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Article

Defection Analysis of Post-Paid Telephone Customers in Nepal Using the Weibull Model

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Abstract: This study examines the defection patterns of post-paid telephone customers based on migrant status and season-wise acquisition using the Weibull model. Data from 48,666 post-paid customers were extracted from the data warehouse of a telephone company in Nepal. After pre-processing, the migrant status and season of acquisition for 48,583 customers were identified. Survival analysis was then conducted using the Kaplan–Meier (K-M) method to estimate the hazard of defection. Finally, the Weibull model was applied to analyse defection patterns concerning migrant status, default status, and season-wise acquisition in relation to survival periods. The results indicate that migrant customers have a significantly higher probability of defection compared to non-migrant customers. Additionally, the season of acquisition has a notable impact on customer survival duration. The study also highlights a higher risk of involuntary defection among migrant customers. These findings can inform the development of marketing strategies aimed at improving customer retention and acquisition in the telecommunications sector. Moreover, the model and methodology employed in this research can be extended to other marketing contexts.

Keywords: customer defection; customer retention; defection analysis; migrant factor; Weibull model



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1. Introduction

In modern business, competition has become intense from several perspectives. Firms' priorities have been focusing on customers, building long-term relationships, and customising products and services based on customer preferences. Marketers apply various strategies and techniques to acquire new customers and retain them for longer periods. The abundance of product varieties and available information has accelerated the commoditization of products and services, resulting in a more competitive market. Today, most products and services are available through various alternative channels and sources. Customers can obtain information about these products and services through advertisements and personal online searches. Therefore, customers are likely to switch providers. In a highly competitive market, even a slight decrease in satisfaction can create an immense drop in loyalty, resulting in defection (Jones et al., 1995). Thus, understanding trends and patterns of consumer behaviour in any organization is critical to its success.

The number of telephone subscriptions in the last decade has seen unprecedented growth worldwide (Taylor, 2023). With the increase in subscriptions, customer defection has become a major challenge in the telecommunications service industry. Customer defection can happen in two ways: voluntary and involuntary. In voluntary defection, customers decide to terminate their service with the provider, and in involuntary defection,

the service provider withdraws the customer service due to administrative reasons, such as abuse of service or non-payment of bills (Linoff & Berry, 2011). Defection is largely driven by psychological or behavioural factors, which can be explained through the theory of planned behaviour. This theory focuses on customers' negative attitudes, perceived lack of value, or social influences from peers, friends, or relatives (Ajzen, 1991; Bushra Shafiq, 2022).

Several reasons have been identified that cause customer defection in the telecommunications industry, such as service quality, competitive pricing, internal migration, customer expectations, professional or organizational change, sales advertisements, billing problems, and others (Alkitbi et al., 2020). In the context of the telecommunications industry, particularly concerning customer defection and churn, dynamic capability theory as suggested by Teece et al. (1997) provides a framework to understand how a firm's ability to adapt, innovate, and respond to rapidly changing environments becomes critically important. As explained by Fornell (2000), business processes aim to maximize shareholder value by enhancing customer asset value, measured in terms of customer lifetime value (CLV). However, empirical evidence in the CLV domain is limited, and further significant research is needed to draw robust conclusions (W. Chang et al., 2012).

To address the problem of customer defection in the telecommunications industry, it is necessary to understand the attributes that influence customer behavioural patterns. Due to advancements in modern transportation over the 20th and 21st centuries, people can easily move to different places or countries for various reasons, including employment, business opportunities, education, and improved quality of life (Duan, 2024). According to (United Nations, Department of Economic and Social Affairs, Population Division, 2019), there were more than 272 million migrants in 2019, up from over 220 million in 2010 and over 173 million in 2000 (United Nations, Department of Economic and Social Affairs, Population Division, 2019). This figure is up by 9 million in one year and reached 281 million migrants in 2020, which is 3.60 percent of the world population according to the 2022 World Migration Report (International Organization for Migration, 2022). In Nepal, internal migration to the Kathmandu Valley, the capital city, from other districts has been particularly significant in the past decade (Timsina et al., 2020).

In Duan (2024), the author scrutinised a collection of 224 studies from the Web of Science and Scopus databases to detect emerging trends in the Immigrant Consumption Behaviour (ICB) literature. They found that ICB is a multi- and interdisciplinary research area with five current trends for further exploration: (1) the immigrant consumption behaviour domain, (2) demographic sub-groups of immigrants and related consuming products, (3) country-, region-, and culture-focused studies, (4) the effects of culture and the acculturation process, and (5) the impact of urbanisation. This research investigates consumer defection patterns based on migrant status in conjunction with the season of acquisition and the CLV after defection. The telecommunications industry was used to analyse patterns, where new customer acquisition drives using various methods are being implemented on multiple fronts. However, customer defection remains an issue, requiring further analysis to determine potential reasons. The outcomes of this study can be applied to retention strategies that ultimately increase CLV.

The key contributions of this research paper are summarised as follows:

- An analysis of customer defection among post-paid telephone customers based on migrant status, involuntary defection, and season of acquisition using the Weibull model.
- The research results show that the probability of defection varies significantly depending on migrant status and also demonstrate that customers' survival duration is significantly related to the season of their acquisition. These findings are crucial for the marketing team in developing strategies on how to manage migrant customers

to increase their survival probability and determine the optimal timing for acquiring new customers.

- This study found that migrant customers face a higher risk of involuntary defection. This finding can be utilised by the revenue team to devise strategies for reducing involuntary defections among migrant customers and enhancing their CLV.

The structure of this paper is as follows: Section 2 provides a brief review of related work. Section 3 outlines the research hypotheses, followed by a detailed explanation of the research methodology in Section 4. The results of various statistical analyses addressing the research objectives are presented in Section 5. Finally, Section 6 summarises the key conclusions drawn from this study. The Appendix includes a list of abbreviations used throughout the manuscript.

2. Related Works

Migration is a common phenomenon in society and occurs both within and outside a country's borders. The growth of population migration in the Kathmandu Valley is among the fastest in South Asia (Timsina et al., 2020). The recent national population and housing census revealed a positive annual growth of 1.5%, 1.6%, and 3.4% in the Kathmandu, Lalitpur, and Bhaktapur districts, respectively, which is significantly higher than the national average of 0.9% (Central Bureau of Statistics, Nepal, 2021). These figures indicate that there is significant internal migration within the Kathmandu Valley.

Several factors contribute to customer defection. A study by Alkitbi et al. (2020) systematically reviewed 30 research studies from 2005 to 2019 on customer retention and found that the most common factors influencing customer retention are service quality, satisfaction, trust, and commitment. Other potential reasons for customer defection in the industry include: (a) the abundance of companies to choose from, (b) the similarity of their offerings, (c) the low prices of handsets (Nath & Behara, 2003), (d) contract type, (e) monthly usage volume, (f) permanence, (g) customer satisfaction, (h) additional facilities and services (Ramadhanti et al., 2023), and customers' purchasing power (Wanchai, 2017). A study by (Prasada & Rechanna, n.d.) in India identified several pertinent reasons for customer defection: price, promotional offers, network connectivity issues, voice quality, customer care quality, and value-added services. These studies highlight that multiple factors contribute to customer defection.

