ENHANCING CUSTOMER RETENTION IN THE MOBILE INDUSTRY: A PROBLEM-SOLVING APPROACH

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ABSTRACT

This paper addresses the challenge of enhancing customer retention in the mobile industry through a problem-solving approach. It advocates for a balanced strategy that shifts emphasis from costly acquisition-focused marketing efforts to more cost-effective customer retention initiatives, grounded in the commitment-trust theory of relationship marketing (Morgan & Hunt, 1996). The current study extends this framework by incorporating predictive modeling based on transactional data from mobile users' problem experiences. A web-based survey was conducted to evaluate the impact of disruptive events on customer retention. Using Binary Logistic Regression analysis, the study identifies key variables affecting customer retention in a hierarchical order, including the type of service problem, the communication channel used for lodging complaints, the frequency of issues, and the level of trust. Moreover, this study introduces a data-based transactional metric, the Net Problem Score (NPS) designed to support proactive recovery strategies and reduce potential customer churn, especially among high-value customers, before negative feedback proliferates on social media. The paper concludes with managerial implications, highlighting the importance of enhancing employees' problem-solving and relational skills to strengthen customer retention efforts.

INTRODUCTION

Acquisition marketing campaigns are prevalent in many industries. Marketing expenses such as brand image advertising, customer and trade marketing promotions, and sales force expenditures, are extensively utilized to gain new customers and drive sales growth. In nowadays' high competition dynamics, these expenses are essential for companies, but they remain pricy. In the telecom industry, myrateplan.com shows that it takes - at least one year of customer relationship, depending on the plan type to make them profitable. Increasing a customer base is a rapid path to reaching short-term revenue, but selling to existing customers can be more lucrative because acquisition costs tend to erode profitability. Once customers have already been acquired, a retention marketing strategy becomes less expensive. According to Landis (2022), acquiring new customers can cost from five to seven times more than retaining existing ones.

Therefore, customer retention becomes the centerpiece of marketing strategy in many industries. In telecom, Bell Canada emphasizes retention processes to minimize customer damage caused by failures, aiming for enhanced loyalty (Dixon et al., 2010). Instead of solely focusing on satisfaction, Bell aims to reduce customer dissatisfaction to improve retention. Marketing research already clearly indicates that customers' experiences of problems increase the likelihood of churn (Buttle & Burton, 2002). Furthermore, the rapid introduction of new technologies in the market increases the results in higher chance of failures (Podolny & Hansen, 2020).

In today's rapidly evolving technological landscape, companies are directing their attention toward addressing the frequency of problems as they strive to minimize desertion. Unfortunately, failures occur more frequently than we often realize in many industries. In banking, customers experience at least one problem with their current bank (Duffy et al., 2006). Similarly, in the utility, customers experience a minimum of two problems with their service providers (Yang et al., 2011).

According to Dixon et al. (2010), 62% of customers have had to repeatedly contact a company to resolve an issue. Consequently, the recurrence of negative experiences erodes customer trust and intensifies the urgency to adopt a relationship-focused problem-solving approach.

Doneley & Cannon (1997) asserted that this approach relies upon promptly and respectfully addressing customer issues to uphold trust and reduce the likelihood of defection. The mediating effect of trust between problems and desertion is well documented in the marketing services literature (Morgan & Hunt, 1996; Frei & Morriss, 2020). Undoubtedly, sustaining customer trust becomes markedly easier when instances of service and device failure are minimized.

A customer relationship devoid of disruptive events occurs when customers seek basic pre- and post-purchase information. In this ideal context, customers search for transactional information such as price, product offerings, service advice, and several other informative queries in a detached manner (Mohammed, 2018). However, when problems arise, what was one a routine informational relationship translates into negative emotions (Herhausen et al., 2019). Depending on the significance of the problem, emotions can span a spectrum from anxiety, deception, and anger to disgust (Herhausen, 2020). To express dissatisfaction, displeased customers have multiple channels at their disposal (Naylor, 2016; Bapat & Williams, 2023). These channels provide opportunities for companies to engage and exchange information, thereby nurturing trust and maintaining the customer relationship.

The channel used by disappointing customers varies within the latter (Bapat & Williams, 2023). As a matter of fact, these complaint transmission channels can be classified into two categories: i) warmer, more personal relation channels such as call centers, and ii) colder, more distant electronic channels such as social media. Dixon et al. (2010) reveal that while 48% of customers with negative experiences share their discontent with 10 others, only 23% of those with positive experiences do the same. It's noteworthy that dissatisfied customers can use both personal and electronic channels to voice their problems. However, Dixon et al. (2010) also note that 59% of dissatisfied customers switch from web-based communication to phone calls to resolve their problems.

In an environment where service failures are commonplace, marketing retention emerges as a pivotal strategy, as incremental sales become more challenging to acquire. Prior marketing research, in the telecom industry in particular, has demonstrated that customer satisfaction is a prerequisite for increasing sales (Abu-ELSamen et al., 2011). Consequently, the link between up-sales and customer satisfaction is evident. As a result, customer satisfaction is valuable in scenarios where a relationship remains undisrupted within a simple informative context. Yet, when failures occur, a shift from a customer satisfaction strategy to a retention-oriented customer loyalty approach becomes paramount (Gao et al., 2022). In this context, marketers must pivot their attention to retaining them through effective customer relations. This paper centers on a problem-solving approach to customer retention when issues arise within the mobile industry using a commitment-trust theory perspective (Morgan & Hunt, 1996). It advocates for a balanced investments between costly acquisition-focused marketing to low-cost (cost-effective) customer retention one. Within this framework, emphasis is placed on enhancing mobile customer loyalty through a relational problem-solving approach. However, this approach must also incorporate accurate transactional data on customer issues to foster employees' ability to effectively manage relationship recovery.

Dixon et al. (2010) suggest utilizing transactional data to prevent complaints rather than solely focusing on managing emotionally dissatisfied customers. They propose a customer effort score (CSE) defined as “a customer’s intention to keep doing business with a company…” (Dixon et al., 2010, p. 121). This highlights the increasing need for companies to better anticipate customer dissatisfaction using various metrics. As an example, the Net Promotor Score metric is wildly used in the telecom sector, measuring customers’ engagement in social media as promoters, passives, and detractors. Additionally, Customer Lifetime Value (CLV) assesses the long-term value of a customer to a telecom provider based on the current relationship (Hughes, 2012). However, these metrics only serve to manage positive and negative comments on social media and assess customer value after interactions have occurred. As a result, they are less effective in predicting behavior before unexpected interactions with a mobile provider. Our framework proposes that transactional data can generate more useful metrics to predict dissatisfaction before customers engage with a telecom operator.

