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A neural network-based predictive decision model for customer retention in the telecommunication sector

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ABSTRACT

Acquiring a new customer is far more expensive than retaining a customer. Hence, customer retention is a key aspect of business for a firm to maintain and improve on its market share and profit. The paper analyses customer retention strategies by employing an artificial neural network-based decision model to a real-life dataset collected from 311 mobile service users in India. Seven linear and non-linear adaptive models are developed using features related to customer dissatisfaction (DSF), customer disloyalty (DLF) and customer churn (CF). Findings of this study suggest that non-linear models are most efficient in predicting customer churn, and both DSF and DLF variables significantly affect the retention strategy. Three groups of customers are discussed in this study in the order of least likelihood of churning to most likelihood. Finally, a priority matrix based on key performance indicators is proposed to help service providers target potential customers to retain.

1. Introduction

The world of business is rapidly growing over time. There is intense competition in every sector, and it has become critical to not only focus on acquiring new customers but also to retain them (Rust et al., 2004; Jiang et al., 2023). The telecommunication sector is no exception to this. The service price and switching costs in this sector have significantly reduced over the years (Ferreira et al., 2019), and therefore customer retention has been a major concern (Óskarsdóttir et al., 2017; Amin et al., 2019).

There are several reasons for retaining existing customers. Firstly, the market is saturated to a point where the untapped customer base is rapidly shrinking (Kostić et al., 2020). Secondly, the cost of attracting new customers is substantially higher, given the scale of advertising and promotion required (Ullah et al., 2019; Pakurár et al., 2019; Sivadas and Baker-Prewitt, 2000; Leong et al., 2022). It costs five to six times more to acquire new customers than to retain existing ones (Verbeke et al., 2011; Kumar, 2022). It is reported that an average 25–30 % annual churn rate is witnessed in the telecommunication sector. Past literature such as Ahmad et al. (2019) and Saleh and Saha (2023) suggested that the churn rate of customers has a huge impact on the long-term value of a business, because it affects the length of service and future revenue. Ullah et al. (2019) and Kumar (2022) also highlighted that a 5 % decrease in churn rate could increase the profit of a firm by 25 to 85 %. Hence, it is important to hold and retain existing customers in the highly competitive market in the telecommunication sector (Babu et al., 2014).

Customer churn is one of the major problems in developing countries like India, particularly due to the unprecedented increase in mobile phone users and the competitive pricing strategies and add-on services provided by the telecommunication companies. India has the second largest number of mobile phone users in the world after China. The exponential growth in this sector in the last few years has primarily been driven by a wider availability of services, affordable tariffs, the portability of mobile numbers, the expansion of the 3G/4G network, evolving consumption patterns of customers and supportive regulatory initiatives (APEDB, 2023). There is a huge penetration of mobile phones in urban parts of the country, but gradually this is increasing to semi-urban and rural parts as well. This has resulted in intense competition between service providers to acquire and retain their customers. Customers now have much wider options to choose from among service providers, and therefore firms are increasingly attempting to understand churn behaviours of customers and devising new strategies to retain their customer bases (Venkatesan and Kumar, 2004). In this context, the paper primarily focuses on developing an intelligent decision framework

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for customer churn prediction and a retention strategy. The paper is guided by two key research questions: (a) *How could customer churn behaviour be predicted more accurately in practice, using neural network-based models considering different sets of inputs?* and (b) *How could a customer retention strategy be shaped by prioritizing the possible churners into different levels?* These two key questions can assist companies to reach out to their important customers first, who could possibly churn.

Developing a robust decision framework for churn prediction demands moving away from conventional techniques based on statistical models like regression frameworks, decision trees, etc., which could be more appropriate for problems with linear relationships (Ahmad et al., 2019; Lalwani et al., 2022). Non-linear predictive models must be used for predicting churn behaviour for greater accuracy of results; however, most non-linear models have also been criticised for being computationally expensive and taking more time for training and testing purposes (Majhi et al., 2009; Basaran et al., 2014). The future usability of some of these models is also very limited; many of the conventional models cannot be reused for new datasets. Therefore, in this paper, an adaptive learning model based on neural networks has been developed to predict the churning behaviour of customers. The proposed model is equipped with a feedback loop to learn from the errors made in prediction and accordingly train for variation in customers' behaviour. The impact of various satisfaction and loyalty factors on churn behaviour has also been considered in the proposed predictive decision model. The model takes less computational time without compromising the accuracy of the results. It is comparatively simpler to train and test in practice. Further, the models discussed in prior studies do not provide an appropriate classification of the churn level of customers for decision makers. The proposed model in this paper also considers this problem and improves the classification accuracy of different churn levels. The adaptive model classifies the churn level of the consumers from low to high based on the performance criteria of the service providers. This enables the service providers to devise custom-made strategies for different levels of churners. This study, therefore, contributes to bringing together two critical aspects of effective churn management, by efficiently predicting customers' churn behaviour and by classifying different churners based on their likelihood of churning to aid service providers to take necessary actions to retain them.

The paper is structured as follows. It begins with outlining the problem context and explaining the importance of understanding customers' churning behaviour in the telecommunication sector. Later, a detailed discussion of churn management theories and empirical studies on predicting customer retention is provided. This is followed by a discussion of the data collection approach and the survey instrument. Subsequently, the proposed model is discussed, and findings are presented. The paper ends with a comprehensive discussion of findings and the contributions of the study to literature and practice.

2. Literature review

Several studies in the past (Reichheld and Sasser, 1990; Reichheld, 2003; Adebiyi et al., 2016; Ascarza et al., 2018; Hochstein et al., 2020) discussed different aspects of customer churn management in a variety of industries. However, a comprehensive analysis of past literature identifies two key clusters of studies: one group of literature focuses on the theoretical aspect of churn management, whereas a second group discusses the empirical methods to predict customer churn behaviour. In this section, both clusters of literature are critically reviewed to discuss the gaps and frame the narratives to explain the significance of this study. This section has been divided into two sub-sections. The first sub-section primarily discusses the literature on proactive and reactive approaches of customer churn management and their fundamental principles. Later, the second sub-section focuses on empirical studies and models developed to effectively manage the churn. The research gaps identified will help to build the rationale to develop adaptive artificial neural network-based models to predict customer churn behaviour.

2.1. Churn management theories

Churn management is primarily about assessing which customers are going to leave a firm and evaluating the most effective insights needed in retaining those customers (Hung et al., 2006). In the current competitive business environment, customers are subjected to several choices and attractive offers when it comes to deciding on their service providers. However, when customers become dissatisfied with the service, they tend to churn, and as a result this impacts the profitability of the firm (Anderson, 1994; Villanueva et al., 2008). The problem of churn has increasingly become critical in the era of digital- and subscription-based service offerings, reducing the switching costs (Hochstein et al., 2020).