Several studies have examined customer churn, attrition, and defection across various countries and contexts. A study on churn among potential Malaysian telecommunications customers, using data from September 2019 and September 2020, found that prompt help desk responses can ensure that customers' needs are met, acting as a mediator in determining an employee's ability to satisfy customers and enhance retention (Mustafa et al., 2021). A study on customer defection in Portugal's fixed telecommunications industry (Portela & Menezes, 2011) concluded that preventing the defection of profitable customers is crucial for ensuring the financial performance of firms. This study analysed the defection patterns of residential customers, incorporating a wide range of covariates, including basic customer information, demographics, defection flags, historical usage, billing, subscription details, credit, and more. It found that customer satisfaction was not a significant factor in customer defection, whereas pricing strategy played a key role in customer retention. Customer retention directly impacts customer lifetime value (CLV) and firm profitability (Blattberg et al., 2001; Reinartz et al., 2005). Two primary drivers of customer retention are goal attainment and satisfaction (Torkzadeh et al., 2022), although these findings contrast with those of (Portela & Menezes, 2011), which many scholars have found to be true in competitive markets. Various data mining models have been used to predict customer

defection for a telecommunications company in Peru, with the XGBoost algorithm achieved 83% prediction accuracy in identifying customers at risk of defection (López et al., 2023).

Churn analyses have been carried out in industries other than telecommunications. In Rahman and Kumar (2020), churn prediction in the banking industry was carried out using 10,000 samples of data and various machine learning algorithms. However, the findings are not clearly articulated in the paper. In Tran et al. (2023), the impact of customer segmentation on the accuracy of churn prediction in the banking sector is examined using machine learning and it was reported that customer segmentation did not significantly impact the precision of predictions. A simplified framework for a predictive model to estimate churn rates using machine learning algorithms in the banking sector is presented in Hassanien et al. (2023). In Oliveira et al. (2019), the authors highlight the factors leading to customer dissatisfaction and defection and assess these using questionnaires in the Brazilian banking sector. An ensemble model for predicting churn in the youth segment of retail banking customers is introduced in Bharathi et al. (2022). Similarly, an analysis of the characteristics of customer defection in a hair salon, considering individual differences, is presented in Iwata et al. (2019), while customer churn in retail e-commerce is discussed in Matuszelański and Kopczewska (2022).

The importance of predicting customer turnover due to churn, attrition, or defection and reducing these rates to increase retention has multiplier effects on profits and profitability. A 5% reduction in the churn rate results in an increase in profits from 25% to 85% (Mishra & Reddy, 2017), and it is 5–10 times cheaper, in terms of cost, to retain current customers than to acquire new ones (Ly & Son, 2022). A research study by Dewasiri and Tharangani (2014) in Sri Lanka found that customer satisfaction, payment equity, and effective commitment impact customer retention in the mobile telecommunications industry.

Customer turnover due to churn or defection, with respect to profit maximisation in the telecommunications industry, has been a subject of significant concern. In Reichheld et al. (1990), the paper highlighted major profit drains caused by customer defections and how small reductions in customer defections result in significant increases in profits. This phenomenon is also observed in the banking industry, where Agarwal et al. (2011) highlighted that a borrower who migrates 190 miles from his or her “state of birth” is 17% more likely to default and 15% more likely to file for bankruptcy, while a borrower who continues to live in his or her state of birth is 14% and 10% less likely to default and file for bankruptcy, respectively. The study by V. Chang et al. (2024) emphasises the importance for customer relationship managers to reduce attrition and promote long-term economic viability in fiercely competitive marketplaces, with strategic implications for improving consumer loyalty and organisational profitability. In regard to complementing customer defection, acquisition is the only way. Highlighting the relationship between acquisition and churn, Yulianti and Saifudin (2020) mentioned that the telecommunications industry experiences an average annual churn rate of 30–35%, and the cost of recruiting new customers is 5–10 times more expensive than retaining existing ones.

The literature review indicates that there are some research studies on customer churn in telecommunications, defection analysis, and telephone services concerning several parameters. However, to the best of our knowledge, the defection analysis of services based on migration, involuntary defection, and the season of acquisition has not been conducted before. Hence, the research in this area is both unique and innovative. Additionally, there is no known record of defection analysis for telecommunications services in Nepal. Therefore, this study aims to examine the defection analysis of post-paid customers based on migrant status, involuntary defection, and season of acquisition in order to address these research gaps.

3. Research Hypotheses

Migration from rural to urban areas is a prevalent demographic trend in developing nations, including Nepal, driven by factors such as employment opportunities, education, and access to better services (Selod & Shilpi, 2021; Timsina et al., 2020). Several reports have indicated that migrants are economically active and contribute to labour markets, entrepreneurship, and economic growth (Chodavadia et al., 2024; Czaika et al., 2022; Roy, 2024; Sinkovics & Reuber, 2021). The paper by Falcão et al. (2024) highlighted the strong sociocultural environment and characteristics of migrant entrepreneurs that influence market orientation decisions and strategies. Migrant entrepreneurs generate jobs, bring cultural diversity, and represent a significant contingent of both low- and high-tech entrepreneurs in most developed nations (Newburry et al., 2022). The paper by Yamin and Kurt (2018) demonstrates the higher cost of overcoming the liability of outsidership (LOO) in a closed target network compared to open networks and highlights how migrant entrepreneurs struggle to participate and integrate into the host society (Kothari et al., 2022).

Evidence suggests that human psychology plays a role in individuals' financial decisions (Kramer, 2014), and seasonality often dictates business strategy (Radas & Shugan, 1998). Differences in shopping patterns were found between the two seasons in the study by Roslow et al. (2000), where it was observed that, in winter, consumers purchased more adult clothing than in the summer, while in the summer, consumers bought more food and beverages and spent more money than in the winter. The purchase patterns often vary over time and across customers (Wunderlich et al., 2022). Analysing these customers can be helpful for customer segmentation, portfolio management, and improving the timing of marketing actions. Based on the observations and deliberations in the research context, the following hypotheses have been formulated to analyse the defection of telecommunications services in Nepal, considering customer status related to migration, involuntary defection, and season of acquisition:

Hypothesis 1 (H1). *The probability of defection, measured through survival analysis of migrant customers, is higher compared to non-migrant customers.*

If the p -value obtained during the regression analysis is significant, the hypothesis will be accepted. Additionally, the inclusion of a dummy variable or variables should not alter the relationship between the dependent and independent variables.

Hypothesis 2 (H2). *The probability of involuntary defection among migrant customers is higher than that of non-migrant customers.*

If the p -value obtained during the regression analysis is significant, the hypothesis will be accepted. Additionally, the inclusion of a dummy variable or variables should not alter the relationship between the dependent and independent variables.

