A Conceptual Review of Churn in Business

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ABSTRACT

The first part of this paper outlines the various types of churn (customer, business and employee) and how each of these churn types have been studied in extant literature. Consequently, a more comprehensive definition of churn that is grounded on the notion of various types of partnerships (B2C, B2B and B2E) is outlined. The authors develop a churn framework after analyzing leading research in marketing and non-marketing journals. They determine that churn can be attributed to a combination of both entity and non-entity characteristics, although entity characteristics appear to be more common. Methodologically, churn continues to be studied through various supervised learning methods in a variety of industries. Finally, a proactive approach to churn management consisting of various propositions that link each of the churn types to firm profitability is outlined. It is the authors hope that future churn research adopt the suggested empirical based approach.

Keywords: churn, customer attrition, customer turnover, customer defection, business churn, employee churn

INTRODUCTION

A growing number of firms in a variety of industries seek to prevent customer churn on the belief that customer retention is invaluable to increasing firm profitability (Van den Poel & Lariviere, 2004). The ability to predict churn in organizational settings has become an increasingly common customer relationship management (CRM) practice (Risselada et al., 2010) and is vital to customer lifetime value (CLV) modeling (Neslin et al., 2006; Fader & Hardie, 2010; Braun & Schweidel, 2011). Consequently, effective churn management contributes to building competitive advantage (Garcia et al., 2017). The following paper seeks to provide a comprehensive survey of this relational construct and its predictive modeling applications.

Section 1 of this paper describes the three major types of churn: customer, business, employee and how each of these forms of churn have been studied in extant literature. Subsequently, the related constructs of turnover, attrition and defection are also briefly discussed. By differentiating between the various forms of churn within an organization, a more comprehensive definition of churn that is grounded on the notion of various types of partnerships: Business to Customer (B2C), Business to Business (B2B) and Business to Employee (B2E) according to the type of churn transpiring is proposed.

The second section of this paper outlines the churn framework and reveals that the churn phenomena can be attributed to a combination of both entity and non-entity characteristics, although entity characteristics appear to be more common than non-entity factors when conducting churn analysis. Methodologically, the framework demonstrates that churn continues to be studied through various supervised learning methods in a variety of industries. We reveal that the churn concept is also researched in a variety of disciplines that include marketing, management, computer science and operations research. Finally, a proactive approach to churn management consisting of various propositions that link each of the churn types to firm profitability is outlined. It is our hope that future churn research adopt this empirical approach.

1. Customer Churn

Customer churn (i.e. commonly termed as churn) is the notion that customers can refrain from doing business with a provider by discontinuing purchases of the good or service provided by the firm (Gordini & Veglio, 2017; Tamaddoni et al., 2016; Knox & Van Oest, 2014; Sharma & Panigrahi, 2011). Hence, customer churn is akin to the concepts of voluntary turnover, attrition and defection (Dawson et al., 2014; Clemente-Ciscar et al., 2014; Kamakura, 2005). Additionally, variants to the churn definition can exist by industry and company (Clemente-Ciscar et al., 2014; Glady et al., 2009; Buckinx & Van den Poel, 2005). Churn commonly arises in transactional dealings that can either be contractual (Ascarza & Hardie, 2013; Fader & Hardie, 2010) or non-contractual (Clemente-Ciscar et al., 2014; Buckinx & Van den Poel, 2005), although contractual churn has been more frequently studied (Jahromi et al., 2014). Subsequently, the churn rate is a measure of churn over the total customer base at specific time periods (Mozer et al., 2000). Churn rates are known to vary by industry and company (McDonald, 2010) and can be measured at different time instances according to standard industry practices (Ascarza et al., 2018). Therefore, churn rates are regularly monitored and churn management involves the process of retaining customers (Sharma & Panigrahi, 2011) by employing preventive techniques to combat customer attrition, customer turnover or customer defection. By ranking customers based on their probabilities of leaving the organization, the highest ranking probability scores serve as targets for incentivized retention campaigns (Coussement & De Bock 2013; Gordini & Veglio, 2017).

A growing number of firms in a variety of industries seek to prevent customer churn on the belief that customer retention is invaluable to increasing firm profitability (Van den Poel & Lariviere, 2004). Thus, customer churn is an integral component to customer relationship management (CRM) (Risselada et al., 2010) as well as to customer lifetime value (CLV) modeling (Neslin et al., 2006; Braun & Schweidel, 2011). From an organizational perspective, customers are often motivated to churn due to both controllable and uncontrollable factors (Braun & Schweidel, 2011). Controllable factors include quality concerns, price changes, privacy concerns, attractive competitor offerings, low switching costs, general customer dissatisfaction and many other reasons (Tamaddoni et al., 2014; Braun & Schweidel, 2011).