Most literature (Winer, 2001; Burez and Van den Poel, 2007; Ascarza et al., 2016) discussed two types of approaches to manage churn: reactive and proactive. Firms following the reactive approach tend to wait until customers request the termination of their relationship with the service provider, and then offer an incentive to retain them. However, the proactive approach suggests identifying and engaging customers in advance of them deciding to churn. Firms following the proactive approach tend to offer targeted provisions or incentives to keep their customers before churning. It involves understanding the factors affecting the churn rate (such as demographics, customer attitude, length of stay, perception of fairness) and analysing customers' potential of churning based on those factors (Bolton, 1998; Bolton and Lemon, 1999; Neslin et al., 2006). Past studies (Lewis, 2005; Ascarza et al., 2018) explained the advantages and challenges of both approaches in detail. For instance, the reactive approach could be simpler, because a firm does not need to engage with customers in advance to identify who is at higher risk of churning and can save the resources and efforts needed to do so. However, this could be more challenging to manage in terms of rescuing all customers who have decided to leave, threatening the long-term sustainability of a firm. As a result, the incentive cost to win back customers is typically high, as compared to the proactive approach (Lemmens and Gupta, 2020). On the other hand, the proactive approach needs systematic engagement with customers starting from identifying who may potentially churn and an investment in advanced analytics to accurately predict the customers' churn. This approach also carefully considers the incentive cost and value of retaining those identified customers.

Several past studies (Keaveney, 1995; Kim et al., 2004; Gustafsson et al., 2005; Sohn and Lee, 2008; Al-Refaie et al., 2018) attempted to understand the reasons behind churn and investigated the relationships among these factors to retain customers. Customer satisfaction and loyalty have prominently featured in literature on churn behaviour. However, there has been an equal number of criticisms in literature relating to loyalty and churn (Bolton et al., 2000). For instance, Reinartz and Kumar (2002) argued that the relation between loyalty and profitability is weak, and they found that long-term customers pay lower prices compared to short-term customers. Ascarza et al. (2018) also discussed that firms need to be aware of a trade-off in engaging with a customer too late or too early. Time to engage with a customer is also crucial because customers may not prefer to stay with a firm if offers come too late, and it becomes too costly for the company. However, connecting with customers too early may look irrelevant to those customers and may even influence them to start thinking about churning. Therefore, analytical tools based on artificial intelligence could play a greater role in facilitating decision makers to develop an optimal system to predict churn and develop their retention strategies.

Targeted retention schemes have the potential to reduce churn rates and have lower incentive costs, but these schemes would not be useful if predictions of customer churn are wrong and do not reflect real-life scenarios. Due to predictive inaccuracies, firms may target the wrong customers or engage with them too early or too late (Ascarza et al., 2016). Therefore, the need of developing an effective churn prediction model is crucial for an efficient churn management system (Adebiyi et al., 2016). Thus, this study largely focuses on the proactive approach to develop a robust predictive model for churn management. The next section provides a review of studies of empirical models of predictive churn management approaches.

2.2. Empirical models of predicting churn

Most past literature on predictive modelling for churn management discussed quantitative modelling approaches; however, a limited number of studies could also be found on qualitative or mixed approaches (Baeke and Van den Poel, 2010). Traditional approaches of customer service and support may not yield great benefits to firms, and therefore new artificial intelligence-based innovative approaches are needed to support proactive churn management. In this regard, this paper intends to support the proactive churn management approach and develops an innovative predictive model for churn management. This will help better understand the needs of customers to predict churn and enhance the optimal development of marketing campaigns.

Recognising that customer churn is a non-linear phenomenon (which implies that contributing factors are non-linearly related to the level of churn), and with an increased availability of data and understanding of features causing churn, several researchers employed statistical models to predict churn. For instance, Neslin et al. (2006) were the first to study data-based algorithms to predict churn, but later several other models like logistic regression, decision trees (McCarty and Hastak, 2007; Lalwani et al., 2022), random forest technique (Lariviere and Van den Poel, 2005; Lalwani et al., 2022), neural network-based models (Zahavi and Levin, 1997; Khodabandehlou and Zivari Rahman, 2017; Yu et al., 2018) and support vector machines (Shin and Cho, 2006; Keramati et al., 2014) appeared. Moreover, Verbeke et al. (2011) proposed a rule induction technique-based customer churn prediction model with improved performance. They applied two data-mining algorithms (logistic regression and decision trees) to build a churn prediction model using credit card data collected from a Chinese bank. Guidolin and Guseo (2015) developed an innovative model that evaluated the effect of competition between competing products both on the dynamics within the products and cross-product word of mouth for pre-recorded music in the US market, contributing to identifying the social and market factors affecting churn. Lamrhari et al. (2022) also used a social customer relationship management (CRM) analytic framework as a feature to improve customer retention. Further, Huang et al. (2012) applied new features and a window-based technique to predict churn in the landline telecommunication sector in China and showed its superiority in yielding better churn prediction performance in landline telecommunication services. A hybrid model based on a genetic algorithm and a neural network has been proposed for predicting customer retention in cellular wireless network services (Huang et al., 2012). It is reported that this new approach outperforms the statistical z-score model on all performance criteria.

Among other sectors, studies in the telecommunication sector on churn behaviour have also featured in past literature. For instance, Idris et al. (2012) used a particle swarm optimization (PSO)-based data-balancing method for churn prediction in this sector and argued that this approach performed better compared to other approaches for predicting churners. Praseeda and Shivakumar (2021) also proposed a fuzzy PSO-based feature-selection method to develop a clustering algorithm for predicting churn. Similarly, Verbeke et al. (2012) developed a profit-driven data-mining approach for churn prediction, and Chen et al. (2018) employed a data-mining approach to identify mobile opinion leaders. However, several literatures (Hadden et al., 2007; Bin et al., 2007; Ismail et al., 2015; Sudharsan and Ganesh, 2022) still argued that limited data-mining techniques have been employed to tackle the problem of customer retention in the telecommunication sector.

Generally, the features used for churn prediction in the telecommunication industry include recency, frequency and monetary variables, customer demographics, contractual data, customer service logs, call details, complaint data, service bills and payment information (Hung et al., 2006; Sudharsan and Ganesh, 2022). Although, Gerpott et al. (2001) argued that customer satisfaction and loyalty values are expected to affect churn prediction, we still found very few studies that focused on considering satisfaction and loyalty as two important attributes to predict customer retention. Studies discussing the combinative impact of satisfaction and loyalty factors on non-linear adaptive models for predicting churn behaviour are also scarce. Therefore, in the present study, an attempt has been made to study the impact of different satisfaction and loyalty factors on churn behaviour.

Furthermore, several studies highlighted the importance of linear/non-linear and simulation methods in developing a predictive model for churn. For instance, Shieh et al. (2014) developed a three-layer hierarchy for factors that affect the adoption of mobile services. A fuzzy analytic hierarchy process (FAHP) was employed to understand the weight of each factor, thereby, to study their significance. Similarly, Coussement et al. (2017) studied the impact of data preparation on customer churn prediction performance, whereas Ahmed and Maheswari (2017) proposed a hybrid firefly classifier model to predict customer churn in the telecommunications industry. Kim and Yoon (2004) developed a binomial logit model to estimate the churn and loyalty of Korean Telecom customers, whereas Keramati and Ardabili (2011) proposed a churn model for Iranian mobile operators using binomial logistic regression. Lalwani et al. (2022) used machine learning models to predict churn after pre-processing the data. Further, Ahmad et al. (2019) developed a churn prediction model to help telecommunication operators predict customers who were likely to leave. Social network analysis (SNA) was used as a feature to develop this model. Amin et al. (2019) observed that different evaluation metrics were also used to understand the significance of the model developed.

Additionally, some of the past studies focused on understanding the relevant factors responsible for churn. For instance, Basaran et al. (2014) studied important factors for deciding on an operator in the Turkish mobile market. Similarly, Jaiswal et al. (2018) studied the impact of factors like acquisition, length of relationship, service communication, product return activity and type of products purchased in online markets on customer retention. Also, Shin and Kim (2008) identified the factors that influence a customer to switch from their current service provider. Recently, Kim et al. (2019) indicated that non-monetary switching costs have a moderating effect on customer retention.