Hypothesis 3 (H3). *Customers acquired in different seasons have significant differences in their survival duration.*

If the p -value obtained during the regression analysis is significant, the hypothesis will be accepted.

4. Methodology

This study employed a quantitative approach to conduct the research. Research begins with the identification of a research gap based on the review of the literature on migration studies in the research context and customer defection in the telecommunications industry,

followed by the formulation of the research problem and the setting up of research hypotheses. Next, data were collected from a privately-owned telephone company operating wireless in local loop (WLL)-based fixed telephone services, and the data were further processed to ensure they were in the proper format for subsequent analysis. The data processing was followed by survival analysis, which included a Kernel Density Estimate (KDE) of survival periods and descriptive statistics of survival periods in terms of failure time analysis. The data analysis of the survival period is further conducted using non-parametric and parametric duration models (Portela & Menezes, 2011). The rationale for using these two models of analysis (over the semi-parametric model) is to achieve flexibility in modelling the baseline hazard (non-parametric) while leveraging parametric models for more efficient estimation and interpretation of covariate effects. This approach is advantageous in survival analysis as it often balances model flexibility and interpretability (Wey et al., 2015). In this research, the non-parametric duration model is implemented using Kaplan–Meier (K-M) analysis and Nelson–Aalen (N-A) smoothed hazard estimates, whereas the parametric model is implemented using the Weibull model.

Figure 1 illustrates the methodology process employed in this research work. In Section 2, we present the findings from the literature review and identify the research gap. The research hypotheses are outlined in Section 3. Subsequently, we discuss the data collection and processing undertaken for the research.

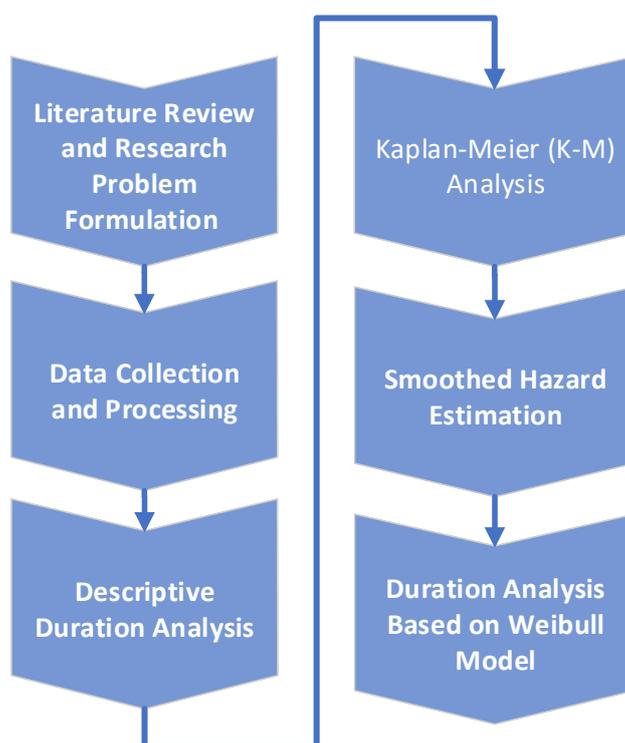


Figure 1. Methodology steps used in the research.

4.1. Data Collection and Processing

In this section, we outline the data collection procedure and the data processing steps undertaken during the research.

4.1.1. Data Collection

Data were extracted from the data warehouse of a telephone company in Nepal. The customers analysed were post-paid fixed phone users utilising WLL based on code division multiple-access technology. In Nepal, post-paid subscribers can be registered

and activated by paying government ownership tax in addition to the activation fee and device charges as per the business scheme. Only meaningful information was extracted and restored from the data warehouse with the assistance of the company's database administrator. The extracted data were normalised using the Microsoft Excel application to deduce the explanatory variables without manual intervention in any data. The data obtained from the telephone company consist of various kinds of information, including *Subscriber IDentity (SID)*, which represents the telephone number (nominal variable), Subscriber Category (SubCat), date of activation, current status, subscriber name, address, balance amount, *Customer IDentification (CID)*, blocked date, and closure date. The subscriber name and address were removed from the data for further processing, as these details were not necessary for this research work. Next, the data obtained from the company were further processed according to the requirements of the research.

4.1.2. Data Processing

The data obtained from the company consist of a total of 48,666 subscribers acquired over six (6) years and ten (10) months. These customers' survival patterns were observed for a minimum period of 4 years, 8 months, and 9 days (1709 calendar days) and a maximum period of 11 years, 6 months, and 9 days (4208 calendar days). These subscribers were activated under 12 different subscriber categories, which comprised 43,003 residential (Res) customers, 2987 business (Bus) customers, 755 special (Spc) customers, 873 Public Call Office (PCO) customers, 329 employee (Emp) customers, 352 student (Stu) customers, 284 shop-keeper (SK) customers, 51 senior citizens, 10 members of the military/police, five (5) non-government agency officials, seven (7) government officials, and ten (10) foreigners. Due to the minimal count of subscribers in the categories of non-government agencies, government officials, foreigners, senior citizens, and military/police, these records were excluded. Therefore, 48,583 subscribers registered under seven (7) categories have been used for further analysis.

How is censoring performed?

Out of 48,583 subscribers, 1351 subscribers were found active as non-defectors still using their services. For the purpose of survival analysis, 1351 subscribers were right-censored, indicating that these customers were considered to have defected at the time of data collection. The *Censoring Status (CenStat)* variable is assigned a value of '1' for active customers who were subjected to censoring during this research process. This variable takes a value of '0' if the customer had already defected. *Censored Subscriber (Cen-Sub)* represents the number of subscribers who underwent the censoring process.

How is migration status obtained?

Kathmandu serves as Nepal's capital city, while the Kathmandu Valley comprises three districts: Kathmandu, Lalitpur, and Bhaktapur. The valley is a pivotal centre within the country for various purposes, including education, finance, and employment. Consequently, there is a trend of internal migration from the other 74 districts to the Kathmandu Valley for socioeconomic reasons, as discussed in Section 2. In Nepal, fixed phone numbers are unique to district area codes. Generally, each district has a unique three-digit area code, '0XX', except for the Kathmandu Valley, which uses a two-digit area code, '01'. Therefore, SIDs beginning with '01' identify customers from the Kathmandu Valley.

The migration status of a customer is determined using the SID (i.e., telephone number) and CID in the data. The CID contains the customer's citizenship certificate, passport, or driving license details. This information includes the document number and the place of issue, including the district name. Customers who do not hold citizenship from the three districts of the Kathmandu Valley but use telephones registered in these districts are

identified as migrant customers. The binary categorical variable *Migrant Status (MigStat)* is used to represent the migration status of the customer, where '0' denotes a non-migrant customer, and '1' represents a migrant customer.

How is defection status obtained?