Predictive analytics models offer several valuable applications within the realm of complaint behavior literature. For example, they can be used to predict future complaints, manage dissatisfaction before employee interaction, develop a relationship strategy prior to a formal complaint, and enhance employees' service recovery abilities. Our problem-solving framework emphasizes the importance of a Net Problem Score (NPS) metric, leveraging transactional data from past disturbing issues to more accurately predict dissatisfaction and increase the likelihood of customer retention.

A significant volume of marketing service research delves into the impact of problems, service recovery, and customer trust on satisfaction and loyalty (Buttle & Burton, 2002; Bougie et al., 2003; Wirts & Mattia, 2004; Dixon et al., 2010; Herhausen et al., 2019; Frei & Morriss, 2020; Nowak et al., 2023). However, none of these studies have directly compared which of these variables exert the most influence on customer defection. So to say, which specific problem type exhibits the most significant effects on desertion? To bridge this gap in marketing literature, a quantitative methodology is employed through a web-administered survey of mobile user behavior. A binary logistic regression model (BLRM) is used to assess the relationship between these variables. Technically, this model is designed to assess how independent variables influence the binary target variable of defection intention.

The paper concludes with managerial implications and recommendations centered on implementing a relational problem-solving approach to retaining mobile users after a failure.

CONCEPTUAL FRAMEWORK, RESEARCH OBJECTIVE AND HYPOTHESIS

The mobile industry presents an appropriate field for investigating the impact of problems on customer desertion due to its frequent occurrence of failures (Podolny & Hansen, 2020). The swiftly evolving mobile landscape serves as an ideal real-world testing laboratory for assessing the framework proposed in this research. While marketing service literature emphasizes the significance of this approach (Herhausen et al., 2020), it fails to distinctly delineate between marketing acquisition and marketing retention within the context of customer mobile failures. Logically, marketing acquisition campaigns center around cultivating customer satisfaction to gain them, whereas marketing retention endeavors hinge on ongoing business relationships.

Conceptual Framework

Marketing campaigns are founded on satisfaction, drawing from deep-rooted customer behavior theories dating back to the seventies (Paz & Vargas Rodriguez, 2023). Thus, customer behavior is harnessed to meet their satisfaction (Larsen & Wright, 2020). In such scenarios, companies need to focus on a customer-based relational retention strategy. Our research centers on Morgan & Hunt’s (1996) relationship marketing theory, which emphasizes the role of commitment and trust in driving customer retention. Therefore, our framework suggests that trust is a fundamental concept for fostering customer retention through effective relationship marketing.

Among various definitions, Morgan & Hunt (1996) define relationship marketing as 'all marketing activities directed at establishing, developing, and maintaining successful relational exchanges' (p. 22). We argue that trust plays a pivotal role in effective service recovery strategies to retain dissatisfied customers after a failure. Thus, trust is positioned as a central variable linking the antecedents of problems to potential customer defection after a service failure.

As Hoyer et al. (2018) asserted, consumer buying behavior encompasses psychological dimensions that require alignment with our conceptual framework. Their decision model focuses on motivation, exposure, attention, perception, and information understanding in the decision-making process. However, these aspects must integrate within a customer retention model, especially when customers encounter disruptive events.

Therefore, the model must evolve to alienate with customer retention percept, where:

- needs awareness transforms into problems awareness;
- information gathering centers around failures information;
- choice evaluation becomes an establishment of trust;
- buying behavior translates into behavior that fosters loyalty;
- post-customer experience directs attention to the channel used for reporting their problem and experience.

In summary, a problem-solving approach requires companies to prioritize building customer loyalty through trust-based relationship marketing. Figure 1 highlights the value of adopting a relational problem-solving strategy to enhance customer retention.

Figure 1
A Customer's Relational Problem-Solving Approach

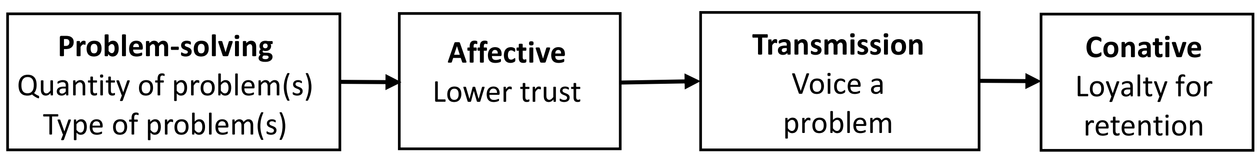


Figure 1 illustrates our problem-solving approach, rooted in the relational trust perspective of Morgan & Hunt's (1996) theory, which addresses discomfort arising from four key facets: i. The customer's cognitive processing of the frequency and nature of undesirable events generates dissatisfaction and prompts efforts to resolve the issue. ii. Trust is critically challenged when these unsatisfactory situations occur. iii. The channels used for post-experience interactions can lead to discomfort, especially in problematic situations. iv. Personalized relational interactions are critical for retaining customers during these challenging situations.

