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TECHNOLOGY SELECTION FOR HUMAN BEHAVIOUR MODELLING IN CONTACT CENTRES

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Abstract

Customer service advisors can play different roles and have different level of autonomy, but at the end they are humans with heart and voice. While product purchases, lifestyle information and billing data provide important information about customers, it is call detail records that describe a customer's behaviour and define their satisfaction with the services offered. Call detail records describe the transactions between customer and the company. This study looks on different techniques that can be used to model customer and CSA (customer service advisor) behaviour within a contact centre environment. A brief overview of the contact centre environment is discussed focusing on issues of customer and service advisor and the need to categorise customer and advisor within contact centre environment. The findings from the case study analysis within the current contact centres, provides the authors with understanding of different behaviour observed for customer and CSA's within contact centres. The study also examines different human behaviour modelling techniques which the authors are interested in using to develop a model which can categorise the human with respect to demographic, experience and behavioural attributes within the context. Through the study it can be seen that soft computing techniques provide a major role in modelling of human behaviour and thus providing better results where this technique can be applied. The authors have also carried out a comparative analysis of all the techniques discussed within the paper and as seen from the analysis that soft computing techniques are widely used to model the user/human behaviour and thus can provide a platform for future research. Soft computing represents a significant paradigm shift in the aim of computing, a shift that reflects the fact that the human mind, unlike state of the art computers, possesses a remarkable ability to store and process information, which is pervasively imprecise, uncertain, and lacking in categoricity.

Keywords: Customer behaviour modelling, Customer Service Representatives, Soft Computing, Human Behaviour modelling, Contact/Call Centre environment

Table of Contents

1. Introduction

For a fast growing technology and communication systems, it is very important for the industry and the corporations to develop new contact centre environment technologies for better customer contact requirements. The integration of customer contact centre into day-to-day organisational operations represents one of the most promising trends in the 21st century economy. The impact is such that contact centres are expected to affect almost all aspects of society from the private sector to public sector in all parts of the world (Brown and Maxwell, 2002). Whatever the nature or point of contact, customers want a seamless interaction throughout their experience with the company. Customers receive more personalised experience, while the company itself can now provide a consistent message across all customer interactions. Customers want to contact companies at their convenience, using the most convenient means. Good service is now a survival issue, and the competition is on the value that customers receive from their relationship with their suppliers. Multimedia, multichannel customer contact centres are at the heart of this changing relationship and represent one of the most important means for companies looking to meet this new challenge. Customer's demands and expectations have increased over a short period of time. With Internet based services available around the clock, customers have come to expect that their questions/concerns be responded to in short order. Customers represent the livelihood of contact centres. The companies knows that it is easier to lose a customer than to gain one; it also knows that it is easier to sell additional services and products to customers who are satisfied with the service provided upon contact; and that a minority of the customer base accounts for the majority of an organisation revenues.

A contact centre must both anticipate and react to customers changing needs and demands to achieve strategic customer care. This is turn, has major implications for the kinds of skills, knowledge and competencies of all CCC staff, the systems and the management. There have been several efforts to develop measures of user information satisfaction (Duxbury, Backhouse, Head, Lloyd and Pilkington, 1999). Based on numerous empirical studies, (Heckman and Guskey, 1998) describes perceived service quality as an attitudinal construct containing five dimensions as; (1) Tangibles which are the appearance of physical facilities, equipment, and communication materials (2) Reliability to perform a promised service dependable and accurately (3) Responsiveness – the willingness to help customers and to provide prompt service (4) Assurance - the knowledge and courtesy of service advisors and their ability to convey trust and confidence and (5) Empathy – the caring attitude which provides individualized attention to customers. 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 cause the customers memory of the incident to be highly satisfactory. In the special customer needs and requests category some aspect of customer situation prompts a request to the service provider. Finally, unprompted employee actions, actions taken by the service providing personnel are believed to be the source of the customer's experienced satisfaction or dissatisfaction (Mohr and Bitner, 1995).

This paper aims on focusing the following issues with regards to identifying techniques which can be used to model customer and advisor behaviour within contact centre environment. The paper is divided mainly into 6 sections where section 1 describes the purpose of the study and outcome of the review of the techniques. Section 2 highlights customer and CSA behaviour and marketing strategy within contact centre environment. Section 3 looks on the importance of human behaviour modelling and section 4 describes the techniques used within the current literature which are used to model human behaviour. Section 5 shows the results from the findings of the case studies and customer and advisor behaviour categorisation. Finally, section 6 shows the comparative analysis of all the techniques briefly discussed within the paper.
The research objectives and questions that are addressed in this paper are as follows:

Research Objectives

- To identify different attributes and matrices to represent customer and advisor behaviour and preference within contact centre (CC) environment.
- To identify the limitations of current techniques for customer and CSA's behaviour modelling.

Research Questions

- How can we characterise customer and CSA's behaviour within a CC environment?
- Can we develop a Soft Computing based methodology to classify customer and CSA's behaviour and preference within the CC environment?

2. Customer and CSA Behaviour and Marketing Strategy

Understanding and adapting to changes of customer behaviour is an important aspect of surviving in a continuously changing environment (Chaochang, 2002).Research in understanding customer preferences, known as 'consumer behaviour study', has been the subject of investigation in psychological marketing area for few decades. It is necessary to understand individual customers from designer side, as well as from the customer's side to provide guidance for customers to find what they want. Customer choice of a product depends on explicit requirements, implicit requirements, available options and latent requirements implied by the product (Zeelenberg and Pieters, 2004). The study of customer helps firms and organisations improve their marketing strategies by understanding issues such as:

- The psychology of how customers think, feels, reason, and select between different alternatives.
- The psychology of how the customer is influenced by his or her environment (e.g. culture, family, signs, media etc.
- The behaviour of customers while shopping or marking other marketing decisions.

