or multi-device plans) and those who opt for premium product bundles demonstrated substantially higher total monthly charges. While some multi-line discounts may apply, the aggregate bill still increases with each additional line, contributing positively to overall revenue. Furthermore, premium plan users frequently subscribe to add-on packages such as extended data, entertainment bundles, or advanced features which incrementally raise their monthly payments. Of note is the impact of value-added services such as device protection or insurance, which showed a clear positive correlation with revenue contribution. These findings emphasize the effectiveness of cross-selling strategies in boosting ARPU. However, this must be balanced with the earlier churn analysis, which suggests that aggressive cross-selling could risk increasing customer attrition. From a revenue-centric standpoint, though, both upselling and cross-selling remain powerful tools for revenue enhancement when executed strategically and with customer satisfaction in mind.

Another influential factor identified was customer tenure particularly very long tenure. The model highlighted that when a customer's Months_in_onevip_MSISDN (mobile tenure) exceeded around 89 months (roughly 7.5 years), their average monthly revenue was about 137.7 units higher than that of shorter-tenured customersfile. This is a significant jump, showcasing that long-term customers tend to accumulate more services or stick to higher plans, thereby paying more. There are a few plausible reasons: long-term customers might have gradually added services over time (a second line for a family member, an upgrade to a better plan as their usage grew, etc.), or prices might have risen and they've remained on older, pricier legacy plans. It could also reflect loyalty in terms of opting into various company offerings. In any case, it underlines the point that customer lifetime value increases with retention not just because of duration, but also because retained customers often deepen their relationship and revenue contribution. This aligns with classic CRM theory that retaining customers can yield more revenue over time via cross-selling and upselling.

Beyond these top factors, some other variables have smaller yet notable effects. For instance, account type can influence revenue: postpaid customers usually have higher ARPU than prepaid. Geography might play a role, customers in urban centers or certain regions could opt for more expensive plans (though our model didn't call out city as a top factor for revenue explicitly, possibly because income levels or competition cause differences). Also, time of activation could indirectly reflect if a customer joined during a particular promotion (which might affect their bill structure). However, the model's primary findings revolve around the scope of services and longevity.

The revenue model's implications for strategy are straightforward: to boost revenue, the provider should focus on increasing the adoption of multi-line plans and value-added services, and migrating customers to higher tiers where appropriate. This is a classic upsell approach, but our data provides evidence of its magnitude and importance. Additionally, the tenure effect suggests a payoff in cultivating long-term relationships. It's cheaper to retain than acquire, and as we see, those retained customers often become more valuable. Therefore, investments in customer retention programs not only save the cost of churn but also likely increase ARPU over the years, a double benefit.

The revenue analysis further confirmed that customer tenure is positively associated with higher monthly revenue contributions. Customers with longer relationships tend to migrate to more advanced plans, accumulate additional services, and display generally higher engagement levels. However, this finding must be viewed in the context of earlier churn results, which indicated that very long-tenured customers may exhibit a renewed propensity to churn. This nuance suggests that while tenure correlates with increased revenue, it does not guarantee retention. Consequently, companies should proactively re-engage their long-standing customers through periodic plan refreshes, personalized communications, or loyalty rewards that reinforce the value of staying, preventing stagnation or the lure of competitor offers.

In addition, the bundling of multiple services such as telecom plans with insurance products emerged as a significant driver to revenue growth. Customers subscribing to device protection, for instance, contributed meaningfully more to average revenue per user. However, such revenue gains are not without risk. If bundling is perceived as non-transparent, overly aggressive, or misaligned with customer needs, it may result in dissatisfaction and elevated churn. For example, if device insurance is sold without clearly communicating its value, limitations, or benefits, customers may see it as an unwelcome charge rather than a value-added service. Similarly, mandatory bundles or upsell pressure may erode trust over time. Therefore, while cross-selling remains a powerful revenue lever, it must be executed with a customer-

centric approach. Companies should evaluate not just the short-term revenue boost from bundled offers, but also their impact on long-term customer satisfaction and retention. Enhancing the perceived value of bundled services such as offering the first year of device insurance for free, simplifying claims processes, or clearly explaining benefits can reduce the likelihood of negative customer reactions. Ideally, cross-selling should feel like a solution to the customer's needs, not a revenue tactic. Balancing profitability with perceived fairness and value is key to maintaining both high ARPU and low churn.