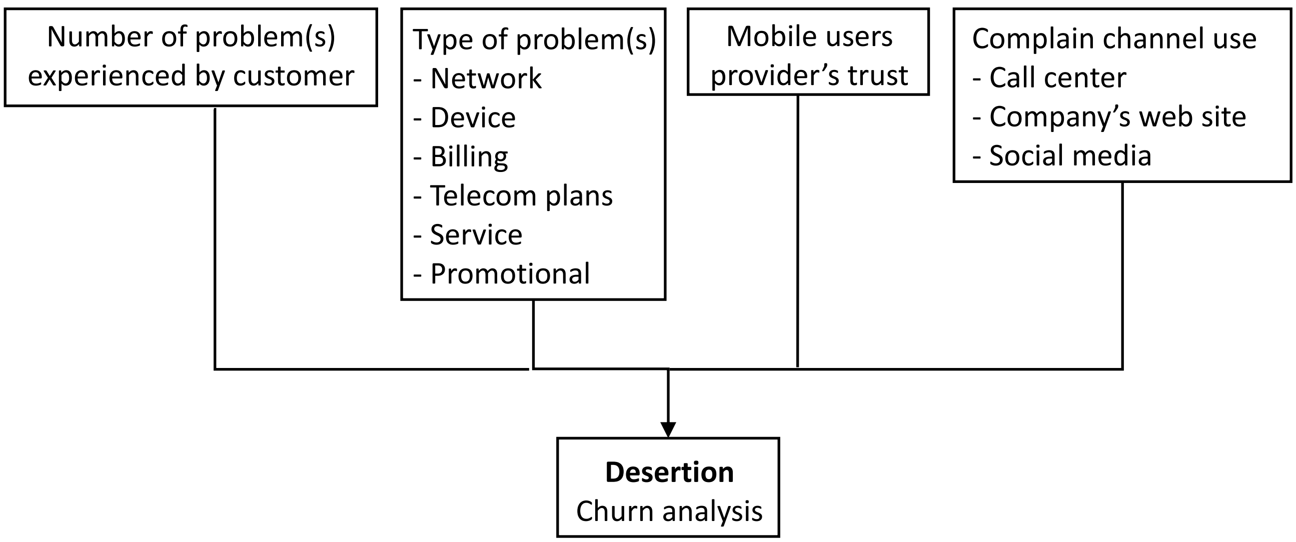
Research Objective and Hypothesis

Figure 2 serves as a tangible manifestation of the relational problem-solving framework introduced in Figure 1, intended to empirically assess the impact of failures on customer desertion within the mobile industry. While marketing literature explores how customer problems impact trust that subsequently results in dissatisfaction (Buttle & Burton, 2002; Wirts & Mattia, 2004; Dixon et al., 2010; Herhausen et al., 2019; Frei & Morriss, 2020), there remains - to the best of our knowledge - a conspicuous absence of studies comparing the impact of these variables on customer desertion, at least within the mobile industry. Consequently, our central research objective is to address this void in marketing literature by juxtaposing the magnitude effects of variables within a problem-solving framework, thereby elucidating the phenomenon of mobile user desertion. More precisely, within a context of failure, existing marketing literature does not delve into whether the magnitude effects of relational variables, such as service problems, trust, and the utilization of warmer communication channels, bear a higher impact on desertion compared to more transactional variables, like device problems and the usage of electronic communication channels.

Within Figure 2, a multivariate model is employed to scrutinize four primary categorical variables: frequency of problems, problem type, customer trust, and channel usage to ascertain their individual contributions to desertion. Consequently, the central hypothesis of our problem-solving approach framework posits that relational variables (specifically, service problem type, reduced trust, and heightened use of warmer call centers) heighten the likelihood of desertion more than their transactional counterparts. It's worth noting that transactional variables encompass problem count, types of transactional problems (network-related, device-related, billing-related, telecom plans-related, and promotional-related), as well as the usage of electronic channels (website and social media) for reporting problems.

Graphically, the present research's aim and main hypothesis are shown as follow (Figure 2):
Figure 2 about here.

Figure 2
A Comparison of Magnitude Effects in a Relational Problem-Solving Approach to Explain mobile User Desertion.



METHODOLOGY

Sampling Method

A web survey was conducted in the province of Quebec, Canada during the summer of 2019. To manage costs, a specialized market research firm was entrusted with administering and following up on the survey. A sample size of 500 was deemed appropriate due to the frequent occurrence of problems within the mobile telecom industry, attributed to rapid time-to-market implementation and swift technological advancements (Podolny & Hansen, 2020). The average completion time for the questionnaire was 9 minutes, with a standard deviation of 5 minutes. To ensure the questionnaire's structural integrity and enhance question quality, a pretest was conducted. The pretest also highlighted the necessity of a minimum completion time of 3 minutes per questionnaire. Consequently, to maintain data validity, 67 questionnaires completed in less than 3 minutes were discarded from the analysis. This led to a final dataset of 436 valid and fully completed questionnaires. Participant selection for questionnaire completion was based on criteria including mobile phone ownership, minimum age requirement, and a history of experiencing at least one problem with their current phone provider within the Quebec province.

Respondents were required to fulfill specific criteria to participate in the survey. These criteria included owning a mobile phone, being above the age of 18, residing in Quebec, and having encountered at least one issue with their current mobile provider within a year.

Once these prerequisites were met by answering each question related to the selection conditions, participants were then directed to respond to a series of 22 questions. These questions covered a range of topics, including the details of their problem experience, their usage patterns concerning telecom and mobile phones, compensation offers related to promotions, the primary channel they utilized to report their problems and socio-demographic inquiries.

Sample Profile

The following tables depict the representativeness of our sample within the context of the Canadian telecom market. Although conducting a direct comparative analysis of complaints information between our sample and the Canadian Commission for Complaints of Telecom-television Services (CCTS) annual 2020-2021 report is challenging, Table 1 does reveal certain similarities. Notably, the CCTS report does not explicitly display instances of network shortages leading to complaints, as this specific data falls within the purview of the operators and is considered "Out of CCTS mandate." Thus, a proxy measure can be established by utilizing this category to partially gauge network problems and compare them with our sample. Comparisons can be drawn between our sample's billing, telecom plans, and service complaint categories and the CCTS's billing, contract, and services complaint categories, except for device problems in our sample.

Table 1:
CCTS 2020-2021 Annual Report Comparison with the Research Sample

CCTS (n)	Total (%)	Sample (n)	Total (%)
Out of CTTS mandate (16477)	36	Network (312)	31
Billing (12809)	25	Billing (184)	18
Contract (8710)	22	Device (177)	18
Services (7855)	17	Service (123)	12
Accessibility (133)	0.3	Telecoms plans (121)	12
		Promotional (87)	9
Total (45984)	100	Total (1004)	**100**

The sample effectively represents the key players in the Quebec province's telecom sector, as indicated by data from Glassdoor.com. Bell Canada takes the lead in the market, closely followed by four other industry competitors (Table 2). Additionally, Table 2 underscores the fact that the profile of respondents in the telecoms sample aligns with the prevalent high mobile phone usage trends across Canada. The average mobile phone usage duration of six years signifies a significant penetration rate of this device within the Quebec population. Furthermore, Table 2 highlights substantial mobile phone usage for activities such as messaging, emails, and internet browsing, in line with the broader telecom usage patterns in Canada, as observed on myrateplan.com.