Although research has suggested that contact employee (CSA's) performance is critical to create customer satisfaction, little has been done to analyse which employee behaviours influence customer encounter satisfaction and which behaviours influence relationship satisfaction (Dolen, Ruyter and Lemmink, 2004). The performance of a

CSA during interactions with customers has been the subject of considerable research, in both sales and service settings. (Dolen et al, 2004) classify CSA's behaviour by five dimensions: mutual understanding, authenticity, extra attention, competence, and meeting minimum standards. Mutual understanding measures the extent to which the interaction with the employee is experienced as communicating empathy and understanding. Extra attention measures the extent to which the employee offered extra attention to the customer in the encounter. Authenticity measures the extent to which the customer perceives the contact employee authentic. Competence measures the functional dimensions of the employee performance. Meeting minimum standards measures the extent to which the employee meets minimum standards of civility (Dolen, Ruyter and Lemmink, 2004). Technology has changed the way organisations manage their relationships with their customers. The modern contact centre enables the organisation to create a two-way dialogue with their customers. Each contact with the customer is an opportunity for that organisation to develop a better understanding of its customer base. Customer issues, positive or negative, are now documented and tracked on an individual basis, for future action.Understanding your customer's capabilities and needs is a necessity when transitioning to a multi channel environment. No longer are customers satisfied with merely having access to multiple channels. Customers are expecting the same level and quality of service across all channels (Wagner and Hansen, 2004). Customer behaviour and CSA's behaviour can be represented with different attributes as shown in figure (1). The attributes represented here can be responsible for behaviour analysis of customer and advisor within CC context.

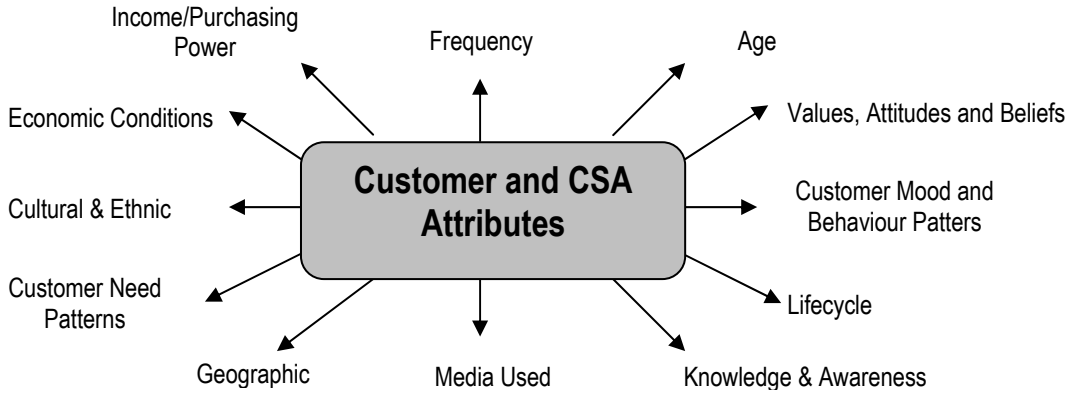

Figure 1: Customer and Advisor Attributes

Age – What is the age group of the buyers?
Values, Attitudes and Beliefs – What is the customer's attitude towards your kind of product/services? What is the advisor's reaction towards the customers attitude, query.
Customer Mood & Behaviour Patterns – Customer satisfaction and dissatisfaction measures, customer behaviour before and after the service encounter, purchase behaviour.
Lifecycle – How long has the customer been regularly purchasing products?
Knowledge & Awareness – How much knowledge do customers and advisors have about a product or service, or industry?
Media Used – How targeted customers learn about the new products? What do they read?

Geographic – Are the customers grouped regionally, nationally or globally? What are the advisor's conditions?
Customer Need Patterns – Customer requirement analysis, tendency to purchase and needs for purchase.
Cultural and Ethnic – What languages do the customer/advisor speaks? Does ethnicity affect the customer's buying preference, or advisor's selling behaviour?
Economic Conditions – What is average household income of the customer?
Income/Purchasing Power – How often does the customer spend on each product? Financial Status
Frequency – What is the customer's shopping frequency, frequency of complaints, degree of satisfaction, buying preferences?

Interactions with the CSA have been transaction based, modern day CSA's are dealing with far more complex and varying customer issues. The technological change is not simply transforming the methods by which the organisation operates, but is impacting the level of skill and education required by both CSA's and management within the contact centre environment. CSA's will need to develop skills that are far more complex than the simple general information questions which have historically been handled within the contact centre environment. The ability of a CSA to provide effective voice service does not guarantee their ability to provide effective email or web chat service and support (Rose and Wright, 2005). They may have the necessary product and service knowledge; but their ability to communicate with correct spelling and grammar is another skill that must be considered in the recruiting and training processes (Rygielski, Wang and Yen, 2002). The CSA can play different roles and have different levels of autonomy, but the important thing is that they are human, with a voice and a heart. But besides the advantages of supporting customers with hearty CSI and higher flexibility, such a solution represents a problem for the companies as it implies high costs of work, costs of training, frequent turnover, no standard answers, no control of the interactions, etc.

3. Human Behaviour Modelling

Customer behaviour can be described by disciplines such as economics, business and marketing studies, social and psychological research. The disciplines differ in their presuppositions about the human nature, influencing factors of customer behaviour, and market response. They also employ different research methods, some of which are described below in the section.