Braun and Schweidel (2011) argue that uncontrollable factors may be triggered by various changes in customer circumstances like personal lifestyle changes, family challenges, job relocation, economic changes, death and many others. However, in general the ability to prevent controllable churn is critical to customer retention and is far more advantageous than costly new customer acquisitions (Sharma & Panigrahi 2011; Keramati et al., 2016; Ganesh et al., 2000).

Correspondingly, good customer retention is known to prevent negative word of mouth advertising (Ganesh et al., 2000), declining sales (Rust & Zahorik, 1993) and can contribute towards firm profits (Van den Poel & Lariviere, 2004). Moreover, the ability to identify churners enables companies to offer special incentives and apply specific customer retention strategies (Jahromi et al., 2014). Accordingly, effective churn management is an integral component to helping ensure competitive advantage (Garcia et al., 2017). Consequently, churn analysis has been applied in a variety of industries that include: telecommunications (Amin et al., 2018; Zhao et al., 2017; Tsai & Lu, 2009), finance (Van den Poel & Lariviere, 2004), cellular networks (Sharma & Panigrahi, 2011), online gaming (Suh & Alhaery, 2016), nursing (Dawson et al., 2014; Hughes et al., 2015), retail (Yu et al., 2011; Buckinx & Van den Poel, 2005), sporting (McDonald, 2010) and many others due to its importance to marketing practice.

Burez and Van den Poel (2007) document that churn management has largely been practiced from two perspectives. Organizations can either employ a reactive (untargeted) or proactive (targeted) approach to churn management. The reactive approach entails the customer approaching the firm about wanting to forfeit usage of the good or service and often involves firms reacting by offering an incentive to retain the customer’s business. Proactive approaches to churn management involve organizations using predictive modeling techniques that identify prospective churners in advance. A growing number of organizations are initiating proactive approaches to anticipating customer churn as it is critical to firm performance and survival.

Essentially, two major streams of customer churn research have emerged in the literature. The first focal area of churn research has examined various causes of churn. For example, Braun and Schweidel (2011) determine a series of eight controllable and two uncontrollable drivers to telecommunications churn and study the impact of these factors on CLV. Sulaimon et al., (2016) also identified various drivers of customer churn in the Nigerian telecommunications industry. More specifically, they found that dubious promotions, weak cellular coverage, unwanted calls, short messaging services (SMS), inefficient internet service, poor message delivery and complexity of mobile number portability (MNP) all increased the probability of churn. Furthermore, Coussement and De Bock (2013) examined the effects of sixty different churn predictors (both behavioral and demographic variables) among gamblers using multiple data analysis methods. Similar studies investigating the drivers or causes of churn have been conducted in a variety of industries (Dawson et al., 2014; McDonald, 2010; Rowley & Purcell, 2001).

The second stream of research has focused on developing newer, more sophisticated churn modeling techniques (including hybrid techniques) and utilizing a combination of different techniques to aid in more efficient churn prediction (Verbeke et al., 2011). Principally, predictive churn models are an example of binary classification (Coussement et al., 2008) and are referred to as supervised learning (i.e. directed) classification models. Common examples of supervised learning models that have been applied to churn research include: naïve Bayes (NB), logistic regression (LR), k-nearest neighbors (KNN), discriminant analysis, neural networks (NN), survival analysis, decision trees (DTs), support vector machines (SVM), random forests (RFs), Markov chains, the hybrid logit leaf model (LLM) and the ensemble learning methods of bagging and boosting (Verbeke et al., 2011; Sharma & Panigrahi 2011; Tamaddoni et al., 2014; Zhao et al., 2017).

A comprehensive review of extant literature reveals that two dominant families of supervised learning classification techniques have emerged in predictive churn modeling: 1) logistic regression and 2) decision trees (De Caigny et al., 2018). Verbeke et al., (2011) showed that both these algorithm forms provide the advantages of predictive power and comprehensibility (De Caigny et al., 2018). An increasing number of churn prediction techniques relate to the artificial intelligence (AI) discipline as well (Risselada et al., 2010). Many more studies cite the usage of combination techniques and hybrid techniques for the purposes of benchmarking and accuracy comparisons (De Caigny et al., 2018).

1.1 Business Churn

Business churn is an extension of customer churn in that the customer is another business. Limited empirical churn research has been conducted in the B2B context (Tamaddoni et al., 2014) due to the limited collection of big data in this arena versus the B2C setting (Wiersema, 2013). Even in instances where B2B data has been available, the ability to transform this data for the purposes of analysis can be difficult (Tamaddoni et al., 2014). Therefore, a greater understanding of the implications of B2B churn is critical as business customers are noted to make larger transactions more frequently and may not be as sizeable in numbers compared to customers in the B2C context. Thus, business attrition can be a significant contributor to financial loss for a company (Tamaddoni et al., 2014) and business retention efforts in the B2B context are increasingly important due to increased online and global competition (Waxer, 2011).