The linear regression confirms that "revenue follows value": the more value (services, premium features) a customer receives (and is willing to pay for), the higher their contribution. It validates the convergence strategy from a financial perspective, customers who embraced convergent offerings (like insurance or multi-service bundles) did have higher ARPUs. The task for management is to encourage more customers to find value in multiple services (thereby raising revenue) while also using the churn insights to ensure those customers remain happy and loyal.

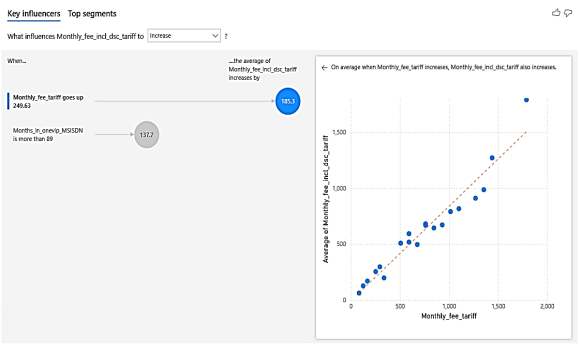

Figure 2. Key influencers of Revenue to Increase

4.2 Cluster Analysis: Customer Segmentation

The clustering analysis revealed three distinct customer segments in our data, each with unique profiles relating to churn behavior, service usage, and value indicators. These segments provide a more refined understanding beyond individual variables, as they capture combinations of characteristics that tend to occur together in the real world. We label them Segment 1, Segment 2, and Segment 3 for reference, and describe each below.

4.2.1 Segment 1: High-Value, High-Churn Customers

This segment is characterized by customers who have above-average spending and multiple services, yet exhibit a high churn rate (Fig. 3). Their typical monthly fee (including discounts) falls in an upper-mid tier (around 635-677 in billing units) these are not the absolute lowest spenders, indicating they likely subscribe to decent-tier plans (and possibly some add-ons). They also tend to maintain more than one mobile line on their account, reflecting a degree of service complexity and family or multi-device bundles. Their tenure with the company is usually moderate (over ~17 months), meaning they have experience with the provider (not brand new customers). Despite these seemingly positive attributes (multi-line, moderate tenure, mid-high spend), Segment 1 customers have the highest churn rate among all segments. In our data, a significant portion of churned customers fell into this group. Geographically, this segment is disproportionately present in the capital city Skopje (around 33% of this segment) and in some smaller cities like Kochani (~15%) and Bitola (~13%). These three cities together accounted for a large share of churn within Segment 1, suggesting possible regional dissatisfaction or competition hotspots.

The paradox of Segment 1 is that these customers are valuable (higher revenue contribution, multi-service) yet they are leaving at high rates. This implies a mismatch between expectations and delivered value. They pay not the lowest price, likely expecting premium service quality or more benefits, and if those expectations are unmet, they may be more resentful and quicker to churn than a low-budget customer. The presence of multiple services indicates they gave the provider a broader mandate (e.g., mobile + perhaps fixed line or insurance), so churn here is especially concerning it's a loss of a high-value relationship. *Strategic implications:* Segment 1 should be a top priority for retention efforts. These customers might respond well to loyalty programs, personalized offers, or "VIP" treatment to make them feel they are getting value commensurate with what they pay. For example, offering exclusive discounts, faster support, or bundling additional perks could entice them to stay. Proactive engagement is key: surveys to identify pain points, targeted service improvements in the flagged regions (Skopje, Kochani, Bitola) to address any local issues, and possibly repackaging of services to ensure they perceive a clear advantage in staying bundled rather than seeking alternatives.