Business management and marketing are concerned with ways of satisfying and retaining customers for the purpose of generating profits, improving companies' competitiveness and securing market share. Some of the major themes in the business management domain include studies of customer relationship marketing, which analyses how customer satisfaction relates to competitiveness and profits, methods for measuring customer satisfaction (Thomson, 1995), and approaches that can help transfer customer satisfaction data into strategies for improvement of customer relations and their retention, (Johnson and Gustafsson, 2000), (Schellhase and Hardock, 2000). The paramount goal of the marketing domain is to understand the customer and to influence buying behaviour. One of the models, reviewed in this study for

understanding the customer buying behaviour, is the model suggested by (Engel, Blackwell, and Miniard, 2001), because it combines the customer decision process with the influencing factors. According to the model, the customer decision-making process comprises a need-satisfying behaviour and a wide range of motivating and influencing factors. Consumer decision making process has the following steps:

1. Need recognition – This process depends on difference between desired and current state of affairs.
2. Search for information - The search for information begins with the internal search for any sort of information, memory, or experience with a product or service.
Pre-purchase alternative evaluation – The assessment of available choices that can fulfil the realised need by evaluating benefits they may deliver.
4. Purchase - The purchase step is associated with a number of decisions that individuals have to make.
5. Consumption - After the product or service is bought, consumers can use it directly, in a period of time or could even abort the consumption process all together.
6. Post-purchase alternative evaluation – The assessment of whether or not and to what degree the consumption of the alternative produced satisfaction.
7. Divestment – The disposal of the unconsumed product or its remnants.

The transition to a service economy has important implications for organizations and how they operate (Bowen and Schneider, 1998). Starting with goods and services which can differ on several dimensions that impact the way they are delivered. According to Schneider and Bowen (1998) there are three characteristics of services (i.e., (a) intangibility, (b) simultaneous production/delivery, and (c) customer participation in production/delivery. It also suggests that these boundary-spanning employees perform two important functions. First, customer service employees, because of their direct contact with customers, are a crucial source of information about customer expectations and attitudes as well as a source of suggestions for improving the quality of the service and its delivery.
Second, and perhaps even more importantly, they represent the organization to the customer. As (Schneider and Bowen, 1995) point out, for most customers, the service employee is the embodiment of the organization.

Consequently, the behaviour of the service employee (CSA), and the experience that behaviour creates for the customer during the service interaction, are critical factors in defining customer perceptions of service quality (Malhotra and Mukherjee, 2004). Given the important roles filled by customer service employees, organizations wishing to deliver quality service must find ways to support and effectively coordinate the behaviour of these individuals (Soteriou and Chase, 1998). The manner in which customer service employees behave toward an organization, customers will have a significant impact on the development of these long term relationships. That is, when employees reported that their organizations expected, supported, and rewarded quality service, customers reported that they received superior service (Froehle and Roth, 2004). The higher levels of employee motivation associated with higher levels of commitment and higher quality exchanges are suggested to result in a higher level of customer service quality on the part of the employee (Cronin, Brady and Hult, 2000).

Social institutions, collective behaviour, and constraints of consumption environments enable and affect consumer behaviour.

Social studies focus on identifying and studying parameters of external environments that influence consumption patterns. The major themes that are studied by sociologists with regard to consumption behaviour are culture, social class, personal influence, ethnic influence, family and household, and situational influences. Sociology studies why people buy products and find various answers to that simple question: products provide function; products should comply with people preferences about the form in which product function could be delivered; products become symbols of meaning in society. Another line of sociological research on consumption analyses institutional influences on consumption patterns. Consumption patterns to a large degree are also affected by social class, because people who belong to the same class share similar values, lifestyles, and interests. Sociologists study the role different goods play in distinguishing between different classes and reinforcing identity within a certain class. Marketing segmentation is also often based on marketing products to a specific social class by using special language, symbols, and appeal, which triggers associations of a particular social class (Williams, 2002).

The major part of psychological research, besides social psychology, studies individual processes. The domain of psychology research on consumer behaviour focuses on identifying and studying personal human qualities that influence consumer behaviour. Psychology is interested in learning how the urge of need is created, how different stimulators influence the personal decision-making process, and how the satisfaction sensation is created and confirmed. It seems that the focus is given to four major topics: consumer resources (time, money), motivation, knowledge, attitudes, personality, values, and lifestyle. Alongside these, three major processes are being studied by psychologists: information processing, influencing attitudes and behaviour, and learning processes (Engel et al, 2001). Behaviourists that support a classical conditioning view study how consumers respond to brand names, scents, colour, and other stimuli when making purchasing decisions based on knowledge they have gained over time. Psychological studies analyse the influence of the emotional state of consumers on purchasing decision. Psychological processes such as attention, comprehension, memory, and cognitive and behavioural theories of learning, persuasion, and behaviour modification constitute an integral part of marketing studies on consumer behaviour. The lifestyle concept comprises a formal process of integration of social practices, through which actors express their individual identity (Witt, Andrews and Carlson, 2004). The Theory of Reasoned Action (TRA) suggests that behaviour depends on the intention to perform the behaviour. The most important determinant of a person's behaviour is behavioural intent. There is a correlation between a person's intention, a person's willingness to try to act and that such behaviour is being performed (Ajzen, 1991). The *Theory of Planned Behaviour* includes the concept of perceived behavioural control, which is the person's belief about feasibility of using the provided opportunity. The main concept is that the greater the perceived behavioural control, the stronger a person's intention is to try to perform the relevant behaviour. The perceived behavioural control can also affect behaviour by making it impossible to perform certain behaviour.