Of the limited number of churn studies in the B2B context, most have largely focused on understanding the implications of B2B churn on predicting customer profitability or for the purposes of resource allocation (Tamaddoni et al., 2014). For example, Rust et al., (2011) proposed a simulation model to predict business customer profitability by utilizing archival firm data. In this study, a technology firm sells various technological products to other businesses (business customers). Business customer profitability results from calculating the net present value and net profit of each business customer. Profitability is modeled on the basis of propensity to spend, gross profit, predicted number of marketing contacts and marketing cost per customer. Business characteristics (number of employees, industry category), past marketing contacts, past purchase behaviors and various control variables (state of the economy) all influence the propensity to spend and gross profit. Ultimately, Rust et al., (2011) were able to show that their predictive customer profitability model had more predictive strength when compared to naive models.

Extending this thought process, Tamaddoni et al., (2014) model business churn in a non-contractual setting. The authors obtained transactional business customer data from an Australian online retailer who sold everyday routine products to other businesses. The predictor variables in the model consisted of recency (calculation of when items were most recently purchased within a certain time frame) and frequency (total number of purchases within a given time frame) as well as monetary variables (changes in total business customer spending during a particular time period). These recency, frequency and monetary (RFM) predictor variables were identified as appropriate variables to model business churn based on previous studies and have been used as appropriate measures to model customer value (Coussement & De Bock; 2013). After constructing a training model that consisted of logistic regression, various types of decision trees and boosting techniques, the training model was applied to the test set. Ultimately, both recency and frequency were important predictors of B2B churn. Less frequent purchases and longer purchase durations contributed to the probability of churning. Additionally, changes in total spending amounts revealed less impact on churn. The authors also employed cumulative lift charts and found that boosting models performed the best in isolating business churners.

Chen et al., (2015) note that the predictors of the RFM customer value model vary by industry and mention other adaptations of the RFM model based on the uniqueness of the business. The measures of length, recency, frequency, monetary and profit (LRFMP) to model logistic business churn have also been used (Chen et al., 2015). Other variations include relationship longevity, recency, frequency and monetary variables (LRFM), product categories, frequency, recency and monetary (CFRM) and the RFMTC (recency, frequency, monetary, first time purchase and customer churn probability). In essence, using unique measures of RFM or its variants as they relate to a specific industry assist in developing models of business churn (Chen et al., 2015)

More recently, Gordini and Veglio (2017) model B2B churn in an Italian e-commerce fast moving consumer goods (FMCG) company with 80,000 customers by employing the technique of support vector machine (SVMauc) and comparing the predictive accuracy of this method to traditional approaches like logistic regression and neural networks. The authors argue that in the B2B context, few churn prediction models exist. Of those that do exist, conflicting results have ensued and more intentional model design that is specific to the B2B context is required. Ultimately, the authors find predictive superiority in the SVMauc model in comparison to the other methods and concur with the predictive merits of this method as found in other studies examining high churn industries (Coussement & Van den Poel, 2008). Hence, the authors suggest that this method may be versatile enough to predict B2B churn in any industry.

1.2 Employee Churn

Formally, very little has been written about employee churn (Strohmeier & Piazza, 2013). Essentially, the concept of employee churn is equivalent to voluntary employee turnover or employee attrition (Saradhi & Palshikar, 2011). Employee turnover and attrition have been studied extensively in the management literature (Cotton & Tuttle, 1986; Griffeth & Hom, 1995; Griffeth et al., 2000; Hom et al., 2017). Saradhi and Palshikar (2011) argue that employee churn is similar but distinct from customer churn. Much like B2C and B2B churn, employee churn also poses significant challenges for a firm. For example, employee attrition is known to be financially costly to a firm. It results in a drop in labor productivity for the affected organization, can lead to customer attrition thereby requiring additional customer retention investments and an assortment of unanticipated additional tasks that can be time intensive and strenuous (Duda & Zurkova, 2013).

Mobley (1977) specifically modeled how job dissatisfaction can lead to employee turnover and depicted the various steps involved in this process. He identified a series of determinants of why employees quit their jobs which include: employee characteristics, organizational factors, job expectations, labor market influences and employee values (Jha, 2009). Likewise, a meta-analysis by Cotton and Tuttle (1986) identified a total of twenty-six variable correlates to employee turnover after analyzing one hundred and twenty academic papers on the subject. Cotton and Tuttle categorized these variables as external, work related and personal correlates. Examples of external correlates include employment opinions, accession rates, union presence and the unemployment rate. Work correlates entail worker compensation (pay), performance, multiple measures of satisfaction, organizational commitment, role clarity and task repetitiveness. Finally, common personal correlates include employee age, length of tenure with an employer, gender, behavioral intentions, intelligence and other measures. Along similar lines Udechukwu and Mujtaba (2007) identified two broad categories contributing to voluntary employee turnover. These two categories are: internal (employer) and external (social affiliate) factors relating to individual employees. Jha (2009) identified both individual and organizational factors of turnover intentions. Individual factors include employee personality, employee skills and abilities, organizational justice, cognitive and non- cognitive factors, ethnicity, age and other variables. Common organizational factors entail job stress, organizational commitment, organizational culture, organizational support, supervisor gender, social comparison and others (Jha, 2009).

