# ANALYZING CUSTOMER CHURN IN TELECOMMUNICATIONS: INSIGHTS FROM DATA PATTERNS AND TRENDS

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***Abstract***

***Customer churn is a term that denotes customers switching from one telecommunications provider to another. This issue has become a major concern for telecoms, especially in competitive situations when many companies provide similar voice and data bundles. Telecom operations lose a lot of money in promotions, advertising, and customer acquisition, but at the same time, they have a hard time keeping their subscribers because today's customers have a lot of reasons to change their mind like easy switching, tempting promos, portability rules, and high-speed service expectations. The research in this area has progressed from conventional statistical analysis to modern predictive models based on machine learning, behavioral analytics, descriptive analysis, survival analysis, and hybrid data mining methods. The objective of this review is to provide a thorough discussion of the various churn research methodologies, determinants, segmentation ideas, prediction approaches, and analytical frameworks previously discussed in the literature while simultaneously illustrating how the problem of churn keeps evolving along with the advent of new technologies and digital services. The review based on nineteen separate studies points out the primary reasons for churn, the development of analytical methods, the behavioral side, the segmentation methods, the computational resources, and the areas that need more research in the future.***

***Keywords: Customer churn, telecommunications, data mining, prediction, retention, machine learning, behavioral analysis, switching behavior***.

## I. INTRODUCTION

Telecommunications has become a major player in terms of the services with the highest growth potential and the most fierce competition in the modern digital society. In the past years, there were very few telecom companies that provided services in each country, the majority of which were state-owned, but now in most countries, there are several telecom operators offering voice and internet services. This in turn allows the customers to choose a provider based on their preferences, the price they are willing to pay, quality of service or special promotions offered by the competing operators. According to Dahiya and Bhatia, the term customer churn is mainly used for the situation when a customer discontinues using the services of a specific provider and decides to switch over to a different one because of unfulfilled expectations or simply as a matter of choice [1].

At present, the telecommunications companies are responsible for producing enormous amounts of data, as each of the call records, messages, internet usage sessions, and billing transactions constitutes a part of the customer's profile. This data, although representing a significant challenge for the telecoms to analyze it manually, is still very useful for predicting the behavior of the customers in the future, as the analysis is done from the data of millions of records created every month. According to Bagri et al., firms can find the individuals who are most likely to leave by applying different customer activity patterns and usage behaviors as inputs in computational approaches and analytical models [2].

Regularly, users of modern communication technology keep making comparisons among different plans as the advertisements of competing services are the loudest and strongest sellers of them all. Sufficiently styled for modern-day users, these ads include high-speed data, unlimited calls, hot spot services, free apps, streaming bundles, and access to social networks. The dissatisfied customers might sometimes do a check-up on new options even before the existing one expires. Hence, telecom outfits must have sunshine on the churn in the form of accurate churn analysis systems, which will eventually bring about customer retention by indicating the users that are more likely to depart shortly and what measures to take to prevent it.

The competitive struggle continues to mount with digital technologies' enhancements. Previously, vocal communication was deemed the prime goal of telecom services, but today internet use, mobile apps, online entertainment, and digital streaming have all taken equal priority. Companies that do not satisfy these requirements easily lose customers. Kayaalp pointed out that turnover rates have changed character and seen the light of day through corporate operational strategy while at the same time just a minimal customer service issue as the cost of changing relationships has come down to zero in many competitive markets since then [3].

Another problem is that customer churn is not always abrupt. Studies reveal that customers first lower their activity levels gradually and then, finally, leave the network. Ahn et al. came up with the notion of partial defection whereby a customer lowers service demand a long time before actually disconnecting from the network [4]. This is making churn analysis harder as the early signals are concealed within the usage patterns rather than being at the subscription level where they can be noticed easily.

To sum up, the study of churn reveals the alterations in consumer behavior caused by the contemporary telecommunication markets and the crucial part that predictive analytics play in the early detection of such risks. The following parts of the paper analyze the different viewpoints, the techniques, the models, the segmentation strategies, and the future directions that were already discussed in previous research.