4.2.2 Segment 2: Low-Engagement, At-Risk Newcomers

Segment 2 is a relatively small segment (only about 8% of the entire customer base), but it has an exceedingly high churn rate in our data, 62.6% of Segment 2 customers were churned, which is over 36 percentage points higher than the overall average churn of ~25.9% (Fig. 4). The defining feature of this segment is that customers have zero mobile lines associated with their accounts. In other words, they either subscribed to a service that doesn't include a traditional mobile line (perhaps only an insurance product or a data-only service, or they registered but never activated a line) or their accounts are essentially inactive from the start.

They also show negligible adoption of any add-ons or bundles essentially no deep engagement with any core offerings. We interpret Segment 2 as likely including very new customers who never fully onboarded, one-time sign-ups that didn't stick, or administrative accounts with no real usage.

The behavior of Segment 2 (quick and high churn) suggests issues in the onboarding process or the initial value proposition. These customers leave almost as soon as they arrive. They might represent those who *subscribe on a trial or promotion and then cancel*, or whose service activation failed or never truly started (hence zero lines active). They could also include accounts that were opened for a secondary product but never resulted in continued telecom usage. From an open innovation perspective, if these were customers who perhaps only wanted an insurance product through the telco channel and then canceled, it indicates a challenge in cross-selling they didn't become telecom loyalists. The churn here might not be very costly revenue-wise (since they were low spenders), but it distorts retention metrics and points to a potential waste in acquisition costs. *Strategic implications:* Even though Segment 2 customers are low-value individually, their extreme churn rate deserves attention because it might signal structural problems. The company should investigate why these sign-ups didn't convert into active customers. Are sales teams bringing in "junk" contracts just to meet targets? Is the onboarding experience confusing or is the product not as advertised? By addressing these issues, e.g., improving the onboarding communication, setting proper expectations, or offering a small incentive for new customers to actually start using the service, the firm could reduce churn in this segment. Moreover, we might decide to not focus heavy retention resources on them (since they have low revenue) but rather fix upstream processes (acquisition and onboarding) to prevent the phenomenon. In the spirit of open innovation, learning from these quick failures (possibly via feedback or exit surveys) could inform better partnership offerings or more suitable customer targeting.

4.2.3 Segment 3: Established Multi-Service Users with Selective Engagement

Segment 3 customers have a profile somewhat in between Segment 1 and the average, but with distinct quirks (Fig. 5). About 46.3% of Segment 3 customers were churned, which is ~20 points above average. So churn is high, though not as extreme as Segment 2. Characteristics of Segment 3 include: medium-to-long tenure (most have been with the provider > 17 months), more often more than one mobile line (so they are not single-line users), and they fall into a bimodal spending pattern – their monthly fees are either very low (≤ 338) or quite high (≥ 804), with fewer in the middle range. Additionally, a common attribute is the absence of the A1 Net Protect service virtually none of them have ever had this value-added security service. They also typically are on mid- to high-tier base tariffs (somewhere in ~592-1100 range), and geographically, this segment is overrepresented in Kochani (~9.7%), Prilep (~10.7%), and Bitola (~7.3%), which interestingly overlaps partially with the regions from Segment 1's concerns (except Skopje is not highlighted here).

Interpreting Segment 3: these customers are reasonably well-established with the company (not new, many have multiple lines), and many pay for higher-tier services, yet a large chunk leaves. Their distinguishing feature is not using the optional security service and having a polarized spending (some very budget-conscious, some premium). One way to see this is that Segment 3 could consist of (a) price-sensitive customers on the low end who maybe have multiple connections (e.g., a family plan with minimal usage) but churn because even slight price issues or lack of value-added services make them switch, and (b) premium customers who use multiple lines and pay a lot but possibly expect comprehensive service (including things like security) the fact they *haven't* taken the security service might indicate they didn't see value in it, or it wasn't offered effectively, and their churn might be due to unmet service expectations or finding better packages elsewhere. The regional aspect suggests that in those specific cities, even substantial customers are prone to switch there could be strong competitor promotions in those areas or local service quality issues. *Strategic implications:* For Segment 3, the lack of engagement with the security add-on (and possibly other add-ons) signals an opportunity. The company could market value-added services more effectively to these customers, showing how services like A1 Net Protect provide benefit this could both generate new revenue and increase stickiness if customers adopt them. Additionally, since these customers are split between very low and very high spenders, a two-pronged strategy is needed: ensure the low-end users feel they are getting a good deal (maybe small perks or reassurance of value), and ensure the high-end users feel they are getting premium treatment. The mid-to-high base tariff range indicates they invest in good plans; bundling an included security service or other perks into those plans might prevent churn by increasing perceived value. Regionally, special retention campaigns in Kochani, Prilep, and Bitola for at-risk high-end customers (maybe dedicated account managers or service clinics) could help. Segment 3 highlights that even a seemingly stable group (long-tenured, multi-line) can hide vulnerabilities in this case, a lack of cross-service engagement and localized issues lead to churn.