This review of past literature highlights that in the last two decades, several literatures (Basaran et al., 2014; Ahmad et al., 2019; Lalwani et al., 2022) have focused on developing numerous approaches to estimate customer churn behaviour. These approaches can be broadly divided into two groups: statistical and soft computing. The statistical techniques are mostly linear methods, whereas the churn prediction problem is a non-linear one. Therefore, the linear methods provide a less accurate prediction of churn. Subsequently, random forest techniques and support vector machines have been applied to predict churn. These soft computing-based methods are non-linear in nature and have been reported to provide improved estimation of churn compared to statistical approaches. However, they are also not free from shortcomings. Accurate classification of churners plays an important role in customer behaviour, as it is directly related to the growth of business in the organisation. The available methods in the literature do not provide an appropriate classification level of customers for decision makers. Hence, this study identifies this as a research gap and attempts to improve the classification accuracy by developing efficient non-linear models. Ascarza (2018) argued that it is not wise to only target customers based on risk of churn but that it should also be based on who might need interventions. The proposed model not only predicts the churn but at the end recommends who the customers to be targeted are as a priority.

The challenges with existing non-linear-based churn prediction methods are that they are computationally expensive and take more time for training and testing operations. As a result, these techniques may not be useful for online prediction purposes. Therefore, in this paper, a novel approach is proposed to address this problem of high computational time without sacrificing the accuracy. Also, the future usability of the models discussed in past literature is very limited; many of the conventional techniques cannot be reused for new datasets in the future. However, the proposed adaptive technique develops the prediction model by training it through old datasets and subsequently develops a model suitable for predicting churning behaviour based on future datasets. Periodic training of the model may be necessary in the future due to variation in the data and outcomes.

3. Data collection and sampling

This study focuses on proposing a neural network-based non-linear adaptive model to efficiently predict the churn level of mobile phone users in India. Primary data for this study were collected through a structured questionnaire sent to mobile phone users from the Andhra Pradesh (AP) telecom circle, one of the highest tele-density telecom circles (licensed service areas – LSAs) in India. The AP circle included mobile phone subscribers from the Andhra Pradesh and Telangana states in India, and it was one of the first circles to introduce mobile phone services in India in 1997 (Mukhopadhyay et al., 2023). The tele density in the AP circle is about 93 % and it provides on average the highest download speed (TRAI, 2023). Further, the AP circle also has the highest number of 5G smartphone models, representing 14 % of all 5G-capable smartphones in India (APEDB, 2023). The AP circle is also among the top five LSAs with the highest number of mobile number portability (MNP) requests in India, reaching 55.73 million in November 2022 (TRAI, 2023). This clearly highlights the high frequency of change in mobile phone service providers and reflects a high rate of churn. The competition among service providers is very intense in this circle. Therefore, the AP circle was the most appropriate to conduct this study to develop an efficient predictive model to estimate customer churn in the telecommunication sector. Customers residing in cities generally get the best possible service from service providers, and wider opportunities to switch between service providers. Therefore, in this study, data were collected from the highest tele-density cities in the AP circle, like Hyderabad, Warangal, Vijayawada and Vishakhapatnam (Khatri, 2022).

A random sampling method was used to distribute the questionnaire to mobile service customers in the AP circle. Random sampling helps to avoid any general bias in collected data. The survey was administered through an online platform by using Google Forms. It was targeted to adult customers of >18 years of age without any further restriction on gender and age. It was initially sent to 400 potential respondents with the intention of receiving a sizable data sample to implement proposed predictive models based on neural networks (Hatcher and O'Rourke, 2013). A similar approach for sampling was also followed by several past studies, such as Babu et al. (2014) and Adebiyi et al. (2016). Data were only collected at one point in time based on the survey instrument described in the next section. 340 responses were received from the customers, but 29 did not respond to all the questions and were therefore not considered for further analysis. Finally, a sample of 311 responses were considered for further analysis in this study.

4. Survey instrument

A structured questionnaire (Appendix A) was developed for data collection to test the efficiency of the proposed neural network-based prediction model. The questionnaire was divided into four sections. The first section consisted of questions on general usage of mobile phones. The responses of customers pertaining to four questions in this section were used as inputs to the model. These questions were (i) the number of years they had been using a mobile phone, (ii) their current service provider, (iii) the expenditure on their mobile phones per month, and (iv) the number of service providers they had used in past. Several past literatures (Bolton et al., 2000; Gerpott et al., 2001; Gustafsson et al., 2005) suggested that the satisfaction and loyalty values of customers are two important determinants for estimating the level of churn. Therefore, in this study, satisfaction and loyalty are used as inputs to the proposed model. The questionnaire consists of 25 questions on satisfaction and 14 questions on loyalty. Respondents were asked to record their responses on a scale of one to five on a Likert scale.

All responses received were subjected to factor analysis based on the principal component analysis (PCA) method. As a result of factor analysis, five factors (Adaptability, Customer Service, Connectivity, Skills of Employees, Advertisement) pertaining to 'satisfaction' and three factors (Reliability, Repurchase Intention, Continuity in Usage) pertaining to 'loyalty' were identified. Total variance explained by the variables for both satisfaction and loyalty are presented in Appendix B. For customer satisfaction, five factors have eigen values >1 and express a cumulative variance of 56.47 %, whereas for customer loyalty, three factors have eigen values >1 and express a cumulative variance of 54.78 %. The summary results of factor analysis are presented in Table 1.

Data were normalized to ensure that each input lay between 0 and 1 for developing the proposed prediction model. It is known that higher levels of dissatisfaction and disloyalty in customers lead to higher probabilities of churning (Bolton et al., 2000; Gerpott et al., 2001; Gustafsson et al., 2005). Hence, these two values were obtained by subtracting the corresponding satisfaction and loyalty levels of the respondents from unity and are used as inputs for model development. Provision was also made in the questionnaire to collect the responses in terms of the churning behaviour of customers. The magnitude of dissatisfaction, disloyalty and four normalized responses to the questions pertaining to churn are used as inputs to the model and the corresponding churn response of the customers is used as a target or desired value of the proposed model.

5. Basis of development of different prediction models

As churn management becomes such a complex problem, where several factors are involved in taking an efficient decision, the fundamental principles of system dynamics would help to bring different viewpoints to overcome the increasing complexity of the issue (Azadeh et al., 2014). The telecommunication industry is a complex system involving customers, service providers, mobile phone manufacturers, retailers and policymakers. Churn management could be considered as one of numerous subsystems, which needs to optimise several variables to reach an optimal outcome. The market dynamics and competitions among service providers significantly affect the cost structure in this sector. Hence, it is necessary to understand all the factors affecting churn behaviour before developing the neural network-based predictive model. In this paper, customer-related variables affecting their churn were identified by directly connecting with them through a survey instrument. Later, once the set of key variables were identified, then an adaptive neural network-based model was proposed with a feedback loop to learn from the errors made in the prediction. The dynamic simulation proposed in the predictive model with the feedback loop would be beneficial to reach to an optimal result (Sterman et al., 2015).