Most recently, Hom and Griffeth (2017) examined the employee turnover literature over the past one hundred years and summarized the antecedents to employee turnover being due to the relationship quality between an employee and organization. More specifically, the researchers identify the role of offered inducements (i.e. salary, training, benefits, job security and others) and expected contributions (performance requirements, organizational commitment, organizational commitment) as key determinants of the relationship. This extensive review listed the various causes of employee turnover being attributed to job features, job dissatisfaction, labor market, professional/occupational and family pressure variables among others. Again, it should be noted that certain variables will be more or less influential in predicting employee turnover based on the industry that is being studied.

Machine learning algorithms are more prominently being used in human resource management research (Saradhi & Palshikar, 2011; Strohmeier & Piazza, 2013; Punnoose & Ajit, 2016). Saradhi and Palshikar (2011) are among a select few researchers who have formally studied employee churn. The researchers developed an employee churn model utilizing a support vector machine classification technique on employer work history data. The authors developed three separate models to study employee churn. In the first model they factored twelve out of twenty-five possible worker attribute variables (e.g. past experience in years, designation level, experience in parent organization, department, employee location, age, gender, marital status, qualification, experience in client organization, client designation, on-site/off-site worker and billed versus not-billed compensation). The second and third models included twenty derived variables (number of promotions in parent organization, promotions in client organization, number of billed/unbilled months, time spent on and offsite, number of transfers and others.) After separating the data into training and test sets and comparing the accuracy rates from support vector machine analysis, random forests and basic Bayesian models, the authors found that support vector machine classification was the most accurate in predicting employee churn. Thus, the authors were able to show the legitimacy of employing kernel based churn prediction methods like support vector machine analysis. Moreover, Saradhi and Palshikar (2011) were also able to develop an employee value model on resigned, released and retained employees. In doing so, they extended the notion of the customer value model to an employee value model based on their ability to predict employee churn. However, their employee value model requires empirical testing (Saradhi & Palshikar 2011).

Strohmeier and Piazza (2013) conducted a comprehensive secondary research review of datamining techniques specific to the four functional domains of human resource management which entail staffing, development, compensation and performance management from 1991-2011. The authors' final analysis of one hundred articles found that sixty-seven of the articles concerned staffing of which twenty one of these were purely concerned with employee turnover and retention based studies. Of all the turnover studies, the researchers found that the classification methods of decision trees, discriminant analysis, support vector machines and neural networks were most frequently used.

Along similar lines, Punnoose and Ajit (2016) compared the performance of a total of seven supervised learning employee turnover models: logistic regression, naïve bayesian, random forest, k-nearest neighbor, linear discriminant analysis, support vector machine and extreme gradient boosting on the Human Resource Information System (HRIS) data of the leadership team of a global retailer over an eighteen month timeline. The researchers found that extreme gradient boosting was the most superior of the supervised learning methods employed in predicting employee turnover.

Correspondingly, Yiget and Shourabizadeh (2017) applied the classification techniques of decision trees, logistic regression, support vector machines, random forest, k-nearest neighbor and naïve bayes on employee attrition data provided by IBM. Each of the supervised learning methods were compared on the basis of multiple confusion matrix measures like accuracy, precision, recall and F- measures. The researchers found that the support vector machine method exhibited superior performance in terms of accuracy, precision, and the F measure. Additionally, a series of dissertations at both the masters and doctoral level have also been written (Zehra, 2014; Attri, 2018) that predict employee churn. Table 1 in (Appendix A) highlights other studies that have utilized machine learning methods to predict employee turnover.

2. Churn Today and Beyond

A number of studies have sought to synthesize existing work in this field (Chen et al., 2015; Sharma & Panigrahi, 2011; De Caigny et al., 2018). Most recently, work by De Caigny et al., (2018) referenced a series of studies portraying different churn prediction models from 2012-2017 as published in the following non-marketing journals: *European Journal of Operations Research, Expert Systems with Applications, Decision Support Systems and Journal of Business Research.* Their paper focused on summarizing the methodological approaches to each study. This paper extends the authors work by creating a churn framework that includes De Caigny's et al.(2018) churn literature review as well as articles published in a select sample of top tier marketing journals from 2012-2017 according to the latest report from Scimago Journal Ranking (2017). The specific journals referenced include: (*Journal of Marketing*, *Journal of Marketing Research, Marketing Science, Marketing Letters, Quantitative Marketing and Economics and Industrial Marketing Management)* due to their frequent publication of churn articles and their largely empirical focus. Each of the extracted articles that were generated from the previously mentioned journals were obtained after searching under the key words of churn and business churn. Moreover, the ensuing churn framework also includes articles written during the 2012-2017 time horizon that explicitly investigated the key search terms *employee churn/employee turnover* and predictive analytics. The employee churn articles for analysis were obtained through Google Scholar, ABI Inform and EBSCO database searches. It is important to note that De Caigny's et al., (2018) review emphasized the classification methods used, performance evaluation (confusion matrix, AUC, lift charts, calibration plots) and the industries studied. Table 1(Appendix A) identifies the authors, year of publication, journal title, industry context, type of churn investigated, summary of key variables explored, and the predictive techniques utilized. The proposed framework extends existing work by grouping existing studies by churn type and categorizing the various churn drivers into either entity (i.e. customer attributes) or non-entity (i.e. non-customer based attributes that include macroeconomic, product/service attributes and competitive offerings) based characteristics across industries. Furthermore, each of the methodological techniques used in these works are also listed along with the industries that were analyzed.

