Soft Computing in the Service Industry

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Abstract*: Customer behaviour modelling and customer churn management are increasingly becoming important in the sales and service oriented industry. Identifying the needs of customer, selecting the prospective customers, understanding the reasons behind customer churn and ways to provide better customer service are the key capabilities all the service industries are looking to develop. It is challenging to provide the good quality service especially when the customer contact is through the channels like telephone, email, chat and internet. The authors focus their study on the use of Soft Computing techniques to provide the capability within the Service Sector. The paper discusses two examples within the Contact Centre environment focusing on (i) Customer behaviour analysis and information requirement modelling and (ii) Customer churn prediction which uses Soft Computing techniques. The first example describes the categorisation of customer and service advisors in contact centre and then uses a fuzzy expert system framework to assign each customer and customer service advisor (CSA) with pre defined category from categorisation. After the authors identify the type of customer and advisor, the minimum amount of information which is required by the advisor to serve the customer can be derived and displayed on the screen. The second example is based on defining a loyalty index that measures decrease in customer satisfaction based on complaints within the contact centre which predicts the time period for churn using customer profiles. A long term estimate on the duration of the customer staying with the company can be derived once the profile has been identified.*

Keywords*: Soft Computing, Fuzzy Logic, Neural Networks, Service Sector, Customer Categorisation, Churn Prediction and Management, Intelligent Decision Support.*

1. Introduction

Service industries have recently witnessed several innovations, one of which is the widespread use of contact centres in the front of customer service management. Service encounters based on contact centres have raised new issues about the management of services. Customer contact centres allow a company to build, maintain, and manage customer relationships by solving problems and resolving complaints quickly, having information, answering questions, and being available usually 24 hours a day, seven days a week, 365 days of the year (Prabhaker, Sheehan and Coppett, 1997). Application of the technologies involved in contact center operations can play a key role in accessing more customers, and in providing better quality services especially where additional or extended services become available. It is necessary to understand individual customers from all levels to enable the advisor to help them more efficiently and thus providing better customer satisfaction. Within the current CCC environment there is a problem of high staff turnover and lack of suitably trained staff at the right place for the right kind of customer. Thus from a business point of view any available advisor should be able to handle a customer with consistent and good quality service (Azarmi, et al., 1998). There is also a shortage of good quality skilled staff due to retention problem that exists within current environment. This is supported by Doganis *et al.,* (2005) who state "due to strong competition that exists today, most manufacturing organisations are in a continuous effort for increasing their profits and reducing their costs". More and more effort is going into customer behaviour modelling and customer retention in a bid to prevent valuable customers from moving to competing companies. This section will discuss the identified research and progress that has been made in the ongoing process of improving company's business strategies using soft computing techniques.

2. Related Research

In service industries such as telecommunications, hotels, insurance, banking, retail, etc; companies are increasingly paying more attention to employees that are in direct contact with customers, to achieve the desired profit and market share goals. Companies are now adopting a people oriented approach as compared to a profit oriented approach (Malhotra and Mukherjee, 2004). In customer contact businesses, the quality of service delivered cannot be separated from the quality of the service provider. Because service delivery occurs through human interaction, customer service advisor during the service encounter largely determine the level of service quality delivered (Bennington, Cummane and Conn, 2000). The most urgent questions facing most businesses that believe in caring about their customers revolve around (1) what is a great service? (2) How can they provide it? (3) How do they get better? Companies that have contact centers as a focus of their customer satisfaction strategy may look like they really care more, differentiate themselves from the competition, and thus are in a better competitive position than a business only available at a store between 8. 00 a.m. to 9.00 p.m (Feinberg, Kim, Hokama, Ruyter and Keen, 2000). There are five dimensions of CSA's (customer service advisor) behaviour that influence customer's perceptions: mutual understanding, authenticity, extra attention, competence, and meeting minimum standards (Dolen, Ruyter and Lemmink, 2004). For many service jobs including CSA jobs, customer satisfaction is viewed as the ultimate performance outcome as it is a strong predictor of customer retention, repeat sales, and positive word of mouth recommendations to other potential buyers (Moshavi and Terborg, 2002). Because of the delivery of the service occurs during the interaction between contact advisors and customers, the attitudes and behaviours of advisors can influence customer's perceptions of the services. The research by Bitner (Mohr and Bitner, 1995) describes the classification for sources of service encounter satisfaction and dissatisfaction into three categories are: (1) Service delivery failures, (2) Special customer needs and requests, and (3) Unprompted service advisor actions. In service delivery failure, when the core service is not delivered as promised; service providers were often able to recover and change the customer memory of the incident to highly satisfactory. In the special customer needs and requests category some aspect of customer situation prompts a request to the service provider.