Across all three segments, certain themes emerge. First, having multiple services (lines or add-ons) generally correlates with being in a higher-value segment (Segments 1 and 3), but it does not guarantee low churn. The quality of those services and alignment with needs are crucial. Second, perceived value and

expectation management are central, both Segment 1 and Segment 3 churn in large part due to perceived gaps in value (Segment 1 felt they paid a lot and possibly didn't get enough; part of Segment 3 might feel similarly at the high end, while others at the low end are very price-driven). Third, execution in acquisition and onboarding stands out: Segment 2's extreme churn is a clear call to improve those early stages, whereas Segment 1 and 3's issues often manifest later in the customer life cycle (post-promotion or during contract renewals).

It's instructive to note that churn is not monolithic across the customer base; it manifests differently in different clusters. Segmenting the base allowed us to see that one-size-fits-all retention solutions won't work, each segment has distinct churn triggers. Our converged industry context adds layers to this: for instance, a typical telecom segmentation might not have considered an insurance or security service variable, but here it proved informative. Also, by identifying high-risk segments that coincide with high value, the company can prioritize retention resources more effectively (e.g., focus on Segment 1 first).

The cluster analysis provides a "market map" for the telecom's converged strategy. Segment 1 is a *high-risk, high-reward* group needing immediate retention focus. Segment 2 is a *red-flag group* signaling issues in customer acquisition/onboarding perhaps needing a process fix more than a marketing fix. Segment 3 is a *mixed-bag group* that requires boosting engagement (through cross-sell of value-adds) and careful attention to both ends of its customer spectrum. These insights validate that convergence (telecom + insurance) strategies must be nuanced and segment-specific. The mere presence of multiple services isn't enough companies must deliver consistent value and address the unique needs of different customer segments in the converged ecosystem.