## II. BACKGROUND AND MOTIVATION

Various factors such as geographical locations, superficial economic conditions, and others determine the customer churn behaviors in different countries. Well-developed telecom markets like Europe and the United States hand over churn by competition among digital services, broadband and network coverage. Gürsoy pointed out that in saturated telecom markets customers often change services not because of major dissatisfaction but small differences in service offerings grab their attention [5]. Since the majority of the people in these areas possess mobile subscriptions, firms depend vastly on churn reduction techniques than birth of new customers.

On the contrary, developing markets show a totally different pattern of churn. The prepaid customer base in some Asian and African nations is so vast that they change service providers very often based on special offers like extra talk-time, weekend data, or discount plans. Mbarek and Baeshen indicated that the customer loyalty no longer exists when somehow new technology or attractive data packages invade the market, because developing region customers are more price-sensitive and willing to shift networks frequently [6].

One more reason behind the customer churn is the mobile technology transitions like 3G, 4G, and now 5G rollout. With every new technology, users get better connectivity, improved coverage, faster speed, and smart applications that keep changing their expectations. The operators who do not follow up these improvements very soon will be the ones losing their subscribers. Unlike the traditional telephony situations where consumers were loyal for many years, modern customers will only be loyal if the service provider keeps offering competitive value, high-speed data, and attractive digital services.

Switching behavior is influenced by customer perception of the promotional benefis, among other aspects. For instance, a big percentage of mobile users will only take short-term plans or recharge frequently without entering a contract for a longer period. In the case of prepaid services, consumers can change networks multiple times during one year, which makes it even harder to predict churn since one won't be able to get through to the rapidly changing and thus hard to unravel simple statistics.

The availability of large amounts of data has also become a source of motivation for churn analytics research to be conducted. Contemporary telecom firms gather a wide variety of data like call data records, surfing habits, applications usage, online recharge preferences, complaints, social media integration, digital payments, and mobile wallet transactions. Despite the fact that this data is highly valuable, companies still need very powerful computational models that can handle it correctly. Traditional approaches that work in other industries are simply not enough anymore since telecom data has grown to be so large, complex, and fast-changing.

The central reason for this review is that churn impacts the revenue, profitability, and the very existence of telecommunications operators in the long run. Therefore, churn research continues to attract both academic researchers and telecommunication companies worldwide..

## III. RELATED RESEARCH ON CUSTOMER CHURN

Various scholars have investigated the phenomenon of customer churn from various perspectives, such as behavioral analysis, service dissatisfaction, contract duration, marketing management, and predictive analytics. The earlier studies primarily considered poor network coverage, call drop problems, unsatisfactory billing practices, and customer complaints as the main causes for churn. However, the latest researches are dealing with more complicated issues like switching for the sake of promotions, digital service expectation, and competitive pricing. Ribeiro et al. conducted a systematic literature review and demonstrated that the turnover research evolution slowly migrated from basic descriptive studies to machine learning and segmentation frameworks that reveal the deeper behavioural patterns [7].

Customer churn has several dimensions to be considered as technological, economic, and psychological factors. The research on one hand centers on the customer's attitude, loyalty perception, emotional dissatisfaction, and service rating. On the other hand, the research deals with quantitative variables like data usage, call duration, complaint frequency, recharge amount, and subscription period. Dash and Dash stated that the traditional research has been largely relying on demographic attributes and customer profiles, but in countries with a large number of prepaid users, behavioural factors such as recharge habits and data usage patterns are the most telling indicators [8].

In the past, researchers mostly relied on customer surveys to find out the reasons for users quitting a specific network. The answers were generally limited to internet speed, poor service response, unattractive pricing, complex billing, and dissatisfaction with customer support. Surveys may provide insights into personal opinions, yet they come with certain limitations since telecom users could give subjective answers that do not truly reflect actual behaviour. Moreover, telecom subscribers frequently switch their views depending on market offers, which implies that survey responses might not be a good predictor of real switching behaviour.