In this study, seven different non-linear models have been developed based on different combinations of inputs. Factor scores (F) obtained from factor analysis of the variables and the direct value (V) estimated from the responses received from the respondent are two different sets of inputs. The basis of selection of these models is explained in the following. Four typical responses pertaining to churn have been collected from the customers and then normalized to serve as inputs

Table 1
Results of factor analysis for satisfaction and loyalty using PCA.

	Key Factors
Satisfaction	Adaptability, Customer service, Connectivity, Skills of Employees, Advertisement
Loyalty	Reliability, Repurchase intention, Continuity in usage

(denoted as FC) to the proposed prediction model. The corresponding prediction model is termed as *Model-1*. The findings of past literature (Bolton et al., 2000; Gerpott et al., 2001; Gustafsson et al., 2005) suggested that factors relating to dissatisfaction as well as loyalty strongly influence the churn level of a customer. Similarly, customer dissatisfaction can reduce the customer base of a firm and impact its reputation (Levesque and McDougall, 1996). Customers who are not satisfied could tell others about their dissatisfaction and might churn (Lejeune, 2001). Lee et al. (2001) also highlighted a high relationship between the switching costs, customer satisfaction and loyalty. Accordingly, from the responses collected, the dissatisfaction factor (DSF) and the disloyalty factor (DLF) of each customer was estimated.

In *Model-2*, the DSF, DLF and FC values have been used as the inputs and the predicted churn level of the customer as the corresponding output of the model. To assess the effect of the DLF, another model is proposed (*Model-3*) in which the DLF and the FC are chosen as inputs. Similarly, in *Model-4*, the DSF and the FC are employed as inputs with an objective to study the effect of dissatisfaction factors on churning.

In *Models 2, 3* and *4* the magnitudes of key factors pertaining to churn as well as the DSF and the DLF computed from responses of the customers are used as inputs. In developing the remaining models, a new strategy is adopted in which the dissatisfaction values (DSV) and/or disloyalty values (DLV) obtained directly from the respondents along with the factors relating to churning are used as inputs instead of using the values of different factors. Accordingly, *Models 5, 6* and *7* are developed with different combinations of the above-mentioned attributes. The details of different combinations of inputs used are termed as Types 1–7, and the corresponding *Models 1–7* are listed in Table 2.

The accuracy of churn prediction achieved from these models is obtained using different combinations of real-life data of customers as inputs and is compared with the proposed models. The development of the proposed models and a discussion on the results are in the next section.

6. Deployment of novel adaptive models

In this section, both linear and non-linear adaptive models are proposed for prediction of churn and their performances are compared using collected data. All models proposed in this section are adaptive in nature. Such models have the advantage of reusability using new/dynamic data of customers and hence can also be used for prediction of churn levels of future customers.

6.1. Adaptive linear prediction model

A simple adaptive model, as shown in Fig. 1, is developed to predict churn.

In Fig. 1, $x_n(r,i)$ and $w_n(i)$ represent the input of n^{th} attribute of r^{th} respondent and connecting weights corresponding to n^{th} attribute during i^{th} experiment respectively. In model development, the following terminologies are used:

N- Total number of input attributes pertaining to churning.

R- Total number of respondents whose data are used for training purposes.

i - Number of experiments conducted.

A unity bias input is also applied through a weight $w_b(i)$ to achieve improved prediction performance. The predicted churn output $\widehat{c}(r,i)$ of the model is obtained as:

$$\widehat{c}(r,i) = \sum_{n=1}^{N} x_n(r).w_n(i) + w_b(i) \tag{1}$$

where the symbols $\widehat{c}(r,i), c(r,i)$ and $e(r,i)$ denote the estimated churning level, the customer's response on churn. The error term between the actual churn value and its estimated one is given by:

$$e(r,i) = c(r,i) - \widehat{c}(r,i) \tag{2}$$

During the training period, when the attributes relating to a customer churn are applied, the model produces an estimated churn level which is then compared with the churn value provided by the corresponding respondent to produce the error term defined in (2).

Using the input value corresponding to each connecting path and the error value given in (2), the change in weight value in each n^{th} path is computed as:

$$dw_n(r,i) = 2 \times \mu \times x_n(r,i) \times e(r,i) \tag{3}$$

For the bias path, the change in weight is given by:

$$dw_b(r,i) = 2 \times \mu \times e(r,i) \tag{4}$$

where μ = convergence coefficient which controls the convergence rate, and its value lies between 0 and 1.

The same process is repeated for all R respondents in a single experiment. At the end of an experiment, each path accumulates R number of weight changes. The average weight change in each connecting path after an experiment is obtained as:

$$adw_n(i) = \frac{1}{R} \lfloor \sum_{r=1}^{R} dw_n(r,i) \rfloor \tag{5}$$

Where $adw_n(i)$ = average change in weight value in n^{th} path during the i^{th} experiment.

Similarly, the average change in weight in the bias path is given by:

$$adw_b(i) = \frac{1}{R} \lfloor \sum_{r=1}^{R} dw_b(r,i) \rfloor \tag{6}$$

Finally, the updated weight value in each n^{th} path is given as:

$$w_n(i+1) = w_n(i) + adw_n(i) \tag{7}$$

The bias weight is updated as:

$$w_b(i+1) = w_b(i) + adw_b(i) \tag{8}$$

where, $w_n(i+1)$ represents the updated weight value at the beginning of $(i+1)^{th}$ experiment corresponding to n^{th} path for r^{th} respondent.

Subsequently, the mean square error $E(i)$ during i^{th} experiment is computed using (9) to plot the training or convergence characteristics of the churn prediction model:

$$E(i) = \frac{\sum_{r=1}^{R} e^2(r,i)}{R} \tag{9}$$

where, R= total number of respondents.

The experiments are continued until $E(i)$ attains the lowest possible magnitude. The convergence plot exhibits the relation between $E(i)$ and the number of experiments *i*. This plot indicates (i) whether the model has attained convergence (when the $E(i)$ value attains the lowest possible constant value), (ii) the number of experiments required for training the model, and (iii) the accuracy of prediction that is achievable from the trained model.

After completion of training, the weights attained by each path represent the final weights of the proposed model. At this stage, the model is complete, and it is ready for validation or testing purposes.

Table 2
Description of models and their inputs.

Model	Inputs	Output
Model −1	Type −1 (FC)	
Model −2	Type −2 (DSF, DLF, FC)	
Model −3	Type −3 (DLF, FC)	
Model −4	Type −4 (DSF,FC)	Predicted churning level/churning value
Model −5	Type −5(DSV,DLV,FC)	
Model −6	Type −6(DSV,FC)	
Model −7	Type −7(DLV,FC)	

6.2. Adaptive non-linear prediction models

$$Z_k(r) = [\, x_1(r)\,, sin\pi x_1(r)\,, cos\pi x_1(r)\,, sin3\pi x_1(r)\,, cos3\pi x_1(r)\,, sin5\pi x_1(r)\,, cos5\pi x_1(r) \ldots\ldots\ldots x_N(r)\,,\,, sin\pi x_N(r)\,, cos\pi x_N(r)\,, sin3\pi x_N(r)\,, cos3\pi x_N(r)\,, sin5\pi x_N(r)\,, cos5\pi x_N(r)\,] \quad (11)$$

In this section, three different non-linear prediction models are developed and analysed. These are structurally simple, easy to implement and, performance-wise, superior to the results provided by previously reported linear techniques such as the regression or adaptive linear combiner model.