4. Modelling Techniques

This section briefly describes different techniques used for modelling of human behaviour in current industry applications. The techniques studied which are used to model customer and service advisor (CSA) behaviour is:

4.1. Soft Computing Techniques

Soft computing (SC) is a new emerging mathematical approach that shows promise in dealing with the inherent complexity of modelling human behaviour (Zadeh, 1996). SC is a discipline situated at the combination of several relatively new and distinct mathematical techniques: fuzzy logic (FL), neural networks (NN) and probabilistic reasoning (PR) which includes genetic algorithms, chaos theory, belief nets and learning theory. The experiment to build and validate the model includes a compensatory task performed by several human subjects to develop training and test set of data in this human behaviour. The realisation that modelling of highly complex systems, that require intelligent systems, must combine knowledge, mathematical techniques and methodologies from several sources.

Fuzzy Logic

Fuzzy Logic (FL) defines a framework in which the inherent ambiguity of real information can be captured, modelled and used to reason with uncertainty. An introduction to FL can be found in (Ross, 2004) (Dote, 1995). FL is not a machine learning technique; nevertheless due to its ability to handle uncertainty it is used in combination with other machine learning techniques in order to produce behaviour models that are able to capture and to manage the uncertainty of human behaviour. A traditional fuzzy logic inference system is divided into three steps: (1) Fuzzification; (2) fuzzy inference; and (3) defuzzification. FL in UM does not necessarily realize these three steps, but a subset of them. Typically FL has been used to implement applications that are based on a recommendation task. In these applications FL provides the ability of mixing different user preferences and profiles that are satisfied to a certain degree. FL has been used to implement recommendation tasks (Nasraoui and Petenes, 2003), where fuzzy inference is used for recommendation purposes using user profiles obtained with hierarchical unsupervised clustering. Better communication can be attained through fuzzy logic because of its ability to utilise natural languages in the form of linguistic variables (Kuanchin and Gorla, 1998).

Neural Networks

Neural networks provide an alternative method of building models of human performance. They can learn behaviour from examples, reducing the need for many identical repetitions and intensive analysis. The data upon which the model is based is a statistical representation of a human's performance through many repetitions of a set of tasks. This means the model is actually only correct for the exact tasks in the statistical base, and its applicability to other conditions is only as good as the manual analysis that went into the model (Fix and Amstrong, 1990). Neural network is quick in predicting new cases if it is properly trained. The drawback of neural networks is that it can never be exact (only accurate), even if it is trained for ever. Neuro fuzzy systems have the ability to incorporate human knowledge and to adapt their knowledge base via

optimisation techniques (Stylios and Groumpos, 1999). Traditionally, NNs have been used for classification and recommendation in order to group together users with the same characteristics and create profiles (Tran, et al. 2003).

Genetic Algorithms

Genetic algorithms (GA's) are search algorithms based on the mechanics of natural selection. A GA begins with a set of solutions (chromosomes) called the population. Solutions from one population are taken and used to form a new population, which are closer to the optimum solution to the problem at hand. GAs is search strategy that is tailored for vast, complex, multimodal search spaces (Rees and Koehler, 2002), (Back, et al. 1996).

Decision Trees

Decision tree algorithms tend to automate the entire process of hypothesis generation and then validation much more completely in a much more integrated way than any other data mining techniques. Decision trees have unique advantages. They produce models that are easy to understand and they are unaffected by missing values in data (Berson, et al. 2000). Decision trees have been used to predict insolvencies in such a way that this prediction can be operationally useful for the process of the telecommunications business handling customer insolvency (Daskalaki, et al. 2002). Decision trees impose certain restrictions on the data that is analysed. Decision trees permit only single dependent variable. In order to predict more than one dependent variable, each variable requires a separate model. Most decision tree algorithms require that continuous data are grouped or converted to categorical data.

Fuzzy Clustering

In non-fuzzy or hard clustering, data is divided into crisp clusters, where each data point belongs to exactly one cluster. In Fuzzy Clustering (FC), the data points can belong to more than one cluster and associated with each data point are membership grades which indicate the degree to which it belongs to the different clusters (Crespo and Weber, 2005). One of the key elements of any FC system is the definition of the concept of distance used for the creation of the clusters. The most widely used algorithm is the Fuzzy C-Means (FCM) Algorithm. Fuzzy clustering processes can be appropriate for grouping users in classes by navigational behaviour. Information in user profiles can be used to customise and identify a user with a social group, done by assigning a general profile related to preferences shown by the user (Martin-Bautista, et al. 2002).

Fuzzy Cognitive Maps (FCM)

Fuzzy cognitive maps (FCM's) combine characteristics of both fuzzy logic and neural networks. FCM can model dynamical complex systems that change with time and use symbolic representation for the description and modelling of the system. A fuzzy cognitive map is consisted of concepts in order to illustrate different aspects in the behaviour of the system, with each concept representing a characteristic of the system, and these concepts interact with each other showing the dynamics of the system (Stylios and Groumpos, 1999). Limitations – This methodology gives more attention to human experience rather than the process being controlled (Stylios and Groumpos, 2000).

4.2. Agent Based Modelling

(Bonissone, 1997), agent-based modelling is a bottom-up approach to understanding systems which provides a powerful tool for analysing complex, non-linear markets (Fazlollahi and Vahidov, 1997). The method involves creating artificial agents designed to mimic the attributes and behaviours of their real-world counterparts. The key feature of agent based modelling is that it involved a bottom up approach to understanding a systems behaviour (Twomey and Cadman, 2002). One of the key strengths of agent based modelling is that the system as a whole is not constrained to exhibit any particular behaviour. The models are also relatively easy to understand as they have a simple, structural correspondence between the target system and the model representation. One of the weaknesses of his method is the potential lack of adequate data. The identification and capturing of appropriate processes underlying the agent's behaviour is also not easy (Ben Said, Bouron, and Drogoul, 2002a).