Soft computing differs from hard (conventional) computing in that it is tolerant of imprecision, uncertainty and partial truth (Zadeh, 1996). For all the available research been carried out in fuzzy logic and the development of fuzzy expert system for customer handling and modelling, little has been done to categorise the advisor (CSA) within the contact centre domain. Soft computing technologies provide an approximate solution to an ill defined problem and can create user models in an environment such as contact centre to identify: (a) customer willingness to buy (b) companies prediction towards customer purchase intentions (c) advisor reaction towards customer attitude and (d) customer behaviour towards advisors communication (Frias-Martinez, Magoulas, Chen and MacRedie, 2005). The elements that a user model captures (goals, plans, preferences, common characteristics of users) can exploit the ability of soft computing of mixing different behaviour and capturing human decision processes in order to implement a system that is more flexible and sensible in relation to user interests. Fuzzy logic provides a mechanism to mimic human decision making that can be used to infer goals and plans. The advantages of these systems over conventional production rule based expert systems may be characterised as follows: (a) fuzzy sets symbolise natural language terms used by experts; (b) since the expert knowledge captured in "If….Then" statements is often not naturally true or false, fuzzy sets afford representation of the knowledge in a smaller number of rules; and (c) smooth mapping can be obtained between input and output data (Ngai and Wat, 2003). The goal of fuzzy expert system is to take in subjective, partially true facts that are randomly distributed over a sample space, and build a knowledge based ES that will apply to them certain amount of reasoning and aggregation strategies to produce useful decisions.

Rygielski (2002) discuss Neural Networks as data mining technique for customer relationship management. According to his work, neural networks provide a more powerful and predictive model than other techniques such as decision trees and regression analysis. Artificial neural networks have been successfully used to estimate intricate, non-linear functions. An artificial neural network is an analogous data processing structure that posses the ability to learn. The concept is loosely based on a

biological brain and has successfully been applied to many types of problems such as classification, control, and prediction (Behara *et al.*, 2002). Neural networks and genetic algorithms have been investigated by Doganis *et al.*, (2005) for the purpose of sales forecasting within the food industry to understand the fluctuations and uncertainties of user demands. Wu *et al.,* (2006) reported a similar finding from the investigation of data envelope analysis (DEA) within the banking service sector. Neural networks helped produce a more robust frontier and helped identify more efficient units than the traditional DEA approach. Chan *et al.,* (2005) used a GA to solve quality related bin packing problems resulting in reduced production costs for the company. They conclude that from case studies, the proposed bin packing GA with different weight combinations could significantly improve production efficiency. Focusing specially on churn prediction, it can be observed that neural networks, decision trees, genetic algorithms, statistical methods and some new techniques have already been investigated. The literature has identified that previous researchers have mainly focused on customer usage and demographic data to predict customer behaviour and customer churn. Due to this problem there is a need to investigate and develop a tool that is adaptable to various types of data along with demographic information and subjective behavioural attributes. Also, decision trees have been used because of their usefulness with prediction and classification. The research from previous literature also identifies that fuzzy expert system development can be adapted for categorising advisors. Neural networks could be potentially very useful for predicting customer churn. However one of the major drawbacks of current research is that although churn can be fairly accurately predicted, in general the methods available do not provide adequate time for companies to identify and retain the predicted churners.

3. Challenges in the Service Industry

The use of intelligent information and soft computing techniques within customer contact centres is gaining a lot of importance in the service industry. The authors have focused here some of the challenges that are faced in the current service industry through case study analysis of customer contact centres and customer management prospective. The challenge is to identify appropriate information necessary to service customer based on advisor background. This task involves categorizing both customer and advisor using their demographic information and subjective behavioral attributes. Soft Computing aims to deal with both these qualitative and quantitative information together.