In terms of socio-demographic profile in the sample, table 3 shows a representative sample in regard of the Quebec population with sex, age, education, revenues, and household composition (point2, 2021). Consequently, the sample effectively mirrors both the telecom usage patterns and demographic profile of the broader Quebec population.

The next section explains the statistical algorithm employed to compare the effects of magnitude variables within the proposed problem-solving approach framework.

Table 2
Respondents Telecoms Usage.

Providers	Total (%)	Telecom profile usage	Mean
Bell	25	Number of years of phone usage	6
Telus	22	Phone calls per month	58
Videotron	22	Text messages per month	205
Rogers	17	Emails per month	75
Fido	14	Internet connexions per month (in minutes)	117

Table 3
Socio-Demographic Sample Profile (n=436)

Sex	%	Age	%	Education	%	Revenues	%	Household	%
Woman	53	18-34	30	Secondary	18	Less 35000$	25	1 person	21
Man	47	35-54	39	College	34	35000-69999	36	2 persons	47
		55 +	31	University	48	70000$ higher	39	3 persons +	32

Variables in the Binary Logistic Regression Statistical Model

Churn analysis serves as a fundamental measure within the mobile industry for assessing customer defection. It is frequently employed to discern the underlying causes of either desertion or retention, subsequently informing the implementation of tailored marketing strategies. Given that churn represents a binary variable (either leaving or staying with the mobile provider), a logistic regression model stands as an appropriate methodology for this research. This model hinges on comparing the odds of an event occurring against the odds of that event not occurring. The problem-solving framework introduced here suggests a combination of variables that exert a positive or negative influence on the likelihood of both high and low desertion probabilities. Respondents were asked about their intention to switch from their current mobile provider following a problem, using a 10-point scale.

Table 4 illustrates how the two distinct groups were formed. The original continuous scale was dichotomized into a two-level binary target variable, thereby mimicking a tangible telecom churn analysis scenario. By adopting a non-metric target variable, the application of an effective binary logistic regression model becomes feasible, much like in an actual mobile business setting. It's worth noting that employing case-wise deletion through logistic regression can diminish the number of cases in the model, thereby impacting the sample size. However, the advantage lies in the fact that non-metric independent variables can be effectively used within a binary logistic regression model. The subsequent section elaborates on how the variables were manipulated to construct our model.

Table 4 below shows the original target variable results in the survey. From the initial 10-point interval scale, a subset consisting of the third lowest intervals (1-3; n: 148) was utilized to form the low desertion intention group. Conversely, the third highest intervals of the original scale (8-10; n: 76) was employed to establish the high desertion intention group. In total, 224 respondents from the initial pool of 436 were retained for further analysis.

To verify the effectiveness of the two-group non-metric desertion intention variable, a discriminant analysis was performed using the transformed non-metric variable as the target and the original continuous variable as the independent variable. As anticipated, the Wilks Lambda statistic (0.06) revealed a substantial relationship between the two variables, leading to the rejection of the null hypothesis (p: 0.00; df: 1). The canonical correlation statistic indicated that the original metric variable accounted for 94% of the variance observed in the target variable.

Table 4
Intention to Leave the Mobile Provider after the Problem

	Cases (n)	Cases (%)	Desertion
1- No intention to leave	57	13	Low intention (n:148;34%)
2	40	9	
3	51	12	
4	45	10	Excluded from the analysis (n:212;49%)
5	77	18	
6	48	11	
7	42	10	
8	32	7	High intention (n:76;17%)
9	15	3	
10- High intention to leave	29	7	
Total	**436**	**100**	

Remarkably, the function centroids yielded values of -2.7 for low desertion intention and 5.3 for high desertion intention, reaffirming a substantial separation between the centroids of the two groups within the discriminant function. Therefore, the transformed binary target variable performed very well and is statistically significant.

Table 5 illustrates the non-metric target variable with two distinct levels within the binary logistic model. Out of the initial 224 cases stemming from the transformed target variable of the two groups, 219 cases were considered for analysis, accounting for instances of case-wise deletion in the model. Precisely, five cases were omitted from the analysis due to missing values about one of the predictor variables. Furthermore, table 5 below shows that the high desertion intention group has been coded as 1. As a result, for an accurate interpretation of the target variable, the impact of a predictor variable should be understood as a heightened likelihood of opting to switch mobile providers. The next paragraphs explain how the predictor variables were manipulated and subsequently utilized within the current binary logistic regression model.

Table 5
Codification of the Target Variable in the Binary Logistic Regression Model

Desertion intention after the problem Dependent variable (n:219)	
Low desertion (n=143)	0
High desertion (n=76)	1

Within our framework (Figure 2), two independent variables are measured as continuous (e.g. frequency of problems and trust) and two are non-metric variables (e.g. problem type and complaint channel used). The first metric is the frequency of problems with their current provider. Participants were asked to report the number of problems they experienced with their current mobile provider. Specifically, respondents report they experienced three problems with their current provider on average. Naturally, it is expected that as customers encounter more issues, their likelihood of leaving increases (Dixon et al., 2010). Consequently, the presence of a significant positive effect of problems within the model could indicate a corresponding positive influence on desertion.

Next, we employed an adapted version of Doney & Canon's (1997) supplier trust measurement on a 10-point scale (ranging from 1, signifying "not agree at all," to 10, representing "totally agree") to assess mobile users' level of trust following a problem occurrence. A high Cronbach's alpha reliability coefficient of 96% provides a strong affirmation of the consistency and dependability of this unidimensional scale. Table 6 shows the unique dimension of that scale with a Bartlett sphericity test of 4531 (df:36; p:0.00). The reduction of the eight items accounts for 76% of the total variance of the post-problem trust factor. Consequently, the binary logistic model used an additive scale as an independent continuous variable.

Table 6
Factorial Analysis Component Matrix of Mobile Users' Trust in the Provider after the Problem.