4.3. Multiple Classifier Combination Methods

Prediction of customer's purchase behaviour can be classified as a classification problem, and classification is also one of the most common tasks in data mining area. There are two families of combining multiple classifiers: serial combination and parallel combination. Serial combination arranges classifiers sequentially and the result from the prior classifier is fed to the next classifier. Parallel combination arranges classifiers in parallel. Some commonly used methods for combining classifiers include majority voting, Bayesian, BKS (behaviour knowledge space), and Borda Count (Kim, Kim and Lee, 2002). Limitations: A method might override the others in classification performance on a specific problem, but in general, it is not possible that one method always outperforms all the other methods for every possible situation. This method is based on the fact that different classifiers potentially offer complementary information about the patterns to be classified.

4.4. Cognitive Process Modelling

It is a designing systems and processes to meet user's changing needs, limitations, expectations and abilities. The modelling of collective human behaviour can be done by taking the characteristics on cognitive psychological aspects and human interactions under collective behavioural situations into account (Nakamura, 2001). As shown from figure (2), the cognitive system performs the higher mental processes of understanding, evaluating, planning, deciding, and thinking, whereas affect refers to feeling responses (Dolen et al, 2004).

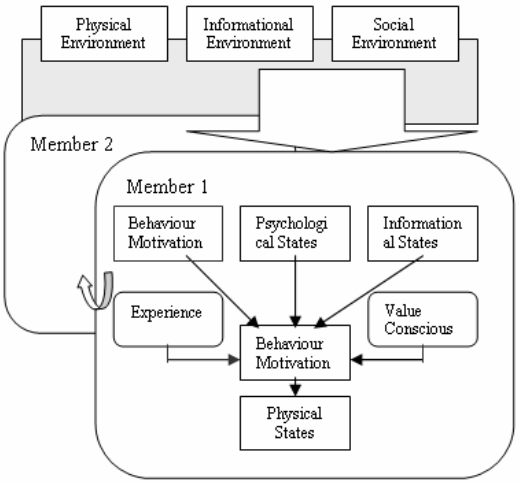

Figure 2: Several aspects of interactions among collective humans **(Nakamura, 2001b)**.

To develop such models the crucial issues are treatments of:

1. Physical, physiological, psychological and informational interactions among persons.
2. Vagueness, ambiguity, uncertainty of human inner states and knowledge.
3. Flexible information processing in human cognitive processes.

4.5. Case – Based Classification Approach

Case based reasoning (CBR) shows significant promise for improving the effectiveness of complex and unstructured decision making. It is a problem solving technique that is similar to the decision making process used in many real world applications. CBR is both a paradigm for computer based problem solvers and a model of human cognition (Chaochang, 2002).

CBR's core steps are: (1) Retrieving past cases that resemble the current problem (2) Adapting past solutions to the current situation (3) Applying these adapted solutions and evaluating the results and (4) Updating the case base. The CBR is a similar machine reasoning that adapts previous similar cases to solve new problems. The reasoning process is as shown below in figure (3).

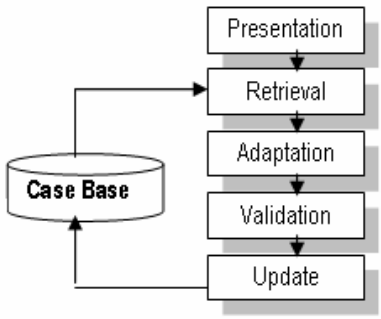

Figure 3: The general CBR process

- Presentation – a description of current problem is input into the system
- Retrieval – the system retrieves the closest matching cases stored in a case base
- Adaptation – the system uses the current problem and closest matching cases to generate a solution to the current problem.
- Validation – the solution is validated through feedback from the user or environment.
- Update – if appropriate, the validated solution is added to the case base for use in future problem solving.

4.6. Living System Theory

Living system theory recognises the system as collection of elements interrelated together to form a whole; the elements, relations and wholes are expressed with different notions. The theory of living system explains the living system as cognitive systems, which is an attempt to explain how cognition can be explained by biological phenomena. "Living system theory can be seen as a right approach to describe consumer behaviour, because the phenomena happening in the area of consumer behaviour are actually mediated through consumers" (Kurniawan, et al. 2003). In modelling the customer behaviour using living system, there are some assumptions taken in order to simplify the model. They are:

- Customers can choose to select components from product family architecture to be assembled into a product or prefer to modify components.

- Customer behaviour is composed of series of activities. These activities are called basic cognitive activities. There are no pre-specified relationships between basic cognitive activities.

Customers can be seen as such system, with the basic cognitive activities as the elements of the system. When a customer performed a basic cognitive activity and then followed by another basic cognitive activity, it will describe the relations between them. It will serve as descriptive tool of the model, describing how customer behaves based on what (s) he has done in the past (Jurniawan et al, 2003). Some of the limitations of living systems theory are of its philosophical approach to understand and model customer behaviour because of its ability to explain the behaviour of human beings as biological system

4.7. ETHOS Modelling and Simulation

Multi agent system (MAS) approach is devised to support the modelling and simulation of agent based models of human social behaviour and culture change. Ethos extends the traditional features in MAS for agent based modelling, with new abstractions specially designed to model human behaviour and culture. These include the transmission of information between agents through observation of performed behaviour and direct generation of social stimulus, management of agent's social relationships, and support for flexible behaviour selection mechanisms. The Ethos framework provides as basic building blocks the kind of entities a modeller is likely to consider when thinking intuitively about human social behaviour and culture (Simao and Pereira, 2003). Ethos currently adds three main modelling constructs to the ones provided by widely used MAS frameworks for agent based modelling. They are namely, social transmission, relationship management and behaviour selection. Ethos is unique compared with these other MAS in providing integrated behaviour selection mechanisms. Limitations – It extends from the traditional features of MAS (Multi agent system). It is currently in prototyping stage. Ethos uses a simple discrete time step scheme to trigger events.