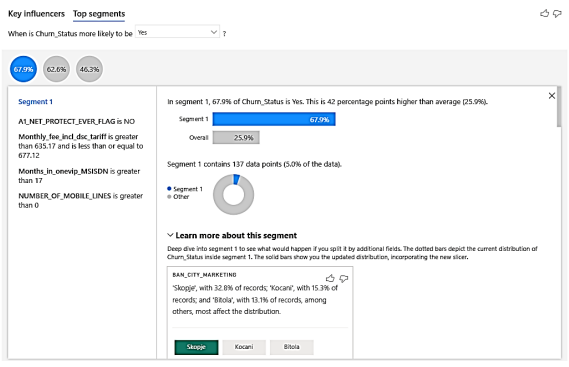

Figure 3. Cluster Analysis: Segment 1

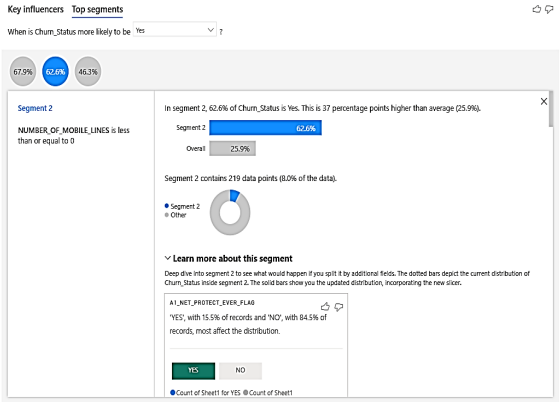

Figure 4. Cluster Analysis: Segment 2

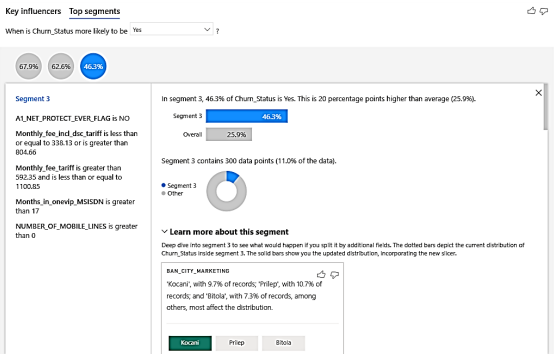

Figure 5. Cluster Analysis: Segment 3

5 Implications

5.1 Theoretical Implications

From a theoretical standpoint, this research enriches the discourse on business ecosystem convergence and open innovation by providing empirical evidence of how cross-industry integration affects customer behavior. Prior conceptual work has posited that converging industries (telecom, finance, etc.) can create synergistic value and new business models (Baumann et. al., 2023). Our findings give granular support to these claims: for instance, we show that a telecom offering insurance (open innovation in action) can increase customer revenue (through cross-selling) and potentially retention (if value is delivered), but it also introduces new complexity in managing customer satisfaction. This underscores the idea that open innovation is a double-edged sword, it opens avenues for value co-creation (more revenue, diversified offerings) but also demands higher coordination and customer-centricity to ensure the innovation truly benefits the user.

We also contribute to the customer analytics literature in telecom and services marketing by examining traditional metrics (churn, ARPU) in an unconventional context (multi-industry service bundles). The results suggest that classic drivers of

churn (like price, tenure, service quality perceptions) still apply, but new drivers emerge in a converged setting (like the effect of add-on services or acquisition channel nuances). This indicates that analytical models need to evolve as industries converge; researchers and analysts should incorporate variables that capture cross-industry engagements when predicting outcomes. Our study provides a framework for doing so and could be a reference for similar analyses in other convergent contexts (e.g., tech companies offering banking services, etc.).

Furthermore, our segmentation analysis offers a practical application of segmenting in an ecosystem context. Traditionally, segmentation might be siloed (telco segments vs. bank segments). We demonstrate a holistic segmentation that spans service types, revealing, for example, a segment of customers who engage with multiple services yet churn due to value gaps. This introduces the concept of a "convergence segment" groups of customers defined by their multi-service usage patterns and corresponding behaviors. Future research can build on this by exploring if such segments exist in other markets and how stable they are over time. It also raises interesting questions for theory: Do converged service consumers exhibit fundamentally different loyalty drivers than single-service consumers? Our work suggests they might, as their expectations are broader.

Another theoretical implication relates to innovation strategy: our study shows tangible outcomes of an open innovation strategy (the telecom's partnership with insurance providers) at the micro level. It provides a case for the often-theorized link between open innovation and performance. Specifically, open innovation in this case led to new products (insurance) that increased ARPU (positive outcome), but also had nuanced effects on churn (some negative signals). This nuanced outcome aligns with the complexity suggested in open innovation literature, where not all collaborations yield straightforward benefits. It suggests that the success of open innovation strategies should be evaluated on multiple metrics, revenue, retention, customer satisfaction, not just one.

Our use of Power BI as an analytical tool in academic-style research is a methodological implication but also a theoretical one for the information systems field: it exemplifies the increasing capability of self-service BI tools to perform advanced analytics, blurring the line between business analyst and data scientist roles. It raises the notion that analytical innovation (in terms of tools and democratization of AI) is part and parcel of digital transformation in organizations. Researchers studying technology adoption could glean from this that advanced analytics are no longer confined to R&D labs; they can be executed in mainstream business software, potentially accelerating data-driven decision-making as part of digital transformation strategies.