Previously, Braun and Schweidel (2011) classified churn determinants as either being due to controllable or uncontrollable factors. On a similar note, Coussement and De Bock (2013) examined the effects of sixty different predictor variables and classified churn determinants as either behavioral or demographic variables. This framework integrates both these viewpoints by recognizing that churn behavior can be the result of both individual as well as non- individual factors (external correlates). More precisely, the framework relies on the entity set model view of data (Chen, 1976; Kanjilal, 2008) that classifies an entity as an object that is distinct, easily identifiable and contains information that can be utilized for modeling purposes. Common examples of entities include individuals, consumers, employees, businesses and events. Consequently, non- entities are classified as non-objects and often include macroeconomic variables. For the purposes of this paper, we specifically regard entity variables as end consumer, business customer and employee characteristics and non-entity variables to include product/service details, macroeconomic variables, customer firm interactions and competitive offerings. The contents of the churn framework are detailed at the end of this paper.

Table 1(Appendix A) reinforces much of what the literature has already documented. The churn phenomena continues to be studied in traditional industries like telecom (Verbeke et al., 2012; Huang et al., 2012) as well as banking and finance (Tang et al., 2014) However, churn analysis is also being applied to non-traditional industries like gambling (Coussement & De Bock, 2013) online retail (Tamaddoni et al., 2014), health clubs (Giudicati et al., 2013), energy (Moeyersons & Martens, 2015) and adventure (Chen et al., 2012). Moreover, there is also evidence to suggest that certain research studies are examining multiple industries as part of the same study (Chen et al., 2012; De Bock & Van den Poel, 2012; Ascarza, 2018). Amongst the three major types of churn, customer churn still remains the dominant form of churn. Only five of the surveyed papers examined the topic of business churn during the 2012-2017 time frame. Furthermore, the topic of employee churn has also been minimally investigated and is housed in non- marketing publications. Thus, these findings suggest that the topics of business and employee churn warrant further research exploration. However, it is important to note that Chen et al., (2012) planted the initial seed to study both customer and business churn together. Additionally, of the 24 churn prediction studies published, a growing number of these papers appeared in non-marketing journals, demonstrating the high applicability of the churn construct to multiple disciplines. The literature analysis also reveals that the bulk of studies focus on entity determinants (i.e. predominantly some form of customer characteristic variables). The most common entity variables include socio demographic and behavioral characteristics. With respect to non-entity determinants, product and customer firm interactions appear to be the most visible. The recent work of Ascarza both in 2016 and 2018 suggest that experimental designs are also being incorporated into churn analysis in addition to just pure archival analysis. Finally, with reference to modeling methods, logistic regression and decision trees remain the most popular of classification methods and are regularly utilized for benchmarking purposes. Each of the studies examined also utilize multiple methods for benchmarking and comparative analysis. Increasingly, more studies are using support vector machine and neural networks as common methods along with various ensemble methods (random forests, bagging, boosting). Nevertheless, specialized techniques like Random Subspace Method, Support Vector Machineauc methods founded on survival analysis as well as evolutionary data mining algorithms are also being developed. Notably, there is also more evidence of non-transactional churn research being conducted with unique customer base and business value analysis models being adopted (Knox & Oest 2014; Ma et al., 2015).

The literature analysis has shown that regardless of the type of churn studied, churn is very much a relational construct and should be viewed in this capacity. Therefore, in the very least, the churn construct involves a discontinuation of a relationship between at least two parties. Hence, the authors propose a more encompassing definition of churn that recognizes this construct as the severing of a type of partnership between at least two entities in an organizational system (i.e. B2C, B2B, and B2E) based on the specific type of churn transpiring. Additionally, it should also be noted that the various types of churn mentioned above have been studied in isolation. The above literature review has revealed that churn is multifaceted and can impact an organization in multiple ways. Therefore, it is argued that this construct should not be restricted to one form. Rather, in instances where applicable, churn analysis should include its varied forms with the individual and combined impact of each churn type on the financial performance of the firm. Furthermore, Table 1(Appendix A) also highlights that there are many different drivers to churn. Thus, we have categorized the various churn drivers into entity (customer, business and employee details) and non-entity (product/service attributes, macroeconomic variables, customer firm interactions and competitive offerings) determinants. Finally, although a multitude of predictive churn techniques have been applied, the practice of employing multiple supervised learning methods appears to be standard to churn research.