4.8. Critical Incident Technique (CIT)

The CIT consists of a set of specifically defined procedures for collecting observations of human behaviour and classifying them in a way to make them useful in addressing practical problems. Through interviews, the critical incident technique records events and behaviours that have been observed to lead to success or failure in accomplishing a specific task. It is a method that is comparable to other inductive grouping procedures such as factor analysis, cluster analysis, and multidimensional scaling. Unlike these procedures, however, CIT uses content analysis of stories rather than quantitative analysis of inductively discover groupings which can be used to explain the underlying causes of satisfaction (Heckman and Guskey, 1998). The use of extreme cases is intended to overcome various biases associated with recall, and also to provide data points which are the most vivid exemplars of the phenomena being investigated. The technique as originally described by Flanagan (1954) and subsequently developed by others is a systematic process which includes three stages which are (1) an explicit definition of the aim and purpose of the activity being studied, (2) A systematic data collection procedure and (3) A rigorous procedure for analysis and classification of the incidents

4.9. CuBeS Simulation Approach

The objectives of the CuBeS project (Customer Behaviour Simulator) are to develop software for simulating consumer behaviours in a competitive market including several brands and to build a virtual population of customers including several thousands of individuals, that reproduce real market properties (segmentation, evolution) independently of a given product. Cubes provide the simulation of (1) Behavioural attitudes (BA) of customers, (2) Impacts of consumption acts resulting from these attitudes, (3) Retroactive effects of these acts on the customer themselves and (4) Brand reactions to the market evolutions and their retroactive effects on the individual behavioural attitudes.
CuBeS take into account, not only individual cognitive features, but also interactions between customers or specific segments that occur in real customer's population. CuBeS model offers an operational and a conceptual richness that covers a large part of customer behaviour aspects. The model provides an interpretation of the main concepts and cognitive features, issued from marketing research and psycho-sociology works on consumption (Ben Said, et al. 2002).

4.10. CDM Method

The development of a system that accommodates the diversity of the user population and improves the user's performance is optimal. One method to improve the user's performance is to categorise the system users into groups, describe and model each group's behaviours and the incorporate this information in the design and operational processes. The CDM method (Categorising, Describing, and Modelling method) was developed as a technique to generate user models. In the CDM method, the user population is first categorised into a reasonable number of groups. The behaviours for each group are described and then qualitatively and quantitatively modelled. The purpose of the CDM method is to build a set of precise and accurate models that represent the interaction of diverse user behaviours with the system (Bushey, Mauney, and Deelman, 1999). Limitations: The CDM method has only been applied to the sales negotiation. CDM method focuses on modelling different users' behaviours; it is best implemented on systems where users' behaviour's are measurably different.

4.11. Valence Based and Specific Emotions Approach

To model the impact of emotions on satisfaction and subsequent customer behaviours two approaches are used: *Valence Based Approach* – It is used to model the impact of emotions on satisfaction through summation of the positively and negativity of the different emotions that customers experience to arrive at an overall judgment of (dis)satisfaction. In this approach, negative emotions are expected to lead to more dissatisfaction, whereas positive emotions are expected to lead to more satisfaction. *Specific Emotions Approach* – It focuses on the elements of specific emotions. Different negative emotions may differentially impact (dis)satisfaction. As research in the field of emotion theory has shown, different specific emotions can have different behavioural tendencies and behavioural consequences. One of the tenets of appraisal theory is that the cognitive appraisal of the situation is the ruling mechanism in both the elicitation and differentiation of emotion (Zeelenberg and Pieters, 2004b).

4.12. Examples of Techniques for Modelling Human Behaviour

This section outlines the different techniques which can be used to model customer and CSA's behaviour within contact centre environment. The analysis briefly describes the techniques used for human behaviour modelling.