These models are almost similar to each other structurally except in the functional expansion block. In this section, models are presented in two different ways using trigonometric and Legendre-based expansion schemes. The details of various expansion schemes are illustrated in Table 3. The objective behind using such non-linear expansion is to map the input data to non-linear values and then employ the non-linearly transformed values as inputs to efficiently estimate the churn level. Adoption of such a strategy, though simple, makes the prediction more efficient. The remaining of these non-linear models such as the connecting weights, the computation of the output, the error values, the weight update schemes, the training and testing methodologies are identical to that of the adaptive linear combiner model dealt with in Section 6.1.

The complete scheme of development of the trigonometric, expansion-based, non-linear churn prediction model is shown in Fig. 2. The Legendre expansion-based models are similar to that of Fig. 2 and are shown in Fig. 3.

In Fig. 2, only odd-numbered sine/cosine expansions are used, as such a combination provides better prediction performance. Further, for the present application, each input is expanded to seven terms, out of which all except the first one are related to the input in a non-linear manner. Such choice of odd-numbered trigonometric expansions is based on trial and error, keeping in view the accuracy in the prediction of the model. M represents the number of each sine and cosine terms. Thus, each single input is transformed into $L = (2M + 1)$ terms. If the number of inputs of the model is N, then the total number of terms after trigonometric expansion becomes:

$$K = N(2M + 1) \quad (10)$$

$k^{th}(1 \le k \le K)$ number of expanded terms for r^{th} respondent corresponding to N attributes are represented as:

The corresponding weight vector during i^{th} experiment is represented as, $W_k(i)$ $(1 \le k \le K)$. The predicted churn of r^{th} respondent during k^{th} experiment is given by:

$$\hat{c}(r,i) = Z_K^T(r)W_k(i) + w_b(i) \quad (12)$$

where $w_b(i)$ represents the weight value corresponding to the bias (unity) input during i^{th} experiment.

The error term $e(r,i)$ is then computed using (2). The expressions for change in weight, the change in bias weight, the average change in weight, the average change in bias weight, the weight update equation, the bias update equation and the mean square error are identical to (3) to (9) respectively. The only exception is that wherever the subscript 'n' appears in these expressions, it would be replaced by 'k'.

6.3. Comparison of different models

As mentioned in the previous sub-section (Table 2), seven prediction

Table 3
Expanded values for different non-linear schemes for a single input case.

Input	Model	Expansion
Single input (x)	Linear	x
	Trigonometric	$x, sin\pi x, cos\pi x, sin3\pi x, cos3\pi x, sin5\pi x, cos5\pi x)$ (odd numbered expansion)
	In general	$sin(2n-1)\pi x; cos(2n-1)\pi x$
	Legendre	$L_1(x) = x$
		$L_2(x) = \frac{1}{2}(3x^2 - 1)$
		$L_3(x) = \frac{1}{2}(5x^3 - 3x)$
		$L_4(x) = \frac{1}{8}(35x^4 - 30x^2 + 3)$
		$L_5(x) = \frac{1}{8}(63x^5 - 70x^3 + 15x)$
		$L_6(x) = \frac{1}{16}(231x^6 - 315x^4 + 105x^2 - 5)$
		$L_7(x) = \frac{1}{16}(429x^7 - 693x^5 + 315x^3 - 35x)$

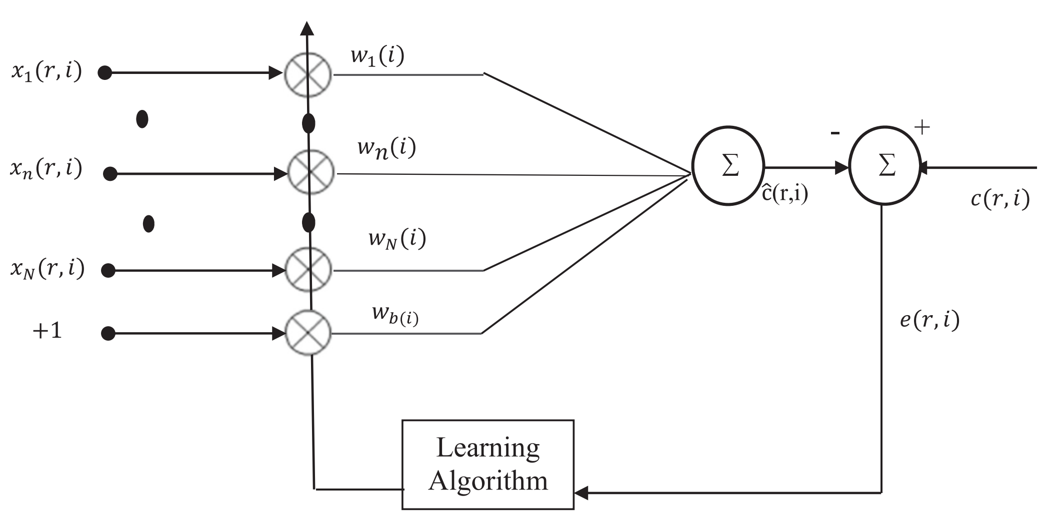

Fig. 1. Adaptive Linear Combiner Model for Churn Prediction.