2.1 Churn and Profitability

The relationship between churn and profitability was investigated by Reichheld and Sasser (1990) who showed that reducing customer defection rates (churn) increased company profits with varying effects by industry. A number of researchers have been able to develop customer profit retention campaigns by modeling customer attrition behavior (Neslin et al., 2006; Verbeke et al., 2012; Jahromi et al., 2014). Neslin et al., (2006) determined that firm profitability is a function of customer churn probability, customer likelihood of accepting a retention offer, the business cost of the retention effort and CLV to the organization. Verbeke et al. (2012) calculated the maximum profit that could be realized from a retention campaign based on the customers who report the highest attrition rates among a sample of telecommunications customers. Finally, Jahromi et al., (2014) established a B2B churn model for non-contractual customers by comparing the data mining techniques of decision trees, ensemble learning and logistic regression on the basis of predictive accuracy. By doing so, the researchers were able to develop a profit retention campaign targeted towards their business customers.

Numerous studies have been conducted to investigate the impact of employee turnover on firm profitability either directly or indirectly (Hogan, 1992; Ongori, 2007; Heavey et al., 2013; Hom et al., 2017). Hogan (1992) estimated the employee turnover cost to be between 400-4000 dollars per employee. Some researchers have found that there is a negative inverse relationship between employee turnover, sales and profit margins (Heavey et al., 2013; Park & Shaw, 2013). However, we have not come across any study that analyzed the combined impact of each of the churn types on company profitability has not been analyzed. Consequently, a series of 4 propositions are developed and suggestions on how each of the churn types can be tested in future research are described. Figure 1 (Appendix B) visually depicts these combined propositions and identifies industries where each of these propositions could be empirically tested.

P1: The combined effects of customer and business churn entities are negatively related to firm profitability

P2: The combined effects of customer and employee churn entities are negatively related to firm profitability

P3: The combined effects of business and employee churn are negatively related to firm profitability

P4: The combined effects of customer, business and employee churn are negatively related to firm profitability

The authors believe that the combined impact of customer and business churn (B2C and B2B) is very applicable to organizations that contain a significant portfolio of both consumer as well as business client customers. For example, firms in the financial services industry, accounting, telecommunications and legal services industry are all good candidates where the dual effects of each of these churn types can be studied as they rely on both types of consumer groups for financial stability. The study of both customer (B2C) and employee churn (B2E) as well as business (B2B) are well suited to organizations that suffer from high rates of employee attrition. High employee attrition rates maybe due to a variety of factors that may include: job demands, stress, burnout, working conditions, compensation, job satisfaction and host of other variables. Typically, sales oriented roles in the financial services and insurance industry are well suited for these types of churn analysis. Additionally, the accounting, hospitality, legal services, IT industry, trucking and nursing industries are also good subjects. Finally, the combined effect of all three churn types can be tested on traditional high churn industries like telecommunications, banking and financial services as well as non-traditional churn industries like legal, accounting and IT to name a few.

2.2 Discussion and Contribution

Henceforth, it is our hope that future churn research adopt this multifaceted view of the churn construct and apply it empirically. Hopefully, this will inspire further research in business and employee churn which has been scarce. Moreover, research scholars and practioners are encouraged to view churn as a relational construct that if not managed effectively results in the severing of various types of partnerships (B2C, B2B, and B2E) according to the type of churn transpiring. The churn framework, as depicted in Table 1 (Appendix A) reveals that churn can be attributed to a combination of both entity and non-entity characteristics across industries. Greater emphasis on incorporating non- entity determinants to churn modeling is recommended. There is also a growing opportunity to study churn in non-traditional industries like gambling, adventure, online retail as well as many others and to combine archival analysis with experimental design as well as research non-transactional situations. Interestingly, the literature review also reveals that neither of the churn types have been studied from the viewpoint of an event study. This may be an interesting research opportunity. Methodologically, the churn construct should continue to be studied by employing comparative supervised learning methods. Again it is our intention that the proposed framework will motivate future churn research by providing an educational landscape to existing work in the field. Churn scholars are encouraged to test the proposed propositions in future churn studies. Finally, churn scholars are also encouraged to conduct a meta-analysis (Ascarza et al. 2018) of the churn literature based on the secondary research already published.