5.2 Practical Implications

For practitioners, particularly managers in telecom, insurance, or any combination thereof this study offers several actionable insights grounded in customer data from North Macedonia. While many findings reflect localized realities, they provide useful guidance that may be adapted to other contexts with proper cultural and market calibration.

Segment-Specific Retention Strategies: One size does not fit all in convergent service retention. We identified concrete customer segments (e.g., Segment 1: high spend, high churn; Segment 2: low engagement, quick churn; Segment 3: established but at-risk). Managers should adopt tailored retention approaches for each segment. For high-value customers who are churning (Segment 1), invest in premium loyalty programs, solicit feedback, and address service quality or feature gaps. These customers are worth the extra effort due to their revenue contribution. For new customers who drop off immediately (Segment 2), improve onboarding: simplify setup, follow up early, and ensure expectations match deliverables, perhaps offer a "welcome" gift or personal call to increase engagement in the first month. For the mixed segment (Segment 3), a combination of upselling value-added services and targeted communication in regions with issues is needed. For instance, if Bitola has network complaints, they address those issues to improve satisfaction, while also educating customers on the benefits of services like A1 Net Protect to increase their service stickiness.

Optimize Acquisition Channels: The analysis, based on customer behavior in North Macedonia, clearly showed that door-to-door (D2D) acquisition channels experienced higher churn rates. While this insight is highly relevant to the local market, its applicability in other regions may vary depending on cultural norms, consumer expectations, and regulatory factors. This finding suggests that marketing and sales teams should critically reassess aggressive acquisition methods. While D2D may drive customer volume, its effectiveness in retaining loyal customers is limited. Companies might consider improving onboarding for D2D-acquired customers, perhaps by pairing the sale with a strong follow-up program or pivoting toward acquisition channels with higher customer retention rates such as online platforms, retail stores, or referral-based programs. Additionally, if companies engage third-party dealers or agents (in line with open innovation strategies), incentive schemes should reward not only activations but also post-sale customer retention (e.g., 3-month or 6-month loyalty metrics).

Bundle Design and Value Communication: Bundling telecom and insurance services is a core element of convergence. Our results highlight both the potential and the risk of such bundling strategies. Customers who subscribed to multiple services, including device protection, tended to spend more and exhibited signs of increased engagement. However, a

subset of these customers still churned, likely due to perceived low value or dissatisfaction with the bundled services. The implication is that companies must design bundles with real, clearly communicated benefits. Simply adding services for an extra charge is insufficient if customers don't understand or appreciate the value. For example, one possible approach might be to explore embedding device insurance into a premium plan as a built-in benefit, rather than offering it as a separate add-on. This *could* elevate perceived value and potentially reduce dissatisfaction, though further validation would be needed. Moreover, if analytics indicate a correlation between certain add-ons and churn, companies should revisit those offerings, for example, by improving the insurance claims process or selecting more trusted underwriters.

Leverage Data for Personalized Upselling: The revenue model revealed opportunities to increase ARPU through upselling strategies, including multi-line plans, premium tariffs, and value-added services. These can be operationalized via internal analytics tools such as Power BI or CRM systems to identify promising customer segments. For instance, a mid-tier customer with one line and no add-ons could be targeted with a family plan upgrade or device protection offer. However, such strategies must reinforce perceived value to avoid triggering churn. If a customer is offered a security app, ensure they understand, activate, and benefit from it. This reinforces satisfaction while increasing spend.

Geographical Focus: The study identified several high-churn regions in North Macedonia, such as Gostivar, Kochani, Prilep, and Tetovo. Practical next steps include localized customer surveys, network quality audits, and regional engagement campaigns. For instance, telecom providers might host local customer appreciation events, offer limited-time regional promotions, or invest in infrastructure upgrades in areas with known service complaints. Ensuring regional consistency in service quality is vital for the success of convergence strategies, especially when expanding into financial services through telecom partnerships. A local churn spike can undermine broader ecosystem innovations if left unaddressed.