	Trust factor
1- My mobile provider keeps promises it makes to me	0.89
2- My mobile provider is always honest with us	0.92
3- I believe the information my mobile provider provides me	0.88
4- My provider is genuinely concerned that I succeed with his phone services	0.88
5- My mobile provider considers my welfare as well as its own	0.81
6- I trust my mobile provider keeps my best interests in mind	0.90
7- My mobile provider is trustworthy	0.88
8- I don’t find necessary to be cautions with my mobile provider	0.83

The two other independent variables included in the logistic model are categorical. The first one in Table 7 represents the percentage of respondents who responded affirmatively to specific problems they encountered with their current mobile provider. As a customer might face multiple problems with their provider, the possibility of multiple responses exists. Consequently, the total percentage surpasses 100%, encompassing a total of 427 experienced. Among these six variables, five are associated with transactional and administrative problem types, encompassing network problems (unreliable connection and network shortages), device problems (Internet, messages, display, and phone), billing problems (contract and billing errors), telecom plans problems (improper mobile plan and changes without notice), and promotional problems (improper cashback and unmet promotion expectations). In contrast, the single relational problem type variable depicted in Table 7, pertains to specific service problem (poor service support, rude and incompetent employees). Table 7 shows that, out of the five transactional and administrative variables, three frequently reported problems encompass network, device, and billing issues. Additionally, the relational service problem constitutes 26% of the overall database.

The second categorical predictor integrated into the model pertains to the main complaint channel utilized by customers to communicate their problems. This variable is also important to consider within the framework, given the diverse avenues through which customers choose to voice their complaints (Naylor 2016; Bapat & Willians, 2023). As outlined in Table 8, the call center, a warmer relational channel, emerges as the most employed means to report problems, followed by external colder electronic channel, such as the company's website and social media platforms. Notably, consumer complaint associations and government websites were omitted from the analysis due to their infrequent usage. Additionally, it's worth noting that 3% of cases within the analysis were excluded due to the lack of usage of any reporting channel.

Table 7
Type of Problem in the Binary Logistic Regression Model

	Problem type % of yes (n)
Network problem (unreliable connexion and network shortage)	63 (138)
Device problem (Internet, messages, display, and phone problem)	36 (79)
Billing problem (contract and billing errors)	35 (76)
Service problem (poor service, rude and incompetent employees)	26 (57)
Telecom plans problem (improper plan and changes without notice)	22 (49)
Promotional problem (unmet promotions)	17 (28)
Total	**199 (427)**

Table 8
Main Complaint Channel Used by Mobile Users in the Binary Logistic Regression model.

	Channel usage % of yes (n)
Call center	64 (140)
Company’s Web site	16 (36)
Social media	10 (21)
Consumers complain association	4 (10)
Government Web site	3 (6)
No complain channel used	*3 (6)*
Total	**100 (219)**

Tables 7 and 8 showed respondents who answered "yes," coded as 1 in the database, in instances where they encountered a specific problem type and employed a particular channel to report the problem. Conversely, when mobile users did not experience a problem and did not use a channel to report their problem and refrained from utilizing a reporting channel, they were coded as 0 in the logistic regression model's database. Consequently, the impact of these variables within the model should be interpreted in the context of whether they did or did not experience a problem or use a reporting channel.

In summary, thirteen of the relational problem-solving framework's four primary category variables have been incorporated into the logistic model. Two of these variables are continuous, one representing the frequency of problems and the other an additive scale for measuring trust. The remaining two are non-metric variables, encompassing six problem types and three primary complaint channels, and their effects on the binary target variable are compared (see Figure 2). The forthcoming section explains the statistical model results.

MODEL RESULTS

Binary Logistic Regression Model Goodness of Fit

To ascertain the relative magnitude effects of the independent variables, the ascending Wald method was employed for variable selection within the logistic regression model. This method uses a likelihood function calculation to introduce the most important independent variables in the model while excluding the effect of others.

Table 9 below reveals that among the thirteen independent variables, four exhibit significance in explaining desertion intention. The model's quality relies on several statistics. Firstly, the log-likelihood statistic of 173.9 presents a good fit for the model, effectively mirroring the original dataset. Secondly, the R2 statistics of the logistic regression model demonstrate the proportion of independent variables that account for the overall variance in the target variable. The R2 Cox and Snell of 39% being just 1% below the ideal 40% threshold criteria, is deemed satisfactory. Meanwhile, the Nagelkerke R2 of 54%, although less stringent than Cox and Snell criteria, still attests to a substantial proportion of independent variables effectively explaining the desertion target variable in the model. Finally, a chi-square value of 10.6 (df:8; p:0.22) coupled with the Hosmer & Lemeshow test implies that the model doesn't deviate significantly from a perfect fit. Consequently, the model exhibits an appealing goodness of fit and is interpretable.

Table 9
Binary Logistic Regression Model Results

	Beta	Exp(B)	Wald	P value
Service problem	1.7	5.4	15.9	0.00
Social media complaint channel	1.4	3.9	3.8	0.05
Number of problems	0.2	1.3	10.6	0.00
Trust	-0.1	0.9	24.4	0.00
Constant	1.3	3.9	3.0	0.08

Likelihood: 173.9; R^2 Cox and Snell: 39%; Nagelkerke R^2: 54%; Hosmer and Lemeshow chi-square: 10.6 (df:8; p:0.22).

Binary Logistic Regression Model Interpretation

With all independent variables included in the model, it is evident that the service problem type exerts the most substantial influence on desertion intention. It's important to observe that among the six problem types considered, only the relational service problem significantly impacts desertion intention. Specifically, the Exp(B) coefficient indicates that for each additional service problem reported, as opposed to when such problems are not reported, the odds of leaving the provider increase by a factor of 5.4. The second most significant effect in the model pertains to the channel used to convey complaints. Notably, among all the variables and the three channels utilized by dissatisfied customers, electronic social media has the most pronounced impact on desertion intention. Specifically, the Exp(B) coefficient indicates that each additional unit increase in the use of social media to report a complaint, as opposed to not using it, enhances the odds of leaving the provider by a factor of 3.9. The third effect in the model pertains to the frequency of problems. The Exp(B) coefficient reveals that for each additional problem experienced by a mobile user, the odds of leaving the provider increase by a factor of 1.3. The final effect in the model concerns the relational variable of trust, which logically displays a negative beta coefficient. The Exp(B) can be interpreted as a decrease of one unit in trust increasing the likelihood of desertion by 90%.

The last step in interpreting the results concerns the predictive validity of the model, which is essential for reliable decision-making. Predictive validity holds the utmost significance as it assesses the model's quality (Hair et al., 2019). A classification matrix assesses the model's validity by comparing the observed low and high desertion intention with the predicted two groups generated by the model. Table 10 shows the extent to which the predicted levels of the target variable correspond with the originally observed target variable.