- **Proper Handling of Customer Requests** - Lack of proper handling of request due to insufficient knowledge available to the advisor. The challenge is to apply soft computing to categorise customer and advisor effectively for better customer handling.
- **Time** – The overall time it takes for any service advisor to deal with the customer query makes the customer feel uneasy about the service been provided to them
- **Lack of Information** – There is insufficient knowledge about the customer in first instance to the service advisor, which in turn makes it difficult to provide better customer service.
- **Proper use of Information** – Once the service advisor identifies the type of customer, the data and knowledge available is hard to find and in some cases examined within contact centres not available to the service advisor to use it completely.
- **Satisfying Customer Requests** – During any customer – service provider interaction it's very hard for the service provider to provide accurate and proper service in the first instance because of the factors mentioned above. Integration of customer requests using soft computing techniques which could enable them to identify the right type of information to be used.
- **Lack of Skilled Staff** – There is always shortage of skilled and experienced staff (advisors) which can help the customer and resolve the customer query in the most efficient possible manner.
- **Predicting Customer Churn** – Can neural networks be used to predict customer churn to help companies identify the prospective customers on the basis of the customer churn ratio.

4. Soft Computing for Customer Handling

Through the proposed methodology for categorisation of customer and advisor, the authors have demonstrated a way which can help to identify the right amount of information which can enable the advisor to deal with the customer more efficiently and thus providing better customer satisfaction. The main parts which are discussed here for the development of soft computing framework for customer handling are as shown below in figure (1).

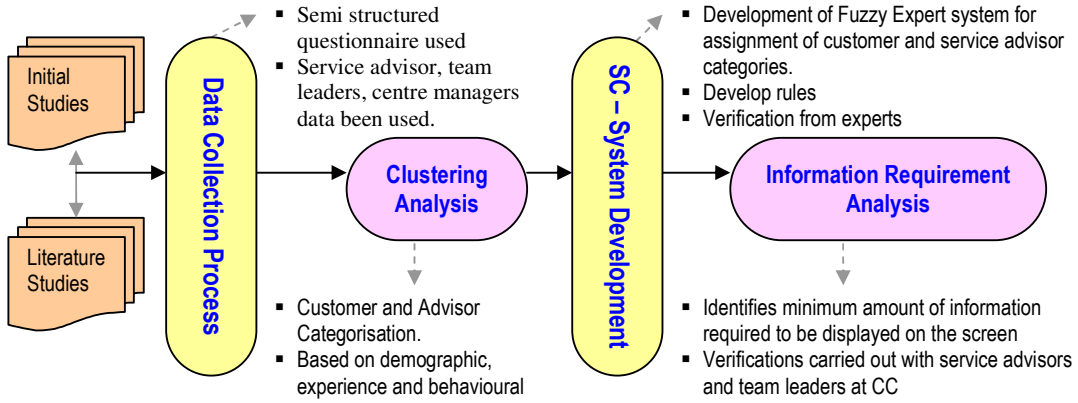


Figure 1 Customer Handling Framework Methodology

- Clustering Analysis – For categorisation of customer and advisor.
- Soft Computing System Development (Fuzzy Expert system) – For assigning any customer and advisor with a pre-defined category.
- Information Requirement Analysis – To identify the required information to be displayed on the screen depending on the customer and advisor.

Data was collected with the help of semi-structured questionnaires for advisors (CSA) and team leaders/managers with respect to their demographic variables, experience and behavioural variables within five customer contact centre focusing on fault and sales and looking on single to multi profile business customers. Please refer to reference (Shah, Roy, and Tiwari, 2005) for full list of the criteria's used for customer and advisor data collection. Clustering analysis derived the identification of customer and advisor categorisation by using statistical analysis method. The development of the fuzzy expert system was carried out to assign any customer and advisor to that of pre-defined category which was derived from the clustering analysis.