Integration of Customer Data and Experience: A key enabler of this study was the integration of telecom and insurance usage data, which is often siloed in real-world partnerships. For convergence to succeed, firms must invest in shared, secure data platforms that allow for unified customer views. Such integration enables better targeting, churn prediction, and offer personalization. For example, if a telecom operator and bank share mobile usage and payment data, they can jointly identify patterns that trigger churn or upsell opportunities. Open data collaboration, governed by privacy standards, should be a priority in converged business models.

Long-Term Customer Management: While tenure was positively associated with revenue, a mild uptick in churn among very long-tenured customers suggests that these customers should not be overlooked. Beyond first-year engagement, companies *may consider testing* "late-tenure" strategies, such as sending personalized thank-you messages, trialing surprise upgrades, or exploring transitions to newer bundled service plans. The potential impact of these approaches should be assessed through targeted pilot programs or experiments. This can refresh the value proposition and reduce complacency-driven churn.

The overarching practical message is that data-driven open innovation strategies offer significant promise but require thoughtful execution. Convergence is not just about adding more services it is about adding the right ones and delivering them in a way that aligns with customer expectations and cultural norms. Managers at the telecom-insurance nexus must foster a culture of experimentation and feedback, pilot offers regionally, closely tracking key performance indicators like churn, and continuously refining their strategies.

Finally, it is important to note that while our insights stem from the North Macedonian market, the practical implications are not intended as one-size-fits-all prescriptions. Factors such as acquisition effectiveness (e.g., D2D), bundling perceptions, or service loyalty may differ significantly across countries and cultures. Therefore, we encourage practitioners and researchers to adapt these strategies in line with local consumer behavior, regulatory constraints, and partner ecosystem maturity.

6 Conclusion

This paper presented an in-depth analysis of industry convergence between telecommunications and insurance through the twin lenses of open innovation strategy and digital transformation, using predictive analytics as a unifying tool. By examining a unique telecom dataset enriched with convergent service information (insurance add-ons), we gained insights into how cross-industry offerings impact classic telecom performance indicators like customer churn and revenue, as well as how they shape the customer segments within the base.

Our findings affirm that convergence strategies when implemented via open innovation can unlock new revenue streams and customer value, but also introduce new challenges in customer retention and experience management. On one hand, customers who embraced multiple services (telecom + insurance) demonstrated higher average revenues, validating the synergy and cross-selling potential of convergence. On the other hand, the churn analysis revealed that simply adding services does not guarantee loyalty; in fact, poorly delivered or misaligned services can contribute to churn. The most at-risk customers included those acquired through aggressive channels and those whose service bundle value did not meet their expectations.

Meanwhile, long-tenured and multi-service customers proved to be the most valuable in revenue terms, underscoring the importance of long-term relationship management in a converged ecosystem.

From a strategic perspective, the research highlights the need for a holistic, data-driven approach to managing convergent business models. Telecom operators venturing into finance or insurance must extend their analytical toolkit and business processes to monitor not just their core metrics, but also the metrics emerging from the interplay of industries (e.g., adoption rates of financial products, their effect on telecom churn, etc.). Open innovation should be complemented by what we might call "open analytics" sharing data and insights across partner organizations to jointly optimize outcomes. The results encourage companies to invest in integrated customer data platforms and AI tools (like the use of Power BI demonstrated) to continually learn from customer behavior and adapt their offerings.

Limitations and future research: While our study provides valuable insights, it has limitations that open avenues for further research. First, the data is from a single company operating in a specific market context; generalizing to other markets or different scales should be done with caution. Future studies could compare multiple cases of convergence to see if the patterns we observed hold broadly, for example, do all telco-finance bundles see a D2D channel issue, or was that specific to this case? Second, our analysis was largely observational and correlational. We identified associations (like device insurance linked to higher churn) but cannot conclusively prove causation. Experimental or longitudinal studies (e.g., A/B testing an intervention where some customers get a bundle and others don't) could strengthen causal inference about the impact of convergence offerings on churn and revenue. Third, we focused on a subset of possible analytics; other techniques like decision trees, survival analysis for churn timing, or advanced machine learning (random forests, gradient boosting) could be applied to possibly improve predictive power. Incorporating social network analysis (using call/SMS graphs) or text mining of customer feedback could further enrich churn models in future research, especially in a converged context where reasons for churn might be multifaceted. Additionally, future research could explore the customer perspective qualitatively: our data tells the "what" but not the "why" from the customer's mouth. Interviews or surveys could reveal, for instance, why those high-paying customers churn, is it network issues, better competitor offers, or dissatisfaction with the insurance service? Such insights could feed back into refining open innovation strategies (e.g., maybe the insurance product needs redesign or the partnership governance needs adjustment).