Overall, the logistic model accurately predicts desertion intention at 85% (132+53/219 a significantly higher rate compared to the 68% proportional chance criteria calculated as the square of 65% (143/219) for the low desertion group and the square of 35% (76/219) for the high desertion group, along with a margin of 25% (0.652 + 0.352 * 1.25 = 68%). Additionally, the logistic model demonstrates effective prediction for both levels of the target variable. The low desertion group is accurately classified at 92%, while the high desertion group is classified at 70%. As a result, the classification matrix indicates a robust overall prediction for explaining mobile users' desertion intention, though it could perform better for the high desertion group. Specifically, the predicted classification rate of 70% for this group is only slightly higher than the overall 68% proportional chance criteria.

Table 10
Binary Logistic Regression Model Predictive Validity with Classification Matrix

	Predicted desertion intention			
		Low (n)	High (n)	Correctly classify % (n)
Observed desertion intention	Low (n)	**132**	11	92 (143)
	High (n)	23	**53**	70 (76)
				85 (219)

DISCUSSIONS AND MANAGERIAL IMPLICATIONS

Problem-Solving Approach Framework Implementation

The findings of the study provide support for both the relational and transactional aspects of the proposed problem-solving approach hypothesis, as evidenced by the four variables that significantly impact desertion intention. While Morgan & Hunt's (1996) commitment-trust theory offers a valuable framework for implementing a relationship marketing retention strategy, our research extends their theory by incorporating transactional problem types. This integration allows for more effective management of customer dissatisfaction, providing a more holistic approach to retaining customers after service issues arise.

Relational factors like service problems and trust are key in driving customer desertion. Conversely, transactional variables such as the number of problems experienced and the use of social media channels also contribute to increased customer desertion. The magnitude effects of these variables on desertion intention follow a sequence: the most significant is the relational service problem, followed by the transactional electronic social media usage, the frequency of problems, and finally, the relational trust of mobile users. These results affirm the importance of implementing a relational problem-solving approach to mitigate desertion, while also acknowledging the relevance of transactional variables. This necessitates adjustments in marketing strategies and information systems to effectively manage problems and reduce service failures.

Mobile providers should restructure their marketing departments and information systems to account for the detrimental impact of problems on potential desertion. Marketing managers should incorporate new processes for identifying problems in information systems and adopt new metrics for assessing marketing effectiveness. Ultimately, the proposed problem-solving approach can enhance customer retention, but its success hinges on the redefinition of responsibilities for both back-end and front-end marketing employees. This comprehensive approach aims to address the root causes of customer dissatisfaction and provide effective solutions, ultimately contributing to higher customer loyalty as an effective retention strategy. However, our model must also emphasize achieving a better balance between expenditures on the proposed retention strategies and acquisition marketing campaigns.

Retention and Acquisition Marketing Campaigns

Customer acquisition and retention are two distinct marketing processes (Hughes, 2012). Acquisition campaigns focus on reducing customer attrition by attracting new customers, while retention efforts aim to generate profits from existing customers through building strong, quality relationships. Despite their differences, these two processes must be integrated and balanced within a cohesive marketing strategy (Rhouma & Zaccour, 2018).

Our model centers on retention marketing, applied after a mobile operator has gained new customers. Unlike acquisition campaigns, which are influenced by a company's own efforts as well as external, uncontrollable factors such as competitors' actions, a retention strategy depends solely on a company's internal relational processes and strategy. Nonetheless, acquisition efforts must still coordinate with our retention-focused problem-solving framework for four key reasons.

Firstly, a company's acquisition marketing campaign is often tailored to meet the specific needs and desires of newly acquired customers. Our model demonstrated that building trust through strong relational processes is effective not only for retention but also for acquisition (Reif et al., 2019).

Secondly, it is possible for a mobile provider to gain new customers as a result of competitors' failures. As shown in our retention model, the frequency of negative experiences and the use of social media to report issues significantly increase the likelihood of customer churn. Our model shows that these variables are critical and remain essential even though they are caused by competitors. These variables, while originating from competitors, remain critical to our predictions. Thirdly, attractive competitor offers—such as advertising campaigns, new mobile services, and promotional incentives—are designed to stimulate customer acquisition. In a highly competitive and mature telecom industry, these offers often drive acquisitions among mobile providers. However, our model emphasizes that newly acquired customers must still be retained through strong relationship quality. Since acquisition and retention strategies should be part of a comprehensive relationship management approach, mobile managers must maintain a balanced ratio of 5:1 in spending between acquisition campaigns and customer retention investments (Landis, 2022).

Fourth, while acquisition and retention marketing expenditures are costly, they are necessary (Furman & Murat Kristal, 2021). Therefore, a balance between acquisition and retention is crucial, as acquisition campaigns are both attractive and necessary (Hughes, 2012). However, acquiring new customers is five times more expensive than retaining existing ones. With the same marketing budget, overspending on acquisition means reduced investments in retention. Our proposed model avoids the financial pitfall of excessive acquisition spending, which can create a dependency, or "hostage" situation, to acquisition costs. Our proposed retention model must also take into account that mobile providers need to adapt their marketing strategies not only to gain market share and drive growth through various acquisition efforts but also to implement internal processes aimed at retaining newly acquired customers. Rhouma & Zaccour (2018) demonstrated that customer equity increases more significantly when acquisition and retention costs are integrated into a unified strategy. Our model highlights the importance of balancing marketing investments between customer acquisition and effective post-acquisition retention.

The following section further explores how attractive promotional incentives can function both as powerful retention tactics and effective tools for customer acquisition.

Promotional Incentives and Compensation Effects After Failures

Tax et al. (1998) highlight the importance of the justice construct in retaining customers following a complaint. They define justice as the right of a customer to seek redress for perceived harm caused by service failures. According to the same authors, justice is subdivided into three distinct dimensions: procedural justice (pertaining to the speed of the recovery process), interactional justice (associated with the quality of employee interactions), and distributive justice (centered on compensation sought by dissatisfied customers). However, distributive justice implies costs for recovery, thus compensating dissatisfied customers. Frei & Morriss (2020) assert that the distributive justice dimension should be approached cautiously, as it may inflate the viral impacts of incentives offered by the company to other customers through social media. However, dissatisfied customers tend to share and exchange information about the compensation they receive, leading to a social magnification effect (Harris et al., 2013). It is argued that distributive justice could potentially serve as an opportunity to enhance customer retention rather than fostering a negative viral effect (Naseem et al., 2024).