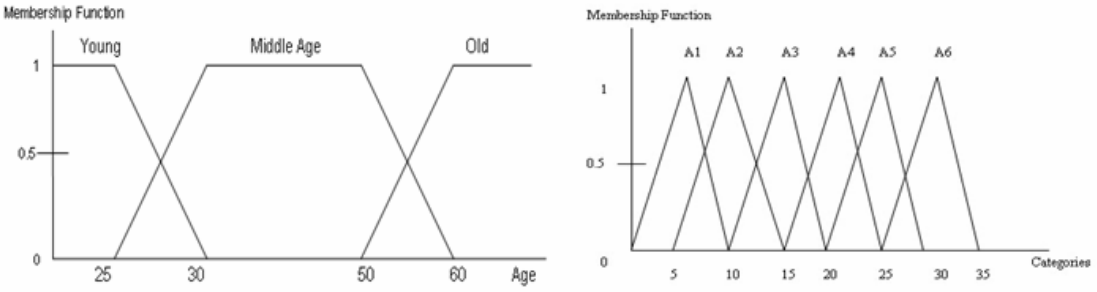


Figure 2 Membership Functions for Age and Categories for Advisor

The critical factors were the input variables of the fuzzy ES which would identify the type of category they belong to. Within the fuzzy expert system model once the membership functions for customers and advisors were derived, fuzzy if…then rule were written which identified the type of input for customers and advisors. Six advisor categories (A1-A6) were derived from 84 data sets of advisors and six customer categories (C1 – C6) from 100 data sets available from the data analysis. An example

of the experiments carried out within the fuzzy expert system model to identify the category for customer and advisor is as shown below. For complete list of the categorisation of customer and advisors and the experimental results from the validation please refer to (Shah *et al,* 2006).

No	Age	Education	Experience	Previous Experience	IT Speed	Positive Behaviour	Negative Behaviour	Output	Category
1	21.5	12	2	1.8	1.5	5.5	3.8	25	A6
2	30	21	4.2	5	4	1.8	5	10	A3
3	20	5	1	0.5	1.3	1.2	1.8	5	A1

The input values for the advisor variables define the type of advisor and output value determines the category for the advisor. For example, the input values in the first experiment is for age=21.5, and from our membership functions it justifies that the input variable for age is young; education=12=college, experience=2=0-5 yrs and so the category assigned from the expert system is A6. The sample examples for customer are shown below which identifies the customer category.

No	Age	Education	Financial Status	Time with Company	Business Value	Positive Behaviour	Negative Behaviour	Output Value	Category
1	20	10.2	2	0.8	4	10	1	15	C3
2	25	5	3	5	2.5	1.2	5	5	C1
3	30	7	8.9	9	6.8	5	0	25	C5

The validation of the fuzzy expert system was carried out with team leaders and managers at contact centres. On the basis of the category assigned to each customer and advisor from fuzzy expert system model, the information necessary to be displayed on the screen of advisor was designed. Information requirement analysis was done on the basis of the set of categories for customer and advisor derived from the clustering and determined from the fuzzy expert system model. The main objective was to identify the minimum amount of information which is required to be displayed on the screen to the advisor which would enable the advisor to help the customer. This information should always satisfy the three important business aspects of customer contact which were (i) Customer Satisfaction, (2) Resolving the conflict and (3) Cross Sell – Up Sell opportunities.

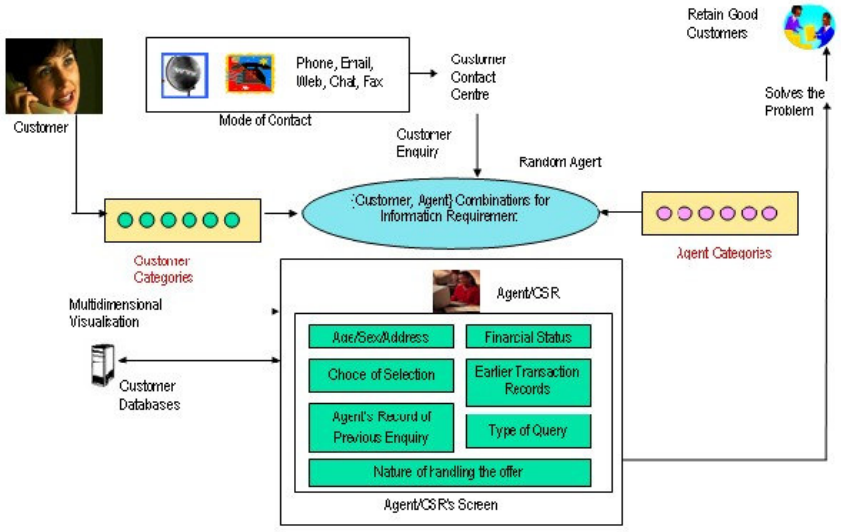


Figure 3 Conceptual Contact Centre Model for Information Requirement Analysis

Information Requirement framework was developed to overcome the *information overload* with the current contact centre environment. Also from the point of customer satisfaction *speed of response*

was crucial and the *right amount of information* which is required to be displayed to the advisor under particular customer – advisor situation was important. From the initial understanding of the contact centre, and from the literature studies; the author designed a template with the complete list of information which would be used during a particular customer-advisor conversation. A total of thirty six scenarios were considered identifying the best case and worst case of customer and advisor contact. A set of two of the scenarios used for validation are discussed below. The scenario identifies the type of customer and advisor and selects the required information based on the customer and advisor attributes from the categorisation (Shah *et al*, 2006).