The data obtained from the company includes billing information in the balance amount field. This billing information is utilised to identify the voluntary and involuntary defection statuses of the customers. Cancelled subscribers with a due amount exceeding NPR 100 are defined as involuntarily defected customers, while the remaining cancelled customers are considered voluntarily defected customers.

The binary variable *Defaulter Status (DefStat)* is used to represent the defaulter status of the cancelled customers. In this context, the value '0' represents non-defaulters, and '1' represents defaulters.

Duration and Season Determination

As discussed earlier, the data obtained from the company consists of the date of activation and the date of cancellation of the service for the customer. This information is used to derive the *Duration (Dur)* and *Season* variables. The variable *Duration* is calculated as the date of cancellation minus the date of activation, and this value represents the survival duration in days. The date of activation is used to identify the season of customer acquisition. The variable *Season* can take four values: '1' for spring, '2' for summer, '3' for autumn, and '4' for winter.

Subscriber Information

In addition to the above variables, we define some variables before presenting subscriber information. *Number of Subscribers (Num-Sub)* represents the total number of subscribers. *Migrant Subscriber (Mig-Sub)* and *Non-Migrant (Non-Mig)* represent the number of subscribers categorized as migrant and non-migrant, respectively. *Involuntary Defection (Invol-Def)* and *Voluntary Defection (Vol-Def)* represent the number of involuntarily defected subscribers and voluntarily defected subscribers, respectively.

The descriptive count of customer data is illustrated in Table 1 based on SubCat, and the number of subscribers is further divided according to migrant types, defection types, and censored categories. The data demonstrate that most customers are in the residential category, followed by the business category. In total, the normalised data of 48,583 customers consists of 28,004 migrant and 20,579 non-migrant customers. Similarly, the normalised data of the 48,583 customers includes 20,543 voluntary defections, 26,689 involuntary defections, and 1351 censored customers. Out of the 48,583 subscribers, 1351 were found to be active non-defectors still using their services. Therefore, the number of defector customers analysed was 47,232. Additionally, for the purpose of survival analysis, 1351 subscribers were right censored by taking the end date when the data was gathered. Out of the 47,232 defectors, a total of 26,689 subscribers were found to have undergone involuntary defection, while 20,543 were found to have undergone voluntary defection.

The descriptive count of customer data is illustrated in Table 2 based on season, and the number of subscribers is further divided according to migrant types, defection types, and censored categories. The data demonstrate that most customers are acquired in the autumn season, followed by winter, summer, and spring. A typical normalised format of customer data after processing is illustrated in Table 3. Tables 4 and 5 have been created to incorporate defection analysis using dummy variables. For each customer, only one dummy variable takes the value '1', while all others take the value '0'. Table 4 has been created to incorporate customer categories as dummy variables to test Hypothesis 1 and

Hypothesis 2. Similarly, Table 5 has been created to incorporate the season of acquisition as a dummy variable to test Hypothesis 3.

Table 1. Customer types as per migration, defection, and censorship.

SubCat	Num-Sub	Mig-Sub	Non-Mig	Vol-Def	Invol-Def	Cen-Sub
Res (1)	43,003	26,267	16,736	18,523	23,601	879
Bus (2)	2987	385	2602	1229	1487	271
Spe (3)	755	184	571	257	428	70
PCO (4)	873	600	273	171	595	107
Emp (5)	329	172	157	106	217	6
Stu (6)	352	244	108	128	213	11
SK (7)	284	152	132	129	148	7
Total	48,583	28,004	20,579	20,543	26,689	1351

Table 2. Subscriber season-wise acquirement per migrant, defection, and censorship.

Season	Num-Sub	Mig-Sub	Non-Mig	Vol-Def	Invol-Def	Cen-Sub
Spring (1)	7110	4018	3092	3423	3495	192
Summer (2)	11,429	6837	4592	5063	6061	305
Autumn (3)	17,116	9539	7577	7214	9408	494
Winter (4)	12,928	7610	5318	6131	6437	360
Total	48,583	28,004	20,579	20,543	26,689	1351

Table 3. A typical format of the normalised data for customers.

SID	SubCat	MigStat	DefStat	Dur	CenStat	Season
012090001	1	0	1	3646	0	2
012130001	7	1	1	2583	0	3
...

Table 4. A format of data for customers based on subscriber category.

SID	SubCat	Res	Bus	Spe	PCO	Emp	Stu	SK
012090001	1	1	0	0	0	0	0	0
012130001	7	0	0	0	0	0	0	1
...

Table 5. A format of data for customers based on season of acquisition.

SID	Season	Spring	Summer	Autumn	Winter
012090001	2	0	1	0	0
012130001	3	0	0	1	0
...

In this research, which applies survival analysis, the variable ‘duration’ represents the waiting time until the occurrence of the event, which is defection. Therefore, duration is the dependent variable. The effect of other variables, such as migrant status and season of

acquisition, explains or predicts the occurrence of defection; thus, these are the independent variables. The dependent and explanatory variables have been transformed into categorical variables and are measured on a ratio and nominal scale with discrete values. According to Corporation (2003), the minimum required estimated number of events and sample size in the absence of censoring for a model with a binary covariate of interest is 66 (page 281, Example 1). Similarly, in the presence of censoring, for the minimum required estimated number of events of 64, the required sample size is 86 (page 283, Example 4). Therefore, the sample size used in this research is acceptable for both data analysis methods.

4.2. Survival Analysis

In this step, we will perform survival analysis, which includes the KDE of survival duration, duration statistics of customers, K-M survival estimates, and the Nelson–Aalen (N-A) hazard estimate. The KDE of the survival duration for all customers over time (in number of days) will be plotted and compared with the standard normal distribution curve. Additionally, the KDEs of the variable survival duration will be plotted separately for migrant and non-migrant customers. This analysis ensures the distribution of survival periods for both the overall customer base and migrant customers is well understood.

Next, we present the duration statistics of customers according to migration status and season of acquisition. While computing the duration statistics, we will measure time at risk, Failure Time (FT), and Incidence Rate (IR). FT(x%) represents the x percentile of customers who underwent defection. IR is the ratio of the number of defections occurring in the study period to the total number of customers. Finally, K-M survival and N-A hazard estimates will be carried out. These K-M survival analyses show the survival probabilities over time for customers based on migrant status and the season of acquisition. The N-A hazard estimate analysis shows the estimate of the cumulative hazard function over time. These two analyses provide a comprehensive assessment of survival based on the data. After assessing the hazard of defection over natural time, the survival time variable takes the form of a Weibull distribution. Therefore, we will proceed to regression analysis using the Weibull model.