A newer category of research has emerged that centers on the switching process as well as the psychological decision-making behind churn. Al-Mashraie et al. investigated churn through the push–pull–mooring framework, which illustrates that customers are "pushed" away from the current provider due to discontent, "pulled" towards the rivals because of appealing offers, and "moored" by personal preferences that delay switching [9]. This model accounts for churn with the help of behavioural triggers, promotional influence, and individual decision-making. The push–pull framework also brings forth the idea that emotional and social influence may sometimes outweigh network performance, especially when considering the young users who are inclined towards promotional digital services.

The churn phenomenon is approached from another perspective, where movement of consumers is considered as a main reason. For instance, urban customers have a larger number of service providers to choose from and more reliable network access than their counterparts in rural areas. Moreover, due to intense competition and heavy marketing in cities, churn is a common occurrence. Sometimes, rural customers are seen as loyal because they have no other options and the costs of switching may be high. This indicates that churn rate is not the same everywhere and is influenced a lot by the market's stage, competition, and socio-economic factors.

The latest research points to a change in focus from the more traditional areas such as customer complaints to more modern techniques like survival analytics, neural networks, and real-time scoring methods. Besides, the emphasis in recent studies is on already having up-to-the-minute intervention strategies, which means that even before a customer decides to leave, the telecom operator will be trying to keep that customer in the fold.

Another direction taken by researchers is to look at churn from the aspect of consumer mobility. For instance, people who live in cities are more likely to switch to different service providers and have better network quality than people who live in country areas. Churn is more common in cities because of strong rivalry and promotional activities. Customers in country areas may still be loyal because of the limited availability of options and the possible high cost of switching. It follows that the geographical distribution of churn is scenario-dependent in a large part as a result of the stage of the market, competition, and socio-economic conditions.

One of the latest research areas is the one dealing with multiple devices, the influence of social networks, and preferences for digital services like online gaming, streaming, and subscription content. These contemporary usage patterns lead to new churn activators that have never been considered before in traditional telecom research, especially where voice service is being replaced by data services to more or less the same extent.

Moreover, the review of earlier research indicates that customer churn studies have been swinging towards predictive modeling and proactive retention techniques rather than post-churn analysis. Modern studies aim at the early detection of churn indicators through using behavioural methods, segmentation, and computational techniques. This change is very evident when looking at research done over several years, where the focus has moved from customer complaints to survival analysis, neural networks, and real-time scoring. In addition, the latest studies point out that the telecom operators are now moving towards a more aggressive and proactive approach in customer retention, that is, they are trying to prevent churn even before the customer decides to leave.

**Table 1 Summary of Key Research Contributions on Churn Analysis**

| **Author / Year** | **Focus Area** | **Contribution** | **Key Insight** |
|---|---|---|---|
| Gürsoy (2010) [5] | Market maturity | Investigated churn in saturated telecom markets | Switching occurs despite satisfaction due to competitive alternatives |
| Mbarek & Baeshen (2019) [6] | Customer loyalty | Examined loyalty intention in developing regions | Loyalty declines when new data offers appear in the market |
| Ribeiro et al. (2024) [7] | Systematic literature review | Analyzed evolution of churn research methods | Shifted focus from descriptive studies to machine-learning frameworks |
| Dash & Dash (2019) [8] | Market-specific patterns | Highlighted limitations of demographic-only churn approaches | Behavioural factors are more relevant in prepaid markets |
| Al-Mashraie et al. (2020) [9] | Switching behaviour | Proposed push–pull–mooring theory for churn | Switching affected by dissatisfaction, alternatives, and personal preference |

## IV. CHURN MODELS AND ANALYTICAL APPROACHES

Churn analysis has its roots in classical statistics. The techniques used were mainly linear regression and descriptive statistics to find out if particular customer traits had an effect on the probability of quitting the service. Ahn et al. brought to our attention the case of partial defection and pointed out that the process of churn is not instantaneous but rather gradual; it begins with reduced service usage and culminates with a complete stop of service. Due to the nature of early churn signals being gradual, classical methods find it difficult to spot subtle behavioral changes, thus often misclassifying them as non-churning customers.