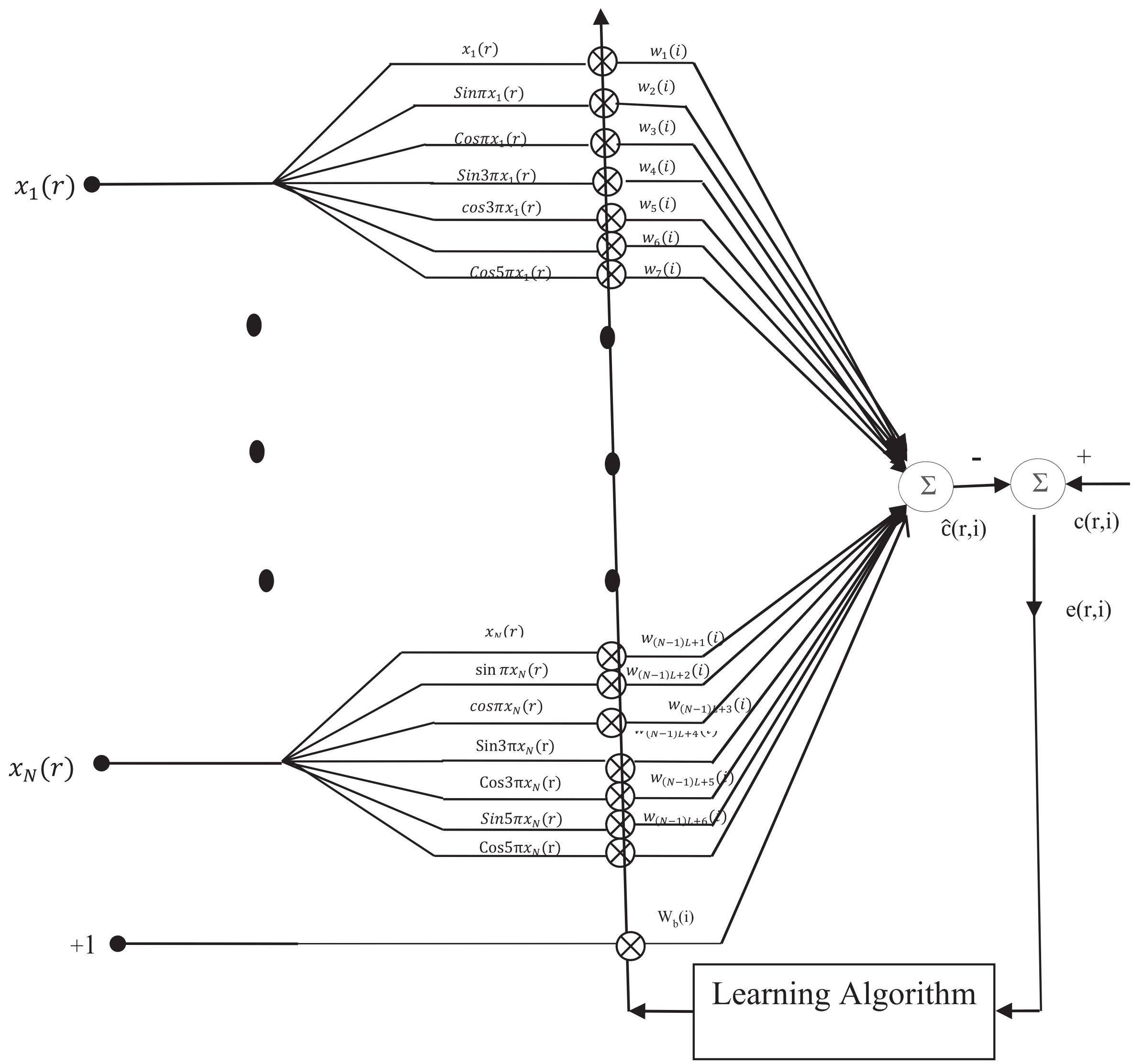

Fig. 2. Trigonometric expansion-based non-linear adaptive model for customer churn prediction.

models have been proposed based on the use of Type 1 to Type 7 inputs. The block diagrams in Fig. 4 explain the way the models are built based on input schemes. These models are simulated using MATLAB software and real-life data obtained from the customers through the survey. 80 % of the collected data is used for training the model, and the remaining 20 % is employed for validation purposes.

Following the procedure discussed in Section 6.1, the training operation is carried out and the convergence characteristics obtained for different models corresponding to different input conditions, as listed in Table 2. The comparison of the training characteristics obtained for *Model-1* for three (one linear and two non-linear) expansions is shown in Fig. 5. Similar models were developed for the rest of the six models and convergence characteristics. The comparison reveals that the rate of convergence of the trigonometric, expansion-based model provides the best prediction accuracy among all the proposed seven models. The comparison of prediction performance in terms of percentage of errors during training and testing has been separately obtained through simulation studies for all the seven models and for all combinations of input expansion schemes. The corresponding results are shown in Table 4. In-depth examination of these results demonstrates that in terms of prediction accuracy, the trigonometric, expansion-based models outperform the other expansion-based models. Further, it is observed that the linear model provides the worst performance, as the problem of churn-level estimation is inherently a non-linear one because the churn level of a customer is related to its input factors in a non-linear manner. Out of the two non-linear models, the performance ranking based on accuracy of prediction is observed to be the trigonometric and Legendre models in that order.

The comparison of convergence characteristics among the best performing six trigonometric, expansion-based, churn prediction models is shown in Fig. 6. A systematic comparison of the accuracy of prediction under identical input conditions is shown in Table 5. It shows that *Model-2*, which refers to Type-2 inputs (DSF, DLF and FC), performs the best, whereas *Model-1*, which takes the input FC, performs the worst.

In Figs. 1 to 4, the approach of studying the relationship between factors and customer churn incorporates the feedback loop through which the weights are updated so that the model converges, as shown in Fig. 5.

Using Table 4, the first five best models based on the accuracy of churn prediction and the corresponding inputs used during training and testing phases are separately obtained from the simulation results and are listed in Table 5.

7. Discussion

Customer retention is critical for the success of a company.

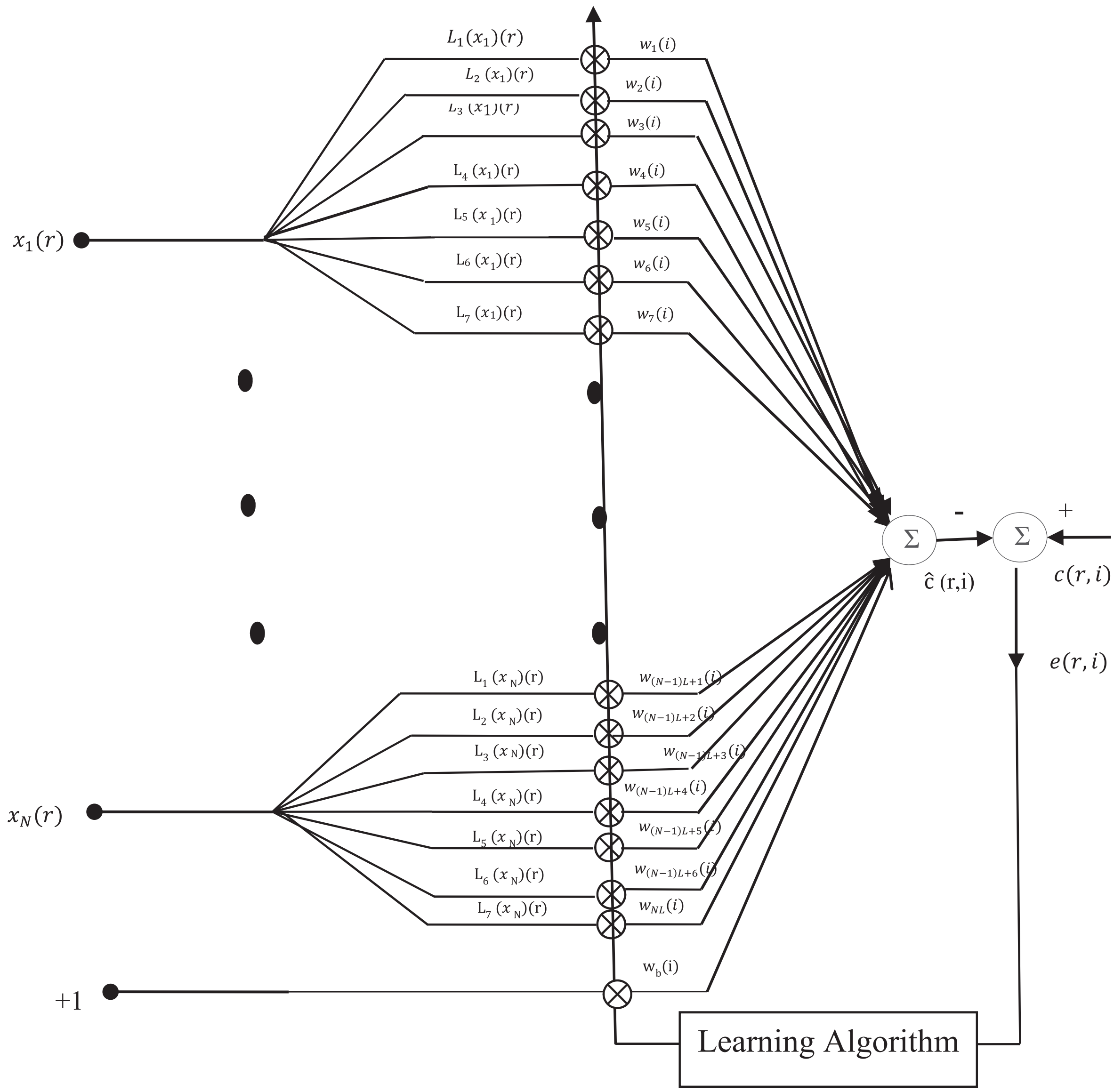

Fig. 3. Legendre expansion based non-linear adaptive model for churn prediction.