4.3. Regression Analysis Using Weibull Model

In this section, we outline the way to develop the Weibull model setup for regression analysis. In general, the probability of defection of the i^{th} customer at time t_i is given by the likelihood function as Equation (1).

$$l(t_i) = \prod_{i=1}^n f(t_i)^{d_i} [1 - f(t_i)]^{(1-d_i)} \quad (1)$$

where $f(t_i)$ is the probability density function of the i th customer for time t_i and the variable d_i denotes the status of the i th customer at any time t (in days) such that $d_i = 1$ if customer i survives until t_i time, and continues his/her service beyond t_i , else the value of $d_i = 0$. Now, taking logarithms on both the sides in Equation (1) gives Log-Likelihood (LL) function (l_i) as

$$l_i = \ln\{l(t_i)\} = \sum_{i=1}^n \{d_i \ln\{f(t_i)\} + (1 - d_i) \ln\{[1 - f(t_i)]\}\} \quad (2)$$

When we consider only survival customers, i.e., $d_i = 1$, Equation (2) becomes

$$l_i = \sum_{i=1}^n d_i \ln(f(t_i)) \quad (3)$$

In the Weibull model, the Weibull density function is

$$f(t_i, \eta_i, Y_i) = \frac{Y_i}{\eta_i} \left(\frac{t_i}{\eta_i}\right)^{(Y_i-1)} \exp\left\{-\left(\frac{t_i}{\eta_i}\right)^{Y_i}\right\} \quad (4)$$

where η_i , Y_i are non-negative parameters. By combining Equation (3) and Equation (4), the LL for the i th customer is

$$l_i = \sum_{i=1}^n d_i \left\{ \ln(Y_i) - \ln \eta_i + (Y_i - 1)(\ln t_i - \ln \eta_i) - \left(\frac{t_i}{\eta_i}\right)^{Y_i} \right\} \quad (5)$$

Now, modelling the parameters η_i and Y_i in the log space, the equation becomes

$$l_i = \sum_{i=1}^n d_i \left\{ \theta_{2i} - \theta_{1i} + (e^{\theta_{2i}} - 1)(\ln t_i - \theta_{1i}) - (t_i e^{-\theta_{1i}})^{\theta_{2i}} \right\} \quad (6)$$

where $\theta_{2i} = \ln Y_i$ represents the probability of defection of that i^{th} customer having constant standard deviation Y_i with respect to that customer i and where $\theta_{1i} = \ln \eta_i$ represents the probability of defection of any i th customer considering explanatory variables and dummy variables and can be defined as

$$\theta_{1i} = \sum_{n=1}^j \{x_{ni}\beta_n + d_{ni}\alpha_n\} + \epsilon_1 \quad (7)$$

where $x_{1i}, x_{2i}, \dots, x_{ni}$ represents measured 1st, 2nd, \dots , n th explanatory variables; β_n represents the coefficient for the respective n th measured variable; $d_{1i}, d_{2i}, \dots, d_{ni}$ represents 1st, 2nd, \dots , n th dummy variables; α_n represents the coefficient for the respective n^{th} dummy variable and ϵ_1 represents the regression error.

In this research, we considered three regression cases namely Model-1, Model-2, and Model-3. In Model-1, we use a single explanatory variable migrant status, (x_{1i}), which has been used to measure the defection rate of customers without and with dummy variables. The regression Model-1 has been computed with and without dummy variables by using Equation (8) and Equation (9), respectively.

$$\theta_{1i} = x_{1i}\beta_1 + \sum_{n=1}^6 d_{ni}\alpha_n + \epsilon_1 \quad (8)$$

$$\theta_{1i} = x_{1i}\beta_1 + \epsilon_1 \quad (9)$$

In Model-2, we use two explanatory variables. In this model we have added the variable involuntary defection (x_{2i}) along with the variable migrant status (x_{1i}) used in Model-1. Thus, this model measures the defection rate of migrant customers undergoing involuntary defection. The regression Model-2 has also been computed with and without dummy variables using Equations (10) and (11), respectively.

$$\theta_{1i} = x_{1i}\beta_1 + x_{2i}\beta_2 + \sum_{n=1}^6 d_{ni}\alpha_n + \epsilon_1 \quad (10)$$

$$\theta_{1i} = x_{1i}\beta_1 + x_{2i}\beta_2 + \epsilon_1 \quad (11)$$

In both the models, Model-1 and Model-2, we consider six dummy variables of customer types (d_1, d_2, d_3, d_4, d_5 , and d_6). The dummy variable d_1 is 1 for residential customer and 0 for all other categories. Similarly, dummy d_2 is 1 for the business category of customers and 0 for all other categories, d_3 is 1 for special customers and 0 for all other categories, d_4 is 1 for PCO customers and 0 for all other categories, d_5 is 1 for the employee category of

customers and 0 for all other categories, and d_6 is 1 for the student category of customers and 0 for all other categories.

In Model-3, we use three explanatory variables to measure the defection rate of all customers with respect to the season of their subscription. Thus, the regression equation for Model-3 is given by Equation (12).

$$\theta_{1i} = \beta_0 + x_{1i}\beta_1 + x_{2i}\beta_2 + x_{3i}\beta_3 + \epsilon_1 \quad (12)$$

where, x_{1i} is the variable for the summer season with its coefficient β_1 , x_{2i} is the variable for the autumn season with its coefficient β_2 , x_{3i} is the variable for the winter season with its coefficient β_3 , and β_0 is the coefficient for the spring season.

5. Results and Discussions

This section begins by presenting and discussing the descriptive results obtained from survival analysis, followed by parameter estimation using the Weibull model.

5.1. Survival Analysis

In this section, we perform density function analysis and survival analysis to compute the descriptive statistics.

5.1.1. Density Functions Analysis

The KDE of survival duration for overall customers with respect to time under the probability area curve, considering the Gaussian nature of event arrivals, has been plotted in Figure 2, and the plot has been compared with the normal distribution curve. We observed that the KDE of survival periods is positively left-skewed. The skewness of this result indicates that the distribution of the survival period for the average customer is earlier compared to the normal distribution of survival periods. Similarly, the kernel probability densities of the survival duration, plotted for migrant and non-migrant customers, are shown in Figure 3. It shows that the KDE of migrant customers is positively left-skewed compared to non-migrants, indicating a tendency for earlier defection among migrant customers than non-migrants. These two figures provide a general overview of the nature of survival periods without indicating the type of distribution. Therefore, we further analysed the data using survival analysis to estimate the descriptive statistics of the survival period in terms of failure time, considering the distribution as a standard normal distribution.

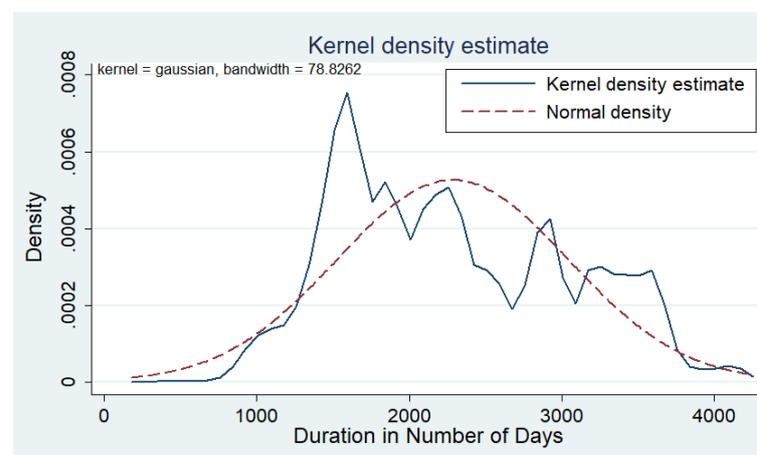


Figure 2. Kernel Density Estimate (KDE) of survival periods of customers.