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APPENDICES

Appendix A: Table 1: Churn Framework

Author(s) and Date of Publication (DOP)	Journal Type and Title M= Marketing O = Other	Churn Context (Industry)	Churn Type (Customer, Business or Employee)	Variables Studied	Categorization of Churn Drivers (E= Entity characteristic, NE = Non-entity characteristic	Predictive Modeling Techniques
Coussement and De Bock (2013)	O (Journal of Business Research)	Gambling	Customer	Customer Demographic and Behavioral characteristics	E	decision trees (CART) Random Forests (RFs) Generalized Additive Models (GAM), ensemble learners (Bagging and Random Subspace Method (RSM)
Coussement et al. (2017)	O (Decision Support Systems)	Telecom	Customer	956 churn drivers, a combination of Customer behavior, customer company interaction variables, subscription details and Customer demographics	E and NE	Logistic Regression, decision trees (CHAID) Bagging, Boosting, Ensemble learners, naïve Bayes, neural networks and SVM
Moeyersoms and Martens (2015)	O (Decision Support Systems)	Energy	Customer	Socio demographic and consumption variables	E	Decision Trees (C4.5), logistic regression, SVM
Kumar et al. (2018)	M (Journal of Marketing Research)	Telecom	Customer	Customer Behavioral activities and firm marketing activities	E and NE	Largely based on survival analysis method
Tamaddoni et al. (2014)	M (Industrial Marketing Management)	Online retail	Business	Customer Value Model (RFM predictors)	E	Logistic regression, decision trees (CART), Ensemble (Boosting)

Gordini and Veglio (2017)	M (Industrial Marketing Management)	Online Retail	Business	Customer Value Model (RFM predictors) Customer data points	E	Logistic regression, Neural network, SVM, SVM_{auc}
Chen et al. (2015)	O (Information Systems E-Business Management)	Logistics	Business	Customer Value Model (LRFMP)	E	Logistic regression, Decision tree, SVM, Artificial Neural Network
Huang et al. (2012)	O (Expert Systems with Applications)	Telecom	Customer	Demographic, grant support, customer account info, Henley segmentation variables, service and telephone line info, historical info, telephone and complaint info	E and NE	Logistic Regression, Linear Classifiers, Naive Bayes, Decision Trees (C4.5), Multilayer Perceptron Neural Networks, SVM and the Evolutionary Data Mining Algorithm
Tang et al. (2014)	O (European Journal of Operations Research)	Financial Services	Customer	Socio-demographic, Macroeconomic	E and NE	Probit hazard rate model with orthogonal polynomial approximation
De Bock and Van den Poel (2012)	O (Expert Systems with Applications)	6 data sets that include: 2 Supermarket chains, bank, DIY supplies, Telecom, Mail order garments	Customer	Customer demographic, Historical information, Financial information	E	GAM, GAM ensembles, bagging, Random Forests, Logistic regression, Random Subspace Method (RSM)
Verbeke et al. (2012)	O (European Journal of Operations Research)	11 Telecom Datasets	Customer	Socio demographic data, Call behavior data, Financial info, Marketing related variables	E and NE	Logistic Regression, Decision trees, logistic model tree, bagging, boosting, Random Forests, KNN, Neural Networks, rule induction techniques, Naive Bayes, Bayesian Networks, SVM
Ballings and Van den Poel (2012)	O (Expert Systems with Applications)	Newspaper Industry	Customer	Customer variables (Sociodemographic) Relationship Variables (RFM, Length of Relationship (LOR)	E and NE	Logistic regression, classification trees, bagging
Chen et al. (2012)	O (European Journal of Operational Research)	3 datasets Food Telecom Adventure	Customer and business	Customer Variables Transactional details Longitudinal Behavioral details	E	logistic regression, proportional hazard model SVM, neural networks, decision tree, RFs

						boosting
Ascarza et al. (2016)	M	Telecom	Customer	Behavioral Details	E	Probit Analysis