To correctly compensate customers, the integration of value-added economic incentives is pivotal. Moreover, promotional offerings could be offered for a finite period, such as free new services, rebates on existing mobile services like data storage, or additional memory surcharge alerts for phones. Furthermore, co-branded promotions involving price reductions in collaboration with restaurants, gas stations, cinemas, amusement parks, and other promotional partners can mitigate customer defection. Value-added promotions, such as contests to win free cinema tickets, access to sports events, and partnerships with other businesses, are likely to generate positive word-of-mouth promotion. In a collaborative design, these partners would share the costs of these incentives. Additionally, compensatory measures provided by mobile service providers, such as rebates, price reductions, and high-value promotions, present an opportunity to enhance the viral effects on social media and customer retention Furthermore, managers should deploy transactional data as a predictive tool to enhance the efficiency of back-end service recovery by employees.

From a Relationship Approach to a Transactional One

Problems experienced by customers must be integrated into a broad effective customer marketing value measure (Dixon et al., 2010; Davidow, 2014). The analytical activities of the back-end marketing team should focus on constructing a Net Problem Score (NPS) based on transactional data to enhance customer retention for dissatisfied customers and develop predictive models within a valuable relational problem-solving approach. A Net Problem Score (NPS) usage within an organization creates value by way of reducing customer defection (Davidow, 2020; Mahajan, 2020; Wiesel, 2022). Moreover, predictive models are useful in predicting desertion prior to customers severing ties with their mobile operators (Gao et al., 2022).

The NPS metric is derived from the customer lifetime value concept (Wiesel, 2022, p. 179) and is defined as the quotient of customer value divided by the number of problems encountered by the customer. Customer value within the telecom industry can be evaluated through various methodologies (Markey, 2020). This may involve standardized, percentile, or decile value measurements, encompassing a composite lifetime value assessment of relationship duration, service usage extent, and service utilization frequency (Gao et al., 2022). For instance, consider a scenario in which a customer encounters three problems, maintains a 10-year relationship, uses three distinct services (e.g., mobile phone, Internet, and cable TV), and actively engages with each service. In this instance, the customer's value would be substantial, such as 90. Consequently, the customer's NPS would be calculated as 30, reflecting the customer value of 90 divided by the three problems faced. This strategic approach would expedite the identification of potential defectors by sorting the customer retention list based on the highest NPS. Furthermore, the NPS metric would effectively predict and prevent potential desertion among high-value customers, aligning with the principle of prioritizing the retention of higher-value customers over those with lower value. Since the usual lifetime value concept doesn’t integrate cost measures, the application of NPS can be effectively paired with cost-based problem-solving metrics.

In cases where a high NPS is observed, it is pertinent to incorporate cost metrics specific to that customer. Essentially, cost metrics pertain to the number of interactions required to solve a problem such as administrative expenses, material costs, equipment expenses, usage of information systems, expenditures tied to employee time dedicated to problem resolution, and the financial resources allocated for customer compensation. The idea is to compute the cumulative costs associated with the entirety of a customer's problems and failures. This computation could extend to encompass a particular timeframe, evaluating the total costs for each of the six problem categories observed in our research as well. As an example, the calculation of total costs for network shortages becomes feasible. Network shortages impact a subset of the customer base, leading to dissatisfaction and an elevated likelihood of defection. In sum, a particular emphasis on business process metrics to increase customer value while concurrently mitigating customer costs is essential key for our framework.

As shown in this research, transactional and administrative problem types such as network shortages, device problems and billing and telecom plans errors are pervasive occurrences that can be readily discerned within back-end information systems. For instance, the illustration of network shortages permits determining the frequency of customer impact and gauging their influence on the net problem metric, thereby enhancing customer retention. When a customer encounters a transactional problem, it is imperative for back-end information systems to promptly identify these instances and automatically compute an effective net problem score for each of them. Moreover, the integration of a back-end automated customer list facilitates swift intervention for immediately adjusting the situation upon the occurrence of a problem, thereby curtailing the risk of customer defection. Currently, mobile providers tend to undervalue customer problems and regrettably, such crucial marketing metrics are not assimilated into their existing business processes.

Secondly, the net problem score (NPS) should leverage the implementation of relational strategies through a specific front-end customer recovery team, including call center employees. The NPS metric should prioritize recoveries based on higher scores, meaning a higher urgency for intervention. This team should promptly engage by calling, writing, and offering apologies, explanations, or compensation to dissatisfied customers, aiming to act before their frustrations escalate on social media platforms (Herhausen, 2020). Back-end information systems' NPS customer lists can empower the front-end recovery team to engage customers authentically, empathetically, and logically, fostering trustworthy relationships (Fiei & Moriss, 2020).

Thirdly, a net problem score would serve customer contact employees such as sales representatives and sales force (Adamson, 2022). Integrating the problem-solving approach into Customer Relationship Management (CRM) software and Sales Force Automation (SFA) systems would simplify the identification process of any potential customer defection. By knowing the customer's NPS before meeting him, a salesperson can tailor his interactions more effectively. Furthermore, sales managers can organize their departments with a special emphasis on mitigating potential customer desertion, shifting, hence, the focus from simple customer satisfaction.
The following section presents the integration of problem-solving processes within a marketing relational design.

A relationship Perspective in Problem-Solving Approaches

Our research findings show that out of the six problem types (e.g., network, device, billing, service, telecom plans, and promotional), service problems have the most damaging effect on desertion. Paradoxically, service problems are less frequently reported by dissatisfied customers (Table 7), however, their impact on desertion is higher than a factor of 5:1. Consequently, addressing service problems becomes imperative to mitigate desertion. Moreover, service problems often go unreported in information system. Obviously, rude, or incompetent employees often manage to avoid being recorded when delivering poor service. This highlights the urgent need to shift from a mere satisfaction approach to a customer-relational problem-solving paradigm. The magnitude of the effect of the service problem on desertion underscores the urge to implement and appropriately training a devoted recovery team to promptly cope with such issues. Our results also show that customers express their problems through specific channels.