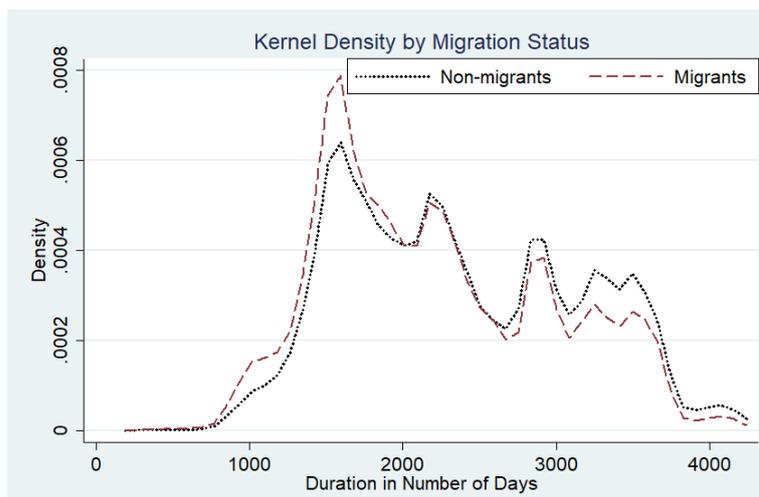


Figure 3. KDE of survival periods of customers based on migrant status.

5.1.2. Survival Analysis

The descriptive statistics of the survival period for all customers under observation showed that the dependent variable, i.e., survival period, ranged from a minimum of 259 days to a maximum of 4159 days, out of the total offered duration of 4172 days. For some of the censored subscribers, the maximum survival period was almost equal to the total offered days. The mean value of survival duration was 2283.6 days, with a standard deviation of 758.1 days. The summary of statistics measured for time at risk, IR, and FT with respect to 25%, 50%, and 75% of survival time for total customers, migrant customers, and non-migrant customers is shown in Table 6. The results indicate a higher IR of defection for migrant customers compared to non-migrants.

Table 6. Duration statistics of customers as per migration status.

	Risk Time	IR	FT (25%)	FT (50%)	FT (75%)
Total	110,943,894	0.0004379	1626	2159	2910
Non-Migrant	48,816,830	0.0004216	1672	2261	2947
Migrant	62,127,064	0.0004508	1610	2094	2835

The summary of statistics measured with time at risk, IR, and FT with respect to 25%, 50%, and 75% of the survival period for customers acquired according to season is presented in Table 7. A significantly higher IR for customers acquired in the summer season indicates a significantly higher risk of defection compared with customers acquired in other seasons. Similarly, a significantly lower IR for customers acquired in the autumn season indicates a significantly lower risk of defection compared with customers acquired in other seasons.

Table 7. Duration statistics of customers as per acquisition by season.

	Risk Time	IR	FT (25%)	FT (50%)	FT (75%)
Total	110,943,894	0.0004379	1626	2159	2910
Spring	16,167,623	0.0004398	1611	2113	2963
Summer	24,319,062	0.00047	1624	1894	2924
Autumn	41,988,770	0.0004076	1812	2319	2941
Winter	28,468,439	0.0004541	1507	2081	2803

In terms of FT, 25% of customers acquired in the winter season underwent defection early (1507 days), followed by the spring season (1611 days), summer season (1624 days), and autumn season (1812 days). However, in the case of 50% FT, customers acquired in the summer season underwent defection earlier (1894 days), followed by the winter season (2081 days), the spring season (2113 days), and the autumn season (2319 days). For 75% FT, customers acquired in the winter season underwent defection earlier (2803 days), followed by the summer (2924 days), autumn (2941 days), and spring seasons (2963 days). This shows a higher survival period for customers acquired in the autumn season compared to other seasons, but further analysis is required to obtain more accurate results for the entire period of observation.

Considering the normal distribution of survival periods, a K-M survival estimate plot for the customers based on their migrant status was computed. The plot is presented in Figure 4. The pattern shows that the survival probability of non-migrants is higher than that of migrants at any point in time. Similarly, a plot of the K-M survival estimate for season-wise activated customers, with respect to time in days, is presented in Figure 5. The figure shows that the survival probability of customers acquired in autumn is higher than that of customers acquired in other seasons at any given point in time. However, there is fluctuation in the survival probability of customers acquired in the other three seasons. The straight nature of the curve represents almost 100% survival probability for the initial 1000 days. This is due to the three-year device warranty and free call offers against monthly rental charges given to customers during that period. This was validated during discussions with company officials.

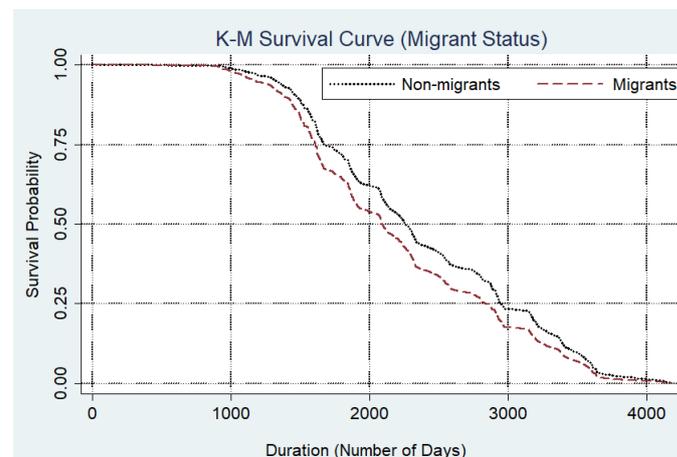


Figure 4. Kaplan–Meier (K-M) survival estimate per migration.

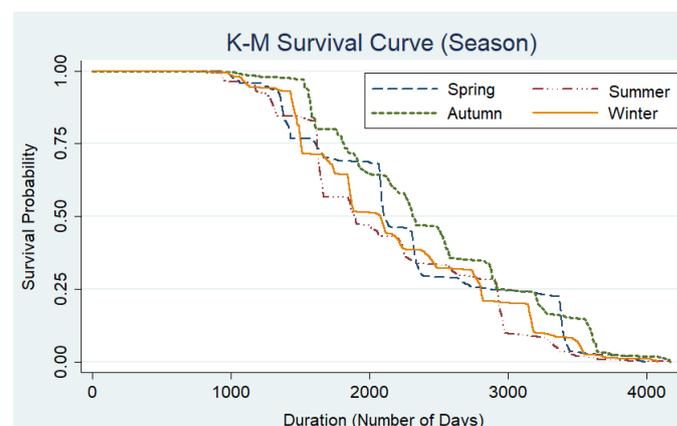


Figure 5. K-M survival estimate per season.