Human Behaviour Modelling Technique	Research Example	Reference
Fuzzy Technique	An expert system for evaluation of the unemployed for certain posts is an example of using fuzzy technique. It uses Neuro – fuzzy techniques for analysing corporate database of unemployed and enterprises profile data. The process of matching an unemployed with an offered job is performed through a Sugeno type Neuro – Fuzzy inference system **Fuzzy Expert System** - The development of fuzzy expert system for hotel selection called HAS (Hotel Advisory System). It assists the tourists in conducting hotel selection using fuzzy logic. **Fuzzy Clustering Technique** - A methodology to cluster customers on the basis of their demand attributes, rather than the static geographic property which is considered extensively in most published vehicle routing algorithms. **Fuzzy Cognitive Maps** - Used for modelling the supervisor of complex manufacturing systems which best utilises existing experience and knowledge in the operation of system. This methodology gives more attention to human experience, rather than process being controlled.	(Drigas, et al. 2004) (Ngai and Wat, 2003) (Tung-Lai and Jiuh-Biing, 2003) (Stylios and Groumpos, 2000)
Neural Networks	Example of an analyser tool which was designed for solving management problems concerning the employee's classification into several projects. It combines neural networks and rule based analysis to match the employee of a company with certain jobs of new projects. **Neuro – Fuzzy Approach** - Framework of using fuzzy logic and neural networks in handling supply chain management has been described. Proposal of a solution to improve the efficiency of a complex supply chain management system by automating the selection of suppliers, and adjustment of order.	(Labate and Medsker, 1993) (Lau, et al. 2002)
Decision Trees	A framework which predicts, manages, visualises and explains travel patterns of a mobile workforce using decision trees is explained. It provides colour coded geographical visualisation of travel patterns. It uses decision trees and Neuro-fuzzy systems that display rule based information about individual journeys.	(Martin and Azvine, 2003)
Genetic Algorithms	GA approach is used and applied to bankruptcy prediction modelling. It is capable of extracting rules that are easy to understand for users like expert systems. GA are applied to extract rules that can predict corporate failure **GA – CBR Approach** – GA based approach to determine the fittest weighting values for improving the case identification accuracy. GA based CBR system is employed to classify potential customers in insurance direct marketing.	(Shin and Lee, 2002) (Chaochang, 2002)
Living Systems Theory	Customer behaviour modelling in customising products using living systems is presented in this example. The authors illustrate it as an philosophical approach to model customer behaviour because of its ability to explain the behaviour of human as biological system	(Kurniawan, et al. 2003)
Ethos Modelling	Ethos framework provides basic building blocks the kind of entities a modeller is likely to consider when thinking intuitively about human social behaviour and culture. It includes objects describing the structure and topology of physical spaces, entities places in the space.	(Simao and Pereira, 2003)
Critical Incident Technique	The study examines service encounters within help desks at IT centres to understand the events and behaviours that can cause customers to identify their satisfaction levels from satisfactory to dissatisfactory with the use of critical incident technique.	(Heckman and Guskey, 1998)
CuBeS Simulation Approach	The following example proposes a consumer behavioural model based on a set of behavioural primitives such as imitation, conditioning and innovativess; which are founded on the new concept of behavioural attitude.	(Ben Said, et al. 2002)

5. Customer and Advisor Behavioural Categorisation

5.1. Introduction

Many telecoms service sector are subjected to failures in service delivery and better customer satisfaction values because they much depend on customer service advisor (advisors) to deliver service to their customers. 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. In their previous studies (Hartline and Ferrell, 1996), also suggested that attitudinal and behavioural responses of advisors are important because of the interactive nature of service delivery. It also showed that advisor's attitudinal and behavioural responses can positively and negatively affect customers' perceptions of the service encounter and their judgments of service quality Figure (4) shows the methodology followed for customer and advisor behavioural analysis within contact centres (Shah, Roy, and Tiwari, 2005).

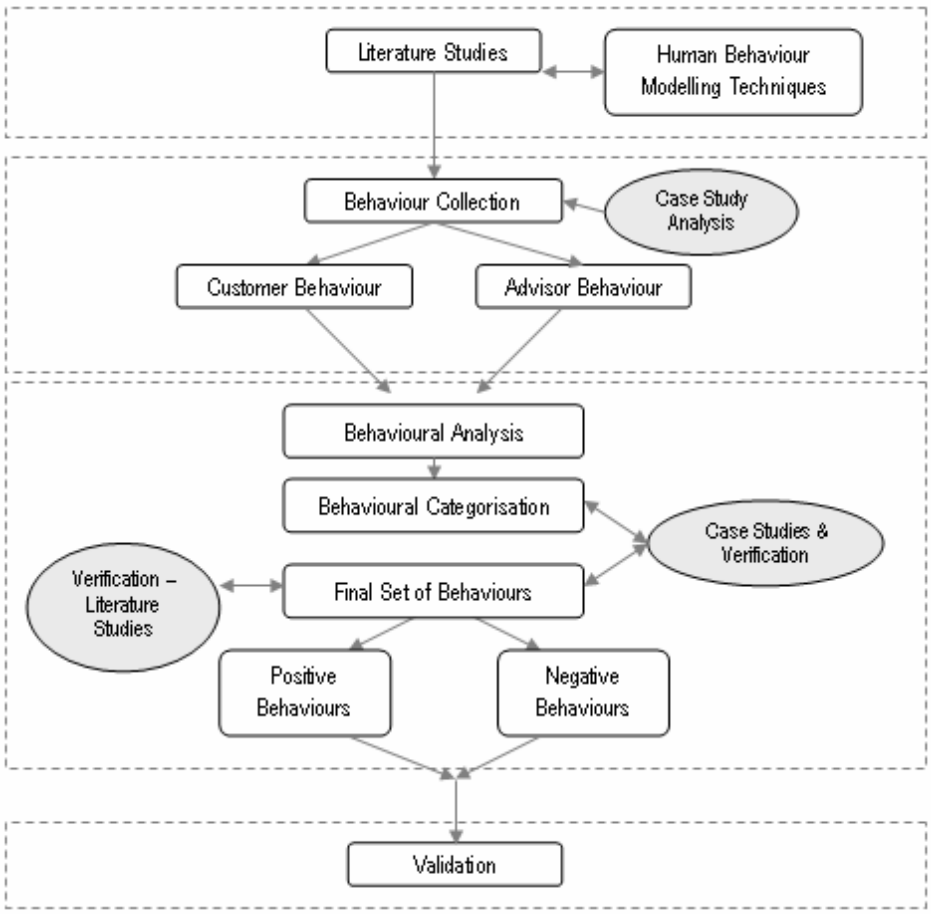

Figure 4: Flowchart for Customer and Advisor Behaviour Analysis

Trust has a moderate but beneficial influence on the development of positive customer attitudes, intentions, and behaviour. Customer service advisor (advisors) has modest influence over the development of trust between themselves and their customer (Swan, Bowers and Richardson, 1999). Research findings indicate that successful advisor often

tailor their presentation to the needs of each customer so that not only product/service desires is addressed but also the customers' sales process needs. Emotional reactions to a sales interaction may affect customer satisfaction with the purchase experience and future purchase intentions (cross/up sell) (Goff, Boles, Bellenger and Stojack, 1997).