Regression-based models became widely accepted merely for the reason of giving interpretations and showing statistical significance at the same time. The researchers looked into factors like billing history, number of complaints, average call duration, declined service requests, and account age. One major drawback of regression models was their strict assumption of linear relationships which, in case of telecom behavior, was often violated. Furthermore, regression analysis was not a suitable technique for large volumes of data or for time-series data.

Kayaalp was the one who took a historical perspective on the telecom churn literature and mentioned that the bulk of the earlier studies was definitive in the use of the demographic analysis and descriptive statistics without permitting the use of computational methods. But, now, tactics that include but are not limited to, neural networks, clustering, and fuzzy modeling allow offering the interpretative predictions of the future with much sophistication.

Zdziebko et al. have proposed a fuzzy logic methodology that distinguishes and categories customers according to their risk levels instead of merely designating them as churn or not-churn customers [10]. This methodology is advantageous since churn is not a dichotomy; it can happen that consumers might get temporarily disconnected and later reconnected. Fuzzy logic systems can make that kind of dynamic interpretation happen.

Survival analysis is referred to as yet another contemporary technique in churn detection. Masarifoglu and Buyuklu harnessed survival analytics to measure customer longevity and predict the moment when a customer would cease to use the service [11]. Through survival modeling, it is easier for companies to define the remaining useful subscription period as well as to assess the risk of churn based on the usage pattern.

On the other hand, machine learning techniques like Random Forest, Support Vector Machines, and Neural Networks fit more to large datasets with the presence of nonlinear patterns, meaning they perform significantly better. Edwine et al. have provided a comparative analysis of various machine learning techniques and have concluded that the accuracy of predictions was enhanced in the case of nonlinear models being utilized [12][13].

Keramati and Ardabili conducted a study where neural networks were the main instrument in the analysis of telecom data and concluded that the neural models' performance was better since they could automatically identify and capture the intricate relationships among the different behavioral variables [14].

Lately, the inclination has been towards the use of hybrid methods. Bilişik and Sarp conceived a hybrid scheme in which clustering complements the supervised models and thus, results in an increase of predictive accuracy [15]. The rationale is that before making any forecasts, the segmentation takes place as the different client groups have already shown different reasons for the churn.

These studies combined signal the gradual transition from the usage of descriptive methods to the employment of sophisticated computational frameworks, thus showing the increasing significance of data-driven churn analysis.

## V. BEHAVIORAL AND SEGMENTATION DIMENSIONS

Behavioural analytics has gained significant recognition as one of the key factors in churn research since customer behaviour is closely tied to dissatisfaction, reduced engagement, and eventual exit. The use of demographic categories such as age, gender, and income is not very helpful in churn prediction since even people with similar demographic profiles will still act differently if they are offered the competitors' products or their needs digitalized through the internet. Therefore, churn analysis is directed not only to the customer but also to his or her behavior.

Pejić Bach et al. pointed out that clustering along with classification contributes to pinpointing the segments that are most likely to undergo churn and consequently allows telecom companies to come up with specific campaigns for not just the customers who are becoming inactive or are dissatisfied with the network but to also make costly promotions to all subscribers [16]. Segmentation makes it possible for retention efforts to be meaningful and cost-effective rather than going in a generic way.

Segmentation typically separates customers based on:

- recharge frequency,
- tenure,
- usage intensity,
- plan type (prepaid/postpaid),
- data consumption,

- call duration,
- complaint frequency,
- region,
- and network preference.

In particular, it has been observed that customers who habitually recharge small prepaid packs are more likely to churn because, every time they recharge, they will be comparing the competing offers. On the other hand, the contracted postpaid customers will take a longer time to switch because the contracts automatically keep them tied to that specific provider. Gradually, age also affects as the younger generation quickly embrace high-speed data services and hence switch networks faster.

Oseman and others showed that customers quitting by behaviour became even more apparent when the service was not satisfactory, there was poor network performance, and attractive offers from the competitors were available [17]. Consequently, the churn in the telecom sector is a combination of both internal problems and external competition. Therefore, modern companies investigate as well the internal network KPIs as the competitors' pricing strategies to estimate the risk of churn.