Considering the normality in the distribution of survival periods, N-A hazard estimates of failure (defection) were plotted. A plot of N-A hazard estimates of failure for migrant and non-migrant customers with respect to time (in days) is shown in Figure 6. The figure indicates that there is a higher level of hazard (risk) of defection among migrant subscribers compared to non-migrant subscribers, and the risk of hazard increases continuously over time. A plot of N-A hazard estimates of failure for season-wise activated customers, with respect to time in days, is illustrated in Figure 7. We observed that the trend of defection increases throughout the duration, but there is fluctuation in defection probability for season-wise activated customers until around 3000 days. However, after 3000 days, the probability of defection is significantly lower for customers acquired in the autumn season compared to customers acquired in other seasons. The plot of survival probability and hazard estimates based on migration status shows that migrant customers have a higher risk of failure than non-migrant customers for all periods of observation. Similarly, the plot of survival probability and hazard estimates based on season indicates that customers acquired in the autumn season have a lower risk of failure than those acquired in other seasons for most of the observation period. We observed that the hazard of defection increases over time, which supports the use of the Weibull distribution model for further survival analysis (Wey et al., 2015). This parametric model was employed for survival analysis to accurately assess the significant differences in survival durations based on observed covariates, such as migrant status, defaulter status, and season of acquisition, in order to test the research hypothesis.

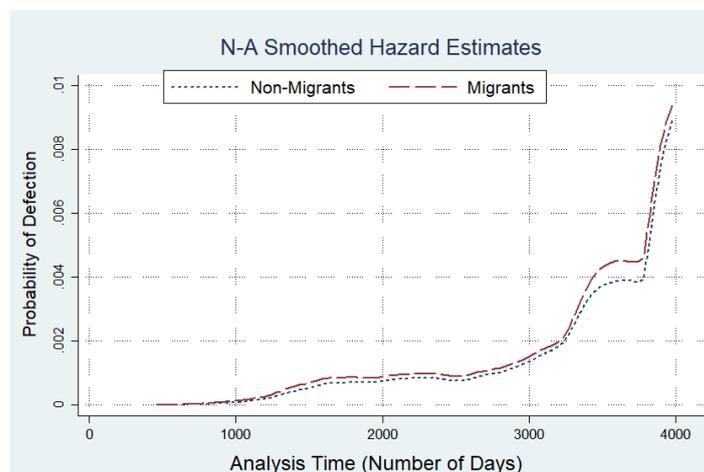


Figure 6. Nelson–Aalen (N-A) smoothed hazard estimates per migration.

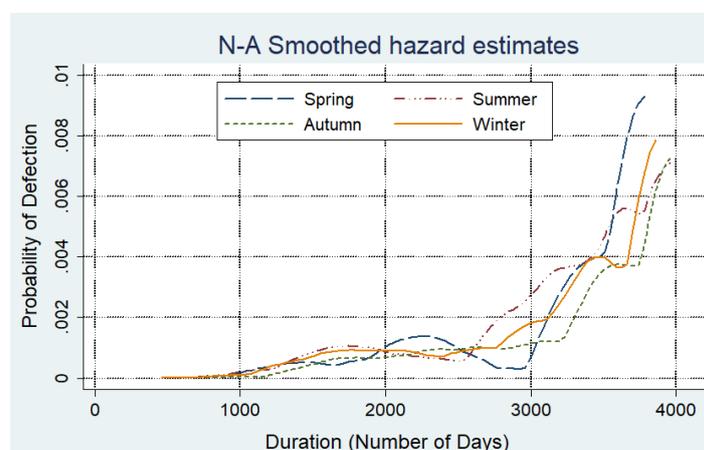


Figure 7. N-A smoothed hazard estimates per season.

5.2. Hypothesis Testing Using Weibull Model

In this section, we compute survival analysis using the Weibull model developed in Section 4.3 based on migration, defaulter, and season of acquisition status.

5.2.1. Analysis Based on Migration Status

The coefficients of regression Model-1 in Equation (8) (with dummy variables representing the category of customers) and Equation (9) (without dummy variables) have been computed and are presented in Table 8. Higher values of LL scores for each case indicate better model fit to the given data. The results in Table 8 show that migrant customers are likely to survive less, i.e., defect earlier, by at least 6.3% (without using a dummy) and 4.3% (with using a dummy) of their maximum survival period compared to non-migrants. This effect remains significant even after the introduction of dummy variables for residential categories of customers as the p -value obtained in the regression analysis is less than 0.05. For other categories of customers, migrants are likely to survive longer than non-migrants, indicating that migrants are economically more active than non-migrants in business and professional contexts.

Table 8. Effect of migrant status on survival and defection.

	Without Dummy	With Dummy
Variables	β , std. error, p -value	β , std. error, p -value
Migrant	−0.0628479, 0.0029049, <0.001	−0.0430897, 0.0029593, <0.001
Residential	-	−0.0217457, 0.0185938, 0.248
Business	-	0.1009762, 0.019488, 0.005
Special	-	0.1999832, 0.0219796, <0.001
PCO	-	0.1281091, 0.0216263, <0.001
Employee	-	0.1754051, 0.0252575, <0.001
Student	-	0.1172348, 0.0238653, <0.001
Constant	7.884828, 0.0022501, <0.001	0.12085, 0.0249517, <0.001
LL score	−382,275.14	−381,687.54

5.2.2. Analysis Based on Migration and Defaulter Status

The coefficients of regression Model-2 in Equation (10) (with dummy variables representing the category of customers) and Equation (11) (without dummy variables) have been computed and are presented in Table 9. Higher values of LL scores for each case indicate better model fit to the given data. The results in Table 9 show that migrant customers are likely to defect earlier by at least 7% (without using a dummy) and 3.9% (with using a dummy) of their survival period, and they are likely to not pay the last bill 25.4% (without using a dummy) and 26.6% (with using a dummy) more than non-migrant customers. This effect remains significant even after the introduction of dummy variables for categories of residential customers as the p -value obtained in the regression analysis is less than 0.05. For other categories of customers, migrants are likely to survive longer than non-migrants, suggesting that migrants exhibit higher economic activity levels than non-migrants in both business and professional spheres.

Table 9. Effect of migrant and defaulter status on survival and defection.