References

Baumann, N., Renier, J., Tang, M., French, C., & Sanchez Soriano, G. (2023). *The ecosystem imperative: Digital transformation of financial services and moving from Open Banking to Open Data*. Institute of International Finance (IIF) and Deloitte.

Chesbrough, H. W. (2006). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Boston, MA: Harvard Business School Press.

Deepthu, D. & Raju Ramakrishna (2021). Machine learning models for customer churn prediction in insurance sector. 12th International Conference on Advances in Computing, Control, and Telecommunication Technologies, pp. 69-73.

Edwine, N., Wang, W., Song, W., & Ssebuggwawo, D. (2022). *Detecting the risk of customer churn in telecom sector: A comparative study*. *Mathematical Problems in Engineering*. https://doi.org/10.1155/2022/8534739

Idris, A., Khan, A., & Lee, Y. S. (2012). Intelligent churn prediction in telecom: Employing mRMR feature selection and RotBoost-based ensemble classification. *Applied Intelligence, 39*(3), 659–672. https://doi.org/10.1007/s10489-013-0440-x

Kazmi, S. (2021). Refine convergence of banking and telecom. *Pakistan & Gulf Economist*. Retrieved from https://www.pakistangulfeconomist.com/2021/07/26/refine-convergence-of-banking-and-telecom/#google_vignette

Lemmens, A., & Croux, C. (2006). Bagging and boosting classification trees to predict churn. *Journal of Marketing Research, 43*(2), 276–286. https://doi.org/10.1509/jmkr.43.2.276

Mukhopadhyay, D., Malusare, A., Nandanwar, A., & Sakshi, S. (2021). An approach to mitigate the risk of customer churn using machine learning algorithms. In A. Joshi, M. Khosravy, & N. Gupta (Eds.), Machine Learning for Predictive Analysis (pp. 133–142). Springer. https://doi.org/10.1007/978-981-15-7106-0_13

Neslin, S. A., Gupta, S., Kamakura, W., Lu, J., & Mason, C. H. (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. *Journal of Marketing Research, 43*(2), 204–211. DOI: 10.1509/jmkr.43.2.204

Prince, J., & Greenstein, S. (2011). Does service bundling reduce churn? [Working Paper]. Bloomington, IN: Kelley School of Business, Indiana University.

Ren, H., Zheng, Y., & Wu, Y. (2009). *Clustering analysis of telecommunication customers*. *The Journal of China Universities of Posts and Telecommunications*, 16(2), 114–116, 128. https://doi.org/10.1016/S1005-8885(08)60214-9

Research and Markets. (2024). *Telco, Fintech, and Insurtech Portfolio Evolution and Positioning Strategies* (Report No. 6029446). Globe Newswire Press Release: The convergence of telecommunications, fintech, and insurtech as key driver for digital services portfolio expansion.

Sharaf Addin, E. H., Admodisastro, N., Mohd Ashri, S. N. S., Kamaruddin, A., & Chong, Y. C. (2022). *Customer mobile behavioral segmentation and analysis in telecom using machine learning*. *Applied Artificial Intelligence, 36*(1), 1–20. https://doi.org/10.1080/08839514.2021.2009223

Wagh, S. K., Andhale, A. A., Wagh, K. S., Pansare, J. R., Ambadekar, S. P., & Gawande, S. H. (2024). Customer churn prediction in telecom sector using machine learning techniques. *Results in Control and Optimization, 14*, Article 100342. https://doi.org/10.1016/j.rico.2023.100342