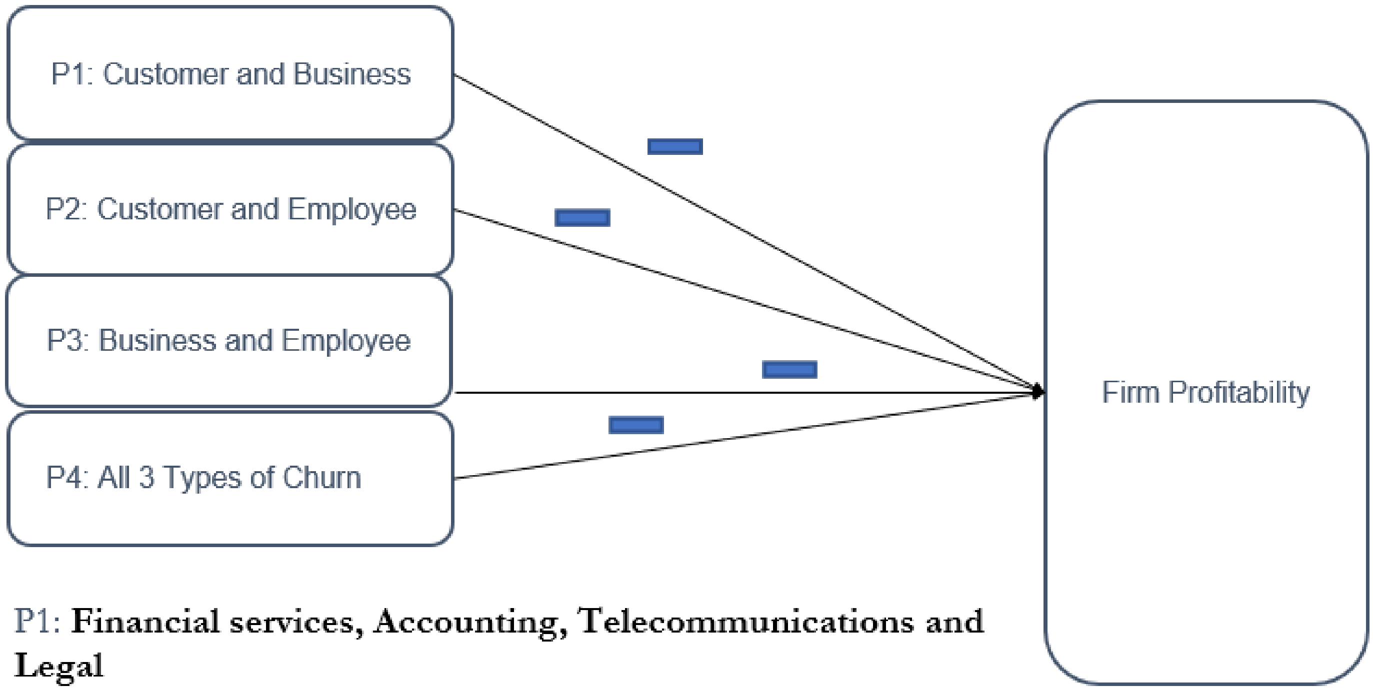
	(Journal of Marketing Research)					
Giudicati et al. (2013)	M (Marketing Letters)	Health Club	Customer	Socialization, Contract tenure, Usage, Demographics, Coexperience network	E and NE	Probit and duration estimation techniques
Knox and Oest (2014)	M (Journal of Marketing)	Online Internet Retailer	Customer	Focus is on non-transactional data (prior complaints, recoveries, prior customer purchases)	E	Residual Lifetime Value (RLV)
Ma et al. (2015)	M (Marketing Letters)	Telecom	Business	Trial and repurchase data	E and NE	The Pareto/ negative binomial distribution (NBD) model Markov Chain Monte Carlo Simulation
Becker et al. (2015)	M (Marketing Letters)	Internet Services	Customer	Behavioral, psychometric, and advertising data points of customers along with competitive firm info	E and NE	Hazard model
Balachander and Ghosh (2013)	M (Quantitative Marketing and Economics)	Telecom/Wireless Services	Customer	Demographic and behavioral, multiple product purchase information by customer	E and NE	Hierarchical Bayesian methods
Hom and Griffeth (2017)	O (Journal of Applied Psychology) *This paper was a non-empirical study	N/A	Employee	N/A	N/A	Ordinary Least Square Regression (OLS), survival analysis, hazard function analysis, Structural Equation Modeling (SEM), Cox regression, call for big data methods

Strohemier and Piazza (2013)	O (Expert Systems with Applications) *This paper was a non-empirical study	N/A	Employee	N/A	N/A	Decision Trees, SVMs, Cluster analysis, Associative analysis, Neural networks, Discriminant analysis, Time series, Logistic regression, Multiple linear regression, Rough set, Naïve Bayes, Multidimensional scaling and Learning preference models
Punnoose and Ajit (2016)	O	Retail	Employee	Demographic,	E and NE	Logistic regression,

	(International Journal of Advanced Artificial Intelligence)			Compensation details, Unemployment rate, household income data		Naïve Bayesian, Random forest, K-nearest neighbor (KNN), Linear discriminant analysis (LDA), Support vector machine (SVM) and Extreme Gradient Boosting (XGBoost)
Yiget and Shourabizadeh (2017)	O (2017 International Artificial Intelligence and Data Processing Symposium (IDAP)	IBM internal data	Employee	Demographic, skills, experience, nature of work	E	Decision trees, Logistic Regression, Support vector machines, Random forest, K-nearest neighbor (KNN) and Naïve Bayes
Alao and Adeyemo (2013)	O (Computing, Information Systems & Development Informatics)	Higher Education	Employee	Demographic and job related variables	E	Decision Tree Methods of CHAID, C4.5 and REPtree

Appendix B:

Figure 1: Multifaceted Impact of Churn on Firm Profitability



P1: **Financial services, Accounting, Telecommunications and Legal**
P2 and P3: Sales roles in the **Financial services, Insurance markets, Accounting, Hospitality, Legal, IT, Trucking and Nursing**
P4: **Traditional and Non-traditional industries**