Variables	Without Dummy	With Dummy
	β , std. error, p -value	β , std. error, p -value
Migrant	−0.0700959, 0.0027422, <0.001	−0.0393353, 0.0027694, <0.001
Defaulter	0.2535734, 0.002749, <0.001	0.2655554, 0.0027097, <0.001
Residential	-	−0.0305521, 0.0173686, 0.079
Business	-	0.1464618, 0.0182132, <0.001
Special	-	0.2329298, 0.0205398, <0.001
PCO	-	0.1438926, 0.0202004, <0.001
Employee	-	0.1305498, 0.0235981, <0.001
Student	-	0.109356, 0.0233057, <0.001
Constant	1.224732, 0.0033877, <0.001	7.710924, 0.0174446, <0.001
LL score	−378,365.42	−377,343.45

5.2.3. Analysis Based on Season of Customer Acquisition

The coefficients of regression Model-3 in Equation (12) have been computed and are presented in Table 10. A higher value of the LL score in this case also indicates a better model fit to the given data. The regression results in Table 10 show that customers acquired in the summer and winter seasons defected earlier by 6.9% and 3.2% in terms of days, respectively, compared to the average survival period of customers acquired in the spring season. Additionally, customers acquired in the autumn season survived longer by 5.4% compared to those acquired in the spring season. These results are highly significant as the p -value obtained in the regression analysis is less than 0.05. According to the Nepali calendar, the major festivals (Dashain, Tihar, and Chhath) occur in the autumn season, while the Nepali New Year takes place in the spring season. During these times, companies launch promotional schemes, and consumers often purchase goods and services as part of the celebrations. The products and services bought during these auspicious occasions were found to be used for a longer duration. Therefore, the festivals and seasonal offers positively impacted customer lifetime value (CLV) and, ultimately, the profitability of the company.

Table 10. Effect of season of acquisition on survival and defection.

Season	β , Std. Error, p -Value
Summer	−0.0690684, 0.0047291, <0.001
Autumn	0.0549039, 0.0044198, <0.001
Winter	−0.032402, 0.0046238, <0.001
Spring	7.852515, 0.0037433, <0.001
LL score	−381,913.12

The findings of this research, summarised for each hypothesis, are presented in Table 11. The study found that migrant customers defect earlier than non-migrants, and the probability of involuntary defection among migrant customers is significantly higher than that of non-migrant customers. Additionally, customers acquired in different seasons exhibit varying survival probabilities, with those acquired in the autumn season having the highest survival probabilities and those acquired in the summer season having the lowest. The plots of survival probability and hazard estimates also showed a smoothly increasing

nature with respect to time, indicating the consistent trends revealed by survival and failure rate estimates. The results obtained from the Weibull model regression analysis precisely measured the average defection value of migrant customers, as well as season-wise customer acquisition.

Table 11. A summary of findings as per hypothesis.

Hypothesis	Statement	Supported?
H1	The probability of defection measured through survival analysis of migrant customers is higher (early in terms of survival duration) compared to non-migrant customers.	Yes
H2	The probability of involuntary defection by migrant customers is higher than that of non-migrant customers.	Yes
H3	Customers acquired in the different seasons have no effect on their survival duration.	Yes

5.2.4. Implications

The outcomes from this research can be applied in various business contexts. To make this feasible, the prerequisite is precise and systematic recording of customer activities related to their service subscription and cancellation. Marketing managers can capture potential factors of defection according to their own hypotheses and conduct empirical testing to identify latent issues in customer care management. Furthermore, marketers can design strategies to mitigate the risk of involuntary defection, particularly for migrant customers, and enhance profitability by offering new schemes aligned with the seasons that have the highest survival period and CLV.

The results obtained in this study are precise and useful from the CLV maximization perspective. This can be achieved through the careful selection and analysis of variables, including the season of customer acquisition, and ultimately developing appropriate marketing schemes. Considering the increasing trend of migration from rural to urban areas, as well as from underdeveloped/developing countries to developed nations, as highlighted in [Central Bureau of Statistics, Nepal \(2021\)](#); [Timsina et al. \(2020\)](#); [United Nations, Department of Economic and Social Affairs, Population Division \(2019\)](#) and the United Nations International Migration Reports of the last two decades, entrepreneurs can devise plans to mitigate the risk of defection, particularly involuntary defection.

The significance of customer defection and its impact have been emphasized in studies by the authors in [Agarwal et al. \(2011\)](#); [V. Chang et al. \(2024\)](#); [Reichheld et al. \(1990\)](#); [Yulianti and Saifudin \(2020\)](#). The empirical measurement of customer defection and the findings from this study can be useful in developing strategies to enhance customer retention and ultimately increase company profits. However, the business context and evaluations through internal and external factor analyses should be carefully considered before implementation.

6. Conclusions

This research identified the behaviour of migrant customers based on their defection patterns and involuntary defection in comparison with non-migrants. The study of survival probability and hazard of defection estimates indicated a higher risk of failure by migrant customers than non-migrants throughout the observation period. Additionally, the plot of the probability density of survival duration of customers to time in terms of the number of days, considering the random nature of the arrival of events, is positively skewed, with a mean survival period of 2159 days.

The analysis of survival probability and hazard estimates showed a consistent upward trend over time, indicating that the survival period follows a Weibull distribution. The results from the regression analysis using the Weibull model found that migrant customers are likely to survive less, i.e., defect early, by at least 4.3% of their maximum survival period compared to non-migrants. This effect is more significant on residential-type subscriptions of migrant customers, while other categories of migrants show a higher survival period than residential ones. This finding is in line with the argument that migrants are professionally and economically more active than non-migrants. The results also found that migrant customers are likely to involuntarily defect early by 3.9% of their survival period. Also, migrant customers are likely to defect without paying the last bill by 26.6% compared to non-migrant customers. The effect of seasonal variation in customer acquisition was studied for its relation to the survival period, which has implications for CLV analysis. This research found that customers acquired in the spring and autumn seasons survive longer as compared to winter and summer.

This study focuses on CDMA technology-based fixed-phone-service customers, without accounting for the potential impact of the increasing dominance of GSM technology-based mobile phone service customers over time. Additionally, the research does not incorporate the effects of acquisition schemes or promotional offers offered by the company during the observation period. This study also does not explore the reasons behind customer defections and their potential effects. These limitations provide valuable avenues for future research.

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Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy reason.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Business	Bus	Censored Subscriber	Cen-Sub
Customer Lifetime Value	CLV	Defaulter Status	DefStat
Duration	Dur	Employee	Emp
Failure Time	FT	Incidence Rate	IR
Involuntary Defection	Invol-Def	Kaplan–Meier	K-M
Kernel Density Estimate	KDE	Log-Likelihood	LL
Maximum Likelihood Estimation	MLE	Migrant Subscriber	Mig-Sub
Migrant Status	MigStat	Nelson–Aalen	N-A
Non-Migrant Subscriber	Non-Mig	Number of Subscribers	Num-Sub
Public Call Office	PCO	Residential	Res
Special	Spc	Shop-Keeper	SK
Student	Stu	Subscriber Category	SubCat
Subscriber	Subs	Subscriber IDENTITY	SID
Voluntary Defection	Vol-Def	Wireless in Local Loop	WLL

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