5. Soft Computing for Customer Management

The second example introduces current ongoing research that uses neural networks to identify a decrease in a customer's loyalty level and provide the company with an estimation of how long the customer is likely to remain with the company. Many different types of artificial neural networks exist. After several experiments the authors chose to use a two layer feed-forward neural network with Bayesian architecture. A neural network has an initial input layer on the far left. Weights and a bias value are applied to the inputs and the values are summed. The neural network uses a sigmoid function; the output is always within a value range of 0 and 1. This value is used to represent the customers churn index. Fig 4 illustrates how the neural network varies the customer's churn index depending on their data values. Customer churn index can be defined as a measure of the churn risk of a customer expressed as a decimal value between 0 and 1. An analysis of the weights established for the twenty four variables that where presented to the neural network suggests that seven variables held more significance for predicting customer churn than the others. These variables are as follows: (i) How many engineers arrived on site, (ii) How long the customer had been with the company, (iii) How long the repair took , (iv) No. of appointments made for repair , (v) The resolution time.

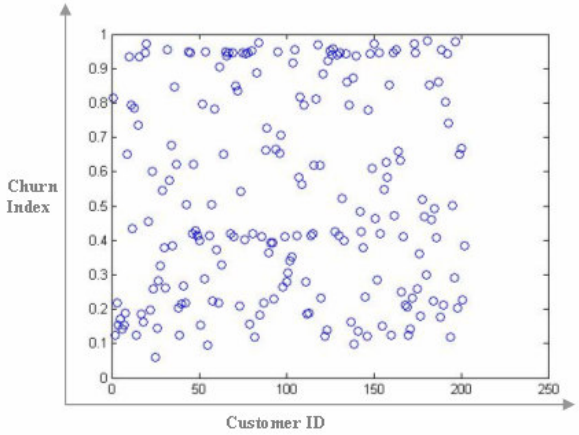


Figure 4 Distribution of the churn indices over the sample

It can be observed from fig 4 that the churn indices are extremely varied. This is because each customer is unique, however as could be expected larger groupings of customer indices are clustering closer to 0 and 1 ends of the scale, while the indices more towards the middle of the graph are wider spread. The closer a customer's index is to 1, the more likely the customer is to churn and the closer to 0, the more likely the customer is to remain with the company. With the churn index established, the values can be converted to loyalty index values. The conversion established by the author is simple in principle by assuming that loyalty is the direct opposite of churn. The loyalty index is defined as Loyalty *Index = 1-Customer Churn Index.* The customer's loyalty index is calculated for each customer over a series of time, e.g. a ten month period. The values are plotted as charts for each customer creating customer loyalty profiles. Each of the resulting profiles are compared for similarities and grouped to form master profiles. A finite set of master profiles should be identified from the customer profiles. An example of a master profile can be seen in fig 5.