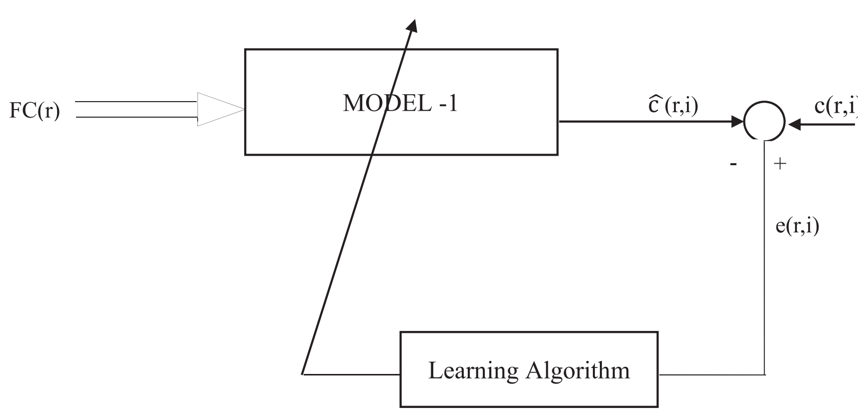

Fig. 4. Block diagram for prediction of churn level of customers using type −1 inputs in model-1.

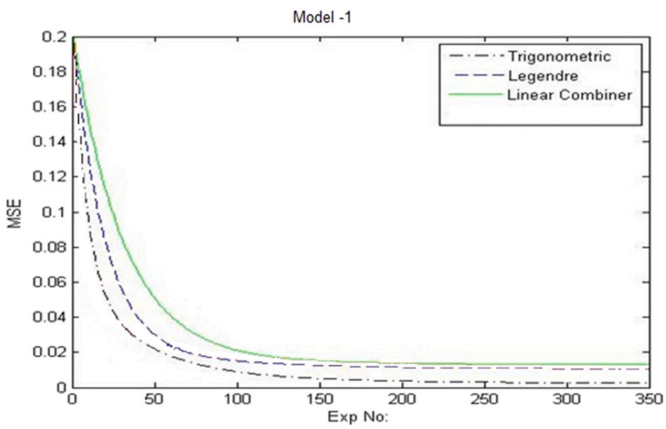

Fig. 5. Comparative performance of the convergence of model-1 using different linear/nonlinear expansions.

Table 4
Model wise comparison of the accuracy of churn prediction.

S. No.	Model No.	Type of polynomial	% error during training	% error during testing
		Trigonometric	9.3138	10.9867
		Legendre	17.3689	18.096
1	Model-1	Linear Combiner	18.2015	23.522
		Trigonometric	5.412	5.6786
		Legendre	12.4357	15.06
2	Model-2	Linear Combiner	15.6138	20.1772
		Trigonometric	7.8104	8.2752
		Legendre	15.7735	16.1618
3	Model-3	Linear Combiner	17.1105	22.6989
		Trigonometric	6.7511	7.6842
		Legendre	13.4733	14.0658
4	Model-4	Linear Combiner	16.0881	21.0761
		Trigonometric	9.104	10.5479
		Legendre	16.5188	17.5761
5	Model-5	Linear Combiner	17.6577	23.0034
		Trigonometric	9.5059	10.8914
		Legendre	16.963	17.7909
6	Model-6	Linear Combiner	17.9247	23.3608
		Trigonometric	8.9763	10.6212
		Legendre	16.7568	17.928
7	Model-7	Linear Combiner	23.1504	17.9157

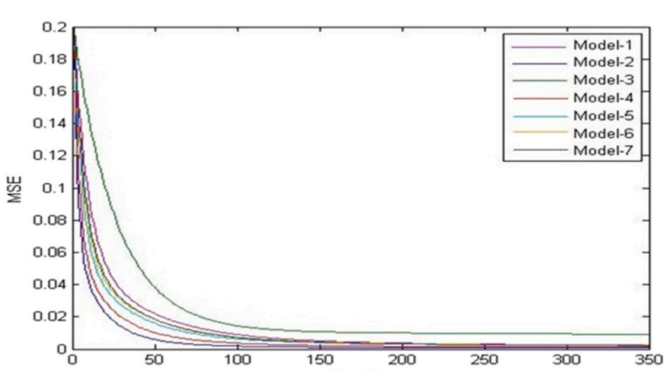

Fig. 6. Comparative convergence performance among the best performing trigonometric expansion based models.

Understanding churn behaviour is important for the mobile service provider to orient their marketing strategy and to enhance customer satisfaction level (Amin et al., 2019). In addition, if the service providers are able to identify possible churning customers, then they are able to devise strategies to retain them (Babu et al., 2014). The models developed in this paper help to predict the churn level, supporting the proactive approach to manage customers' churning behaviour (Ascarza et al., 2018). To further aid the service providers, this study also assists to categorise customers based on their churn level (Table 6) and key performance indicators like monthly revenue and longevity of the customer. Some past studies (Hwang et al., 2004; Sharaf Addin et al., 2022) have also segmented customers into different groups based on various criteria; however, the combinative effect of satisfaction and loyalty factors on predicting churn behaviour has not been extensively discussed.

After completion of training of all seven churn prediction models, it is observed that in all cases, the trigonometric, expansion-based models perform the best. Further, out of all input combinations, the DSF, DLF and FC inputs corresponding to *Model-2* produce the highest accuracy of prediction. This indicates that factors related to satisfaction, loyalty and churn behaviour contribute to predicting customer churn. These factors were also considered important in past studies (such as Gerpott et al., 2001; Gijón et al., 2013; Díaz, 2017; Pasape, 2022). Based on the aforesaid explanation, the best grouping of 63 customers under testing is given as 8, 37 and 18 for Groups A, B and C respectively, as shown in Table 7. From these findings, it is evident that 18 out of 63 customers, that is 35 %, belonging to Group C would most likely churn. The primary focus of the service provider should be given to this group (C) as there is a high chance that these customers might churn in the near future. Group B should be given the next focus, as they are next most likely group of churners.

The present investigation has provided segments of customers who might churn in the near future, and service providers must work on improving the satisfaction level of customers of Groups B and C so that customer retention increases and thereby the service providers' growth rate improves. Further grouping of customers is done based on key performance indicators like monthly revenue and longevity (age). This enables service providers to find out who they should be targeting or prioritizing. A matrix is developed considering the significant customers that fall into Group C and then taking into account the longevity of using the service and the revenue they are contributing on a monthly basis. The reasons for considering these two metrics are that revenue represents the contribution the customer is making, and age represents the loyalty of the customer. This matrix further helps to filter the profitable and loyal customers, as shown in Fig. 7.

The customers who generate revenue for the service providers and who have stayed for a long time and been loyal must be first reached out to by the service providers to understand their pain areas and retain them. This will enable revenue generation and the retaining of loyal customers. In Fig. 7, it can be observed that there are around four customers in the quadrant who are generating INR 350 of monthly revenue and have stayed for more than two and a half years with the service provider. In essence, the accurate estimation of churn level of mobile phone customers greatly helps the service providers to adjust their service strategy to reduce the number of churners and thereby help in the growth of service providers.