One other significant advancement is the real-time churn scoring, where the customer behavior is constantly assessed by the predictive systems as the new usage data comes in. Rahman and co-authors have shown that the survival-based real-time systems are superior to the periodic churn prediction in terms of performance because they identify the risk sooner and hence, the operator can take action before the customer actually has a switch...

In the same manner, Tamuka and Sibanda investigated in terms of real-time churn scoring the use of continuous machine-learning methods. Their model automatically updated the churn probability on the event of the customer changing his/her behaviour, e.g. when his call usage decreases, he/she stops recharging, or he/she frequently browses through the telecom network portal to competing operator websites [19]. Such interpretation of behavior, which is dynamic, allows for customer retention strategies like personalized offers, discount alerts, or targeted communication to be implemented proactively.

As a result, segmentation transforms the process of churn modeling from general analytics into a specific decision-making strategy based on the behavioural profiles and network interactions.

## VI. CHALLENGES AND RESEARCH LIMITATIONS

The advanced computational methods have indeed resulted in the significant enhancement of churn predictions; however, a number of difficulties still persist. The first of them is that emotional, psychological, and subjective variables are, unfortunately, missing from most of the telecom datasets. As per Pandey et al., it is absolutely essential to fuse demographic and usage features in order to get accurate prediction models since the behavior of people, though categorized with similar profiles, still varies [20]. When datasets consist only of network logs, they won't be able to fully uncover the reasons behind customer churn or specify the exact conditions of dissatisfaction that triggered the churn.

The inability to interpret the models is another major barrier. Most of the machine-learning algorithms, like deep learning, which are really the best in prediction, are categorized as "black boxes," meaning their internal decision logic is not very easily understood and cannot be explained to the telecom managers. Consequently, the operators refrain from deploying intricate models because the business departments will not be able to interpret the algorithmic output very well.

Dash and Dash have noted that often the research does not account for regional and cultural factors, especially when it comes to developing countries where the factors of affordability, language diversity, and regional network conditions considerably influence the decision-making process. For instance, customers residing in the city switch their network providers mainly because of the availability of faster 5G connectivity, while those living in the countryside do that for the reason that prepaid balance costs a lot. If the churn datasets take no notice of the socioeconomic factors, the retention strategies will be only addressing a part of the problem.

Yet, another very important limitation has to do with the cost of computation. For real-time churn forecasting, large data processing areas and constant machine learning updates come as a necessity. Telecommunication companies in developing nations that are very sensitive to prices might not be able to afford the costly computational systems even when the effect of churn is very high.

Most of the current churn models focus on achieving high accuracy, but in doing so, they overlook interpretability, user experience, personalized recommendation, retention psychology, and proactive feedback mechanisms. Hence, churn prediction is just a segment of the problem; the more significant and pressing issue is churn prevention.

## VII. CONCULSION

Customer churn is still one of the major challenges businesses face in the telecommunications sector. For the last twenty years, there has been a significant transition from the use of leveraging customer data for descriptive analysis to predictive analytics, machine learning interpretation, behavioral segmentation, and real-time monitoring. The traditional methods comprising regression and demographic analysis provided help in the initial period of research but failed to keep up with the changing nature of telecom behaviors and the digital expectation of the competition.

Recent studies embark on the novel and cutting-edge methods: fuzzy logic, neural networks, hybrid learning, survival analytics, segmentation strategies, behavioral clustering, and real-time scoring models. These methods allow operators to recognize risks sooner, to comprehend individual usage patterns, and to take preventive measures that call for customer retention.

Churn behavior is based on different factors worldwide, the factors being socioeconomic class, the use of prepaid plans, the demand for mobile data, technology readiness, promotional switching, and network coverage in the area. Hence, the telecommunications industry of the future will require analytics that combine explanatory intelligence and predictive intelligence.

With the combining of machine-learning prediction and segmentation strategies, together with preventive measures policy, telecom operators can not only cut down the costs of customer retention but also enhance service quality and lessen revenue loss caused by customer churn.

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