Out of the three types of channels used to report problems (call center, company website, and social network), social network usage amplifies desertion by nearly a factor of 4:1, even though it is less frequently used by dissatisfied customers (table 8). Herhausen (2020) argues that only 3% of complaints become viral, emphasizing that even a small number of dissatisfied customers can significantly influence others. Among these channels, electronic social media usage significantly impacts desertion. In line with Bapat & Williams (2023), our results showed that complaining customers turned more on technological platform such as social media to voice discomfort. This result suggests that, compared to a warmer channel such as a call center, a colder electronic channel makes it easier to complain. Deploying a color spectrum analogy shows that writing (filing) a complaint on a distant social media is less engaging, involving, and stressful than direct interactions with call center employees. Additionally, the use of cold electronic channels can negatively influence others without the company's knowledge. Since the complaint is not reported in internal channels like the call center, the company's image could be adversely affected. To lower the impact of social media virality, the problem-solving recovery team must track social media quickly to limit the spreading of customers' bad humor. To mitigate the impact of social media's viral transmission, the problem-solving recovery team must promptly monitor the latter to contain the spread of negative comments. The daily NPS customer list, as previously proposed, would enable the front-end recovery team to swiftly manage electronic viral transmission on social networks. Herhausen et al. (2019) research indicates that effective employee responses can decrease the virality of negative posts by up to 11%. Hence, to minimize the impact on desertion, a specific problem-solving techniques training program must be implemented.

Relational Problem-Solving Approach Training

Optimizing employees' relational problem-solving skills and techniques is fundamental. Our results suggest implementing a proactive recovery strategy to anticipate potential desertion of current customers from the service provider (Nowak et al., 2023). In the meantime, effective problem-solving necessitates tailored adaptative and reactive recovery strategies (Nowak et al., 2023) that consider both the emotional dimensions of dissatisfied customers and the ways in which problem types, frequency, and trust influence their dissatisfaction. Employee training should encompass important aspects such as:

Understanding the importance of using a proactive recovery strategy entails the Net Problem Score metric to predict current mobile users with a higher chance to leave and limit the damaging effects of social media usage.

Learning when and how to ask specific questions to adapt to unsatisfied customers' concerns and maintaining and rebuilding trust with them.

Understanding the interplay of emotions and their types in the context of dissatisfied customers to react in a proper manner and contain negative emotions from frustrated customers.

The previous aspects emphasize the necessity for training the recovery team to promptly discern what should be done to manage dissatisfied customers.

CONCLUSIONS AND LIMITATIONS

Implementing a relational problem-solving approach revolves more around fostering a marketing culture than other managerial considerations (Chaug, 2021). In this context, marketing managers bear the responsibility of establishing a specific, dedicated, and efficient customer recovery team, comprising both back-end analytical experts and front-end marketing personnel. The endeavor to forestall problems using the transactional Net Problem Score Metric (NPS) serves as a simple and sound predictive tool for discerning the adverse impact on a mobile provider's customer base (Dixon et al., 2010). Customers with high NPS values can be swiftly recovered following a problem occurrence, as customers manifest a desire for prompt and respectful resolution of their concerns. Paradoxically, our findings reveal that service-related problems, such as those stemming from interactions with discourteous or/and incompetent employees, exert the most significant effect on customer defection. Notably, these service issues elude detection within information systems, as employees tend to hide such undesirable benefits.

The current research underscores the exacerbating effect of service failures on customer dissatisfaction, driving them to voice their grievances through social media platforms. Furthermore, our findings bring to light an intriguing behavioral dilemma, wherein poor service problems, intrinsically tied to human interactions, elevate the risk of customers defection, those later tend to opt for the cold electronic channel of social media to express their concerns, clearly, this dilemma stems from the presence versus the absence of human interactions into the proposed problem-solving approach (Nowak et al., 2023). This paradox highlights how easily social media can be used as a platform for complaints and emphasizes the urgency of a proactive recovery strategy with a trained team intervention to prevent customers from turning to social media and spreading irreversible negative comments (Gao et al., 2022). Therefore, the critical necessity for targeted training in customer recovery processes for both back-end and front-end employees is paramount within our approach. These trainings would develop competencies about how to minimize desertion while enhancing awareness to work in a customer-predictive environment (Berinato, 2019). Hence, mobile providers must transcend the conventional perception of being mere network or technological facilitators and assume the role of service providers (Chung, 2021).

In this context, the culture of customer service goes beyond mere satisfaction for acquisition, embracing therefore the delivery of services framed by a problem-solving approach to foster customer loyalty. Although customer information gathering is useful, it alone proves insufficient to pursue an effective retention-oriented marketing strategy. In this context, our problem-solving approach framework elucidates the key role of trust as a determinant factor that amplifies the likelihood of defection. Thus, specialized recovery training should foster a trustworthy customer relationship even under a conflictual scenario (Nowak et al., 2023). As illustrated, adopting a culture of problem-solving approach entails the implementation of a series of practical new business metrics and processes.

Conducting practical research in the real-world mobile industry is highly valuable. The main objective of such research would be to empirically validate our findings in a genuine telecom churn analysis business context. This further research would confirm the viability of our proposed problem-solving approach framework subjecting our findings to empirical validation within an actual telecom churn analysis. Such forthcoming research endeavors would not only validate the viability of our proposed problem-solving approach framework but also gauge its profitability within the context of this study's domain. However, certain limitations should be acknowledged to enhance the validity and practical applicability of our model.

Firstly, the service-related problems highlighted in our research are less likely to be easily and satisfactorily resolved compared to other types of transactional issues, such as network interruptions. Service problems, such as rude or incompetent employees, tend to evoke stronger emotional responses and require more effective human interactions to resolve. It is likely that service issues involve a higher degree of emotional engagement than transactional ones. Our model showed that respondents who experienced service-related problems were more likely to leave their current provider. However, future research should assess the impact of emotions triggered primarily by service incidents, as well as other types of problems, on customer attrition.

Secondly, our research did not consider whether the problem was resolved, which should be addressed in future studies. Future research should evaluate the influence of problem resolution on customer desertion by incorporating it as a covariate in a binary logistic model. Comparing the effects on both low and high desertion groups would allow for a more accurate prediction.

A third limitation involves the absence of a time-based measure in our model. Future research should enhance the model's predictive validity by considering the time between when the problem was experienced and when respondents completed the survey. As all respondents in our study had encountered an issue with their current provider within the past year, we propose that trust intensity diminishes over time. Future studies should explore how individuals who experienced a problem more recently may report higher trust intensity, which could, in turn, have a stronger impact on their intention to abandon the provider. Thus, individuals with more recent issues may exhibit a greater loss of trust compared to those who experienced problems over a longer time frame.

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