8. Conclusion

This paper analyses the dynamics of customer churn, which is an important factor in a firm's strategy of customer retention. Customer satisfaction and customer loyalty are assumed to determine customers' tendency to stay with a firm or to move away. Since customer churn is a non-linear function of both customer satisfaction and customer loyalty, the typical linear regression methods have been ineffective in the prediction of customer churn. Therefore, this paper developed the non-linear adaptive models which are far more accurate in studying customer behaviour. Using real-life data collected from customers of mobile phone service providers, the performance of proposed models during training and testing has been evaluated. The paper concludes that the second model using trigonometric expansion and inputs such as the DSF, the DLF and the FC has performed the best. This indicates that

Table 5
List of five best models along with the inputs based on the accuracy of churn prediction.

	Training phase			Testing Phase		
Rank Based Performance	Model No.	Types of Expansions	Inputs used	Model No.	Types of expansions	Inputs used
1	2	Trigonometric	DSF,DLF,FC	2	Trigonometric	DSF,DLF,FC
2	4	Trigonometric	DSF,FC	4	Trigonometric	DSF,FC
3	3	Trigonometric	DLF,FC	3	Trigonometric	DLF,FC
4	7	Trigonometric	DLV,FC	5	Trigonometric	DSV,DLV,FC
5	5	Trigonometric	DSF,DLV,FC	7	Trigonometric	DLV,FC

Table 6
Grouping of the customers based on churning levels.

S. No.	Churning level range	Group
1.	<0.33	A (Less likelihood of being churners)
2.	0.34–0.66	B (Medium likelihood being churners)
3.	0.67–0.99	C (High likelihood of being churners)

Table 7
Grouping of Customers Using Different Models and Types of Expansions.

S.No.	Model No.	Trigonometric Expansion			Legendre Expansion			Linear Model (No expansion)		
		No. of customers			No. of customers			No. of customers		
		A	B	C	A	B	C	A	B	C
1.	Model-1	10	31	22	7	31	25	0	60	3
2.	Model −2	8	37	18	10	37	16	10	37	16
3.	Model −3	9	29	25	7	32	24	0	60	3
4.	Model −4	6	36	21	7	32	24	1	59	3
5.	Model-5	7	30	26	5	34	24	0	60	3
6.	Model-6	9	26	28	6	32	25	0	60	3
7.	Model-7	7	30	26	5	33	25	0	59	4

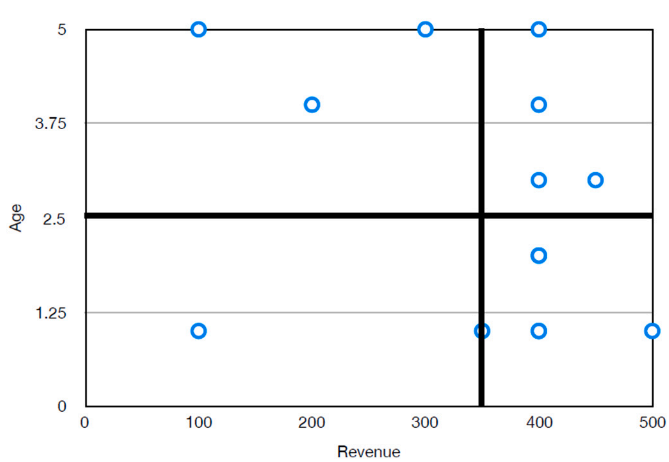

Fig. 7. Possible churners prioritisation matrix.

dissatisfaction and disloyalty factors greatly influence the churn level of customers.

The paper also highlights the novelty of the proposed model, which is adaptive in nature and uses a feedback loop that can minimize training errors and provide more accurate results. It also helps in categorising customers based on their likelihood of being churners and on certain key performance indicators. The ability of the proposed model to predict customers' churn behaviour and their potential likelihood of leaving their current service providers will be beneficial for service providers to develop tailor-made strategies to retain different customer groups. Past approaches discussed in the literature tended to focus more on only predicting the churn in general and not specifying different categories of churn levels. The paper provides a comprehensive approach for service providers to understand and predict the churn rate of their customers and guides them to devise innovative retention strategies according to varying churn levels.

8.1. *Contributions to literature*

The paper significantly contributes to the body of knowledge in churn management. Although in the last two decades several literatures (Ahmad et al., 2019; Lalwani et al., 2022) have applied numerous methods to estimate customer churn, most of these suffer from either inaccurate prediction due to a mismatch of the nature of the problem and the model used (e.g. statistical models) or inappropriate classification of churners, which does not provide sufficient insights for decision makers. This study has attempted to improve the accuracy of prediction and provided appropriate classification categories of customers with the help of customer data and an adaptive neural network-based prediction model with a feedback mechanism. The proposed model not only predicts the churn but at the end recommends who the customers to be targeted are as a priority. This paves the way for developing the right strategy for customer retention by service providers. Further, existing non-linear-based churn prediction methods are computationally expensive and take more time for training and testing operations. As a result, these techniques may not be useful for online prediction purposes. The proposed model in this study also addresses this problem of high computational time without sacrificing the accuracy. Moreover, the future usability of the models discussed in the literature is very limited. Many of the conventional techniques cannot be reused for new datasets in the future. However, the proposed adaptive technique develops the prediction model by training it through old datasets and subsequently develops the model suitable for predicting the churn behaviour in the future. Periodic training of the model may be necessary in the future due to variation in the data and outcomes.

8.2. *Managerial implications*

The predictive decision model proposed in this study will greatly benefit managers to accurately understand the churn behaviour of customers, which will return in better retention of those customers. Using the best model and range of churn level, the customers under testing were grouped into three categories, namely no churners (Group A), churners (Group B) and highly possible to churn (Group C). For any business, it would be important to devise effective retention strategies for different groups of customers and prioritize those who have a higher chance of leaving. The model could help practitioners to reduce the incentive cost by not targeting low-risk customers. Also, in a large organisation, if a similar model was run, there would be a possibility of a large set of possible churners. Hence, to further prioritize customers to target, a two-by-two matrix considering the revenue and longevity of a customer has been developed in this study. Service providers could also consider any other performance indicators relevant to them to classify potential customers to target. Consequently, the service provider can focus first on those groups that have higher importance and ensure that their profit-creating and loyal customers do not leave. The proposed model in the paper follows the proactive churn management approach and provides a research-driven guide to managers in their quest for the optimal development of marketing strategies to retain valued customers.

8.3. Potential limitations and future scope

The model in this study is developed to run in real time. If the features are to be modified, then it needs to be retrained. It is built to address the computational time issues that neural network models usually have. However, similar models can be developed to assess customer churn with different variables and can also be connected to CRM databases to run in real time. Considering the limited resources and time, only a generic sample of respondents was used for this study, which does not provide a detailed analysis of gender-, age- and income-level factors and their relative impacts on churn behaviour. However, a study with a large dataset in the future could test these different effects. Moreover, the validation of the models was only compared using the data collected at one point in time and was not tested with longitudinal datasets. However, future research could make contributions in this direction. The validation of the proposed model can be done on CRM databases to improve its validity and reliability.

CRediT authorship contribution statement

Rahul Thangeda: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Niraj Kumar:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Ritanjali Majhi:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis, Data curation, Conceptualization, Methodology.

Data availability

Data will be made available on request.

Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2024.123250.

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