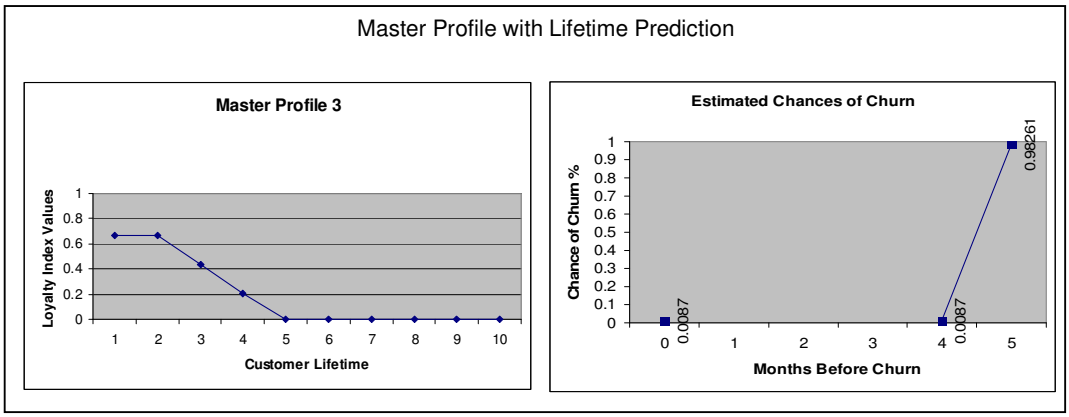


Fig 5 Master Customer Profile

As seen in fig 5, the chart on the left illustrates the master profile and the chart on the right can provide the company with estimations about when the customer might leave the company based on what the system learns about how other customer falling into the same category behaves. As more customers are accurately matched to the category and churn, the more accurate the likelihood on the estimated time to churn will become. Earlier research in the field of customer retention has shown that churners can be identified reasonably well; however the timeframe between identification of the customer churning and the actual event of churn is small. Using the NN based proposed method, customer churn could be identified months in advance giving the company time to deploy a successful retention campaign and can be implemented using real time monitoring. As events occur which cause the customers loyalty to reduce to a critically low level it can be recorded and flagged immediately. By using the NN model, the authors are able to calculate the loyalty index of a customer. This research has shown how these loyalty indices could be used to develop customer profiles and predict customer churn. With this knowledge and the initiative to improve the service offered, customer churn could be reduced to the absolute minimum.

6. Business Benefits

Customer handling and customer management are two main issues the authors have described in this paper. As shown from the literature it was observed that the reasons for the service industries to operate on issues and challenges faced were to provide better customer service and increase the satisfaction levels of their customers. Through this paper the authors have demonstrated two areas of customer facing environments within the service industry. The main business benefits of the proposed use of soft computing techniques such as fuzzy logic, and neural networks are as shown below:

- **Proper Use of Information** – there can be proper use of information which the service provider has about the customer and which would enable the service advisors to efficiently use this information and provide better customer service.
- **Customised Information –** presenting customised information on the screen based on both customer and advisor categories derived from categorisation.
- **Customer Handling** – with the help of proposed soft computing methodology levels of customer handling can be improved where customers are provided with the service they expect from their service provider.
- **Customer & Advisor Categorisation** – the important attributes such as demographic and experience levels of customer and advisor are categorised along with behavioural variables which enables the service providers to identify their key customer and advisors.
- **Any Advisor and Any Customer Situation** – any advisor should be able to serve any customer and provide good service.

- **Customer Churn Prediction** - Using the proposed method, customer churn could be identified months in advance giving the company time to deploy a successful retention campaign.
- **Real Time** - A further benefit for a company using the proposed method is it could be implemented using real time monitoring.

7. Discussion and Conclusions

The authors have described the use of soft computing techniques for customer handling and customer management within the service industry. A method through which the customised information is displayed on the screen of the customer service advisor (CSA) to serve the customer more efficiently within contact centres is described in the paper. This information is customised on the basis of {customer, advisor} combinations derived once the categorisation of customer and advisor is carried out through soft computing technique. Development of fuzzy expert system was carried out to assign any customer or advisor to that of the pre-determined category from the clustering analysis. Information requirement analysis identified the type of information required to be displayed on the screen depending on the customer and advisor background. The research has shown that fuzzy expert system could be used to categorise customers and advisors within contact centre environment effectively for better customer handling. The cost and maintenance analysis of the framework would be considered for future research and will form part of the continuing work carried out within the project. Further research should develop a framework to map customer and advisor behaviour and demographic information directly to the type of information required to be presented on the screen, rather than a fixed template based approach. The future research should expand the framework to include learning from day to day use of the system to adapt categories and the information requirement model.

The use of NN for customer management example shows that churn can be successfully predicted using technologies such as decision trees and neural networks. The author's investigations into these technologies have identified neural networks with Bayesian architecture as the best for predicting churn when using customer repairs and complaints data. The neural network predicted churn with a 70% accuracy when applied to the validation dataset. This means that customers who churn following multiple small events can be identified by the churn management system. Establishing the master profiles of loyalty index will enable to determine the churn rate of a customer that will provide the company with a timeframe of how long they have to act to retain the customer. The master profile analysis has clearly shown that customers experiencing similar negative interactions with the company churn at similar rates.

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