5.2. Observations and Analysis

The following section describes the observations and analysis of the type of behaviours identified by the authors at the contact centres for advisor and customers. The validation of these behaviours was carried out with team leaders/managers and service advisors and the results of the validation are discussed later within section 5.3. The authors used a semi-structured questionnaire for identification of these behaviours on the basis of their understanding of the contact centre environment and from the knowledge supported by the literature studies as discussed earlier within the paper. The advisor behaviours noticed during the contact centre monitoring process are shown in table 1.

Attentive	Capable	Efficient	Unorganised	Helpful	Angry	Aggressive
Concentrate	Speed with service	Friendly	Generous	Understanding	Emotion	Polite
Good Speech Manner	Knowledge Oriented	Sales Awareness	Less Product Knowledge	Business Promotions	Customer Focus	Product Awareness
Communicative	Happy	Co-operative	Unaware	Fast Speech	Annoyed	Confused

Table 1: List of Advisor Behaviours

Similar to the list of advisor behaviours, the authors also noticed the same pattern of customer behaviours from hearing to the calls, and also the way the advisors used to derive their customer once the call was finished. Lu and Lin indicate that customer attitude is influenced by belief about brand equity (value), which is affected by the content, context and infrastructure. Customer loyalty is determined by attitude and belief about the context in which the products or services are offered (Hsipeng and Lin, 2002).

Understanding	Knowledgeable	Time Wasters	Afraid	Complaint Frequency	Annoyed
Trustworthy	Patience	Helpful	Angry	Attentive	Polite
Unaware of situation	Pleased	Concentrated	Generous	Unhelpful	Confident
Useful	Aggressive	Language problems	Joyful	Co-operative	Sad

Table 2: List of Customer Behaviours

Based on the classification of this behaviours observed by the authors at the contact centre for advisors and customers, it was not possible to consider all of those behaviours for further analysis and study of the research. For this reason, the authors then identified which of the behaviours were the most repetitive ones which were observed through out the monitoring process and through the expert judgement from the team leaders and advisors at the centre.

5.3. Validation Process

During a particular call situation, the researcher highlighted the key observations in terms of advisor's behaviour changes or the way the customer was dealt with. From the customer's point of view, it was purely hearing the calls during the conversation, and the researchers own understanding and judgement which was derived from the literature studies and earlier knowledge of the contact centre. Once the situation was observed and analysed, it was then checked and validated with the advisor, where the observation was correct or not. It was also checked with the team leaders, and after the validation from both sides was done, it was then structured as shown in the data structuring charts.

5.3.1 Results from Team Leaders for Advisor Behaviour Analysis

Based on the initial set of behaviours for advisors, the authors had a selection of behaviours and asked the team leaders to verify the list on their experience within the real environment.

Advisor Behaviour	Team Leader 1	Team Leader 2	Team Leader 3	Team Leader 4	Team Leader 5
Attentive	Agree	Agree	Slightly agree	Agree	Agree
Capable	Slightly Agree	Slightly Agree	Disagree	-	Disagree
Angry	Agree	Slightly Agree	Agree	Agree	Slightly Agree
Confused	Disagree	Disagree	Slightly Agree	Disagree	Disagree
Language Prob.	Disagree	Disagree	Disagree	Disagree	Disagree
Emotional	Slightly Agree	Disagree	Disagree	Disagree	-
Friendly	Agree	Agree	Agree	Slightly Agree	Agree
Compliments	Disagree	Slightly Agree	Disagree	Slightly Agree	-
Calm	Slightly Agree	Disagree	Disagree	-	Disagree
Unaware	Slightly Agree	Agree	Agree	Agree	Agree
Annoyed	Agree	Agree	Agree	Slightly Agree	Agree
Aggressive	Agree	Agree	Agree	Agree	Agree
Service Speed	Slightly Agree	Slightly Agree	Disagree	Slightly Agree	Disagree
Customer Focus	Agree	Agree	Slightly Agree	Agree	Agree

Table 3: Advisor behaviour analysis results from team leaders

5.3.2 Results from Advisor for Customer Behaviour Analysis

Based on the observations from the customer call monitoring process, the authors listed the key customer behaviours from the overall understanding of the environment, and then validated it with the advisors in form of table with slightly agree, completely agree or disagree. Further suggestions were also asked by the authors to verify that the behaviours captured from the observations were valid in the real environment.

Customer Behaviour	Advisor 1	Advisor 2	Advisor 3	Advisor 4	Advisor 5
Understanding	Agree	Agree	Slightly Agree	Agree	Agree
Trustworthy	Disagree	Slightly Agree	Disagree	-	Disagree
Angry	Agree	Agree	Slightly Agree	Agree	Agree
Patience	Slightly Agree	Agree	Disagree	Slightly Agree	-
Distressed	Disagree	Slightly Agree	Agree	-	Disagree
Language Prob.	-	Disagree	Slightly Agree	Disagree	Disagree
Aggressive	Agree	Agree	Agree	Slightly Agree	Agree
Helpful	Agree	Agree	Agree	Agree	Agree
Unclear	Slightly Agree	Disagree	Agree	-	Slightly Agree
Joyful	Agree	Slightly Agree	Agree	Slightly Agree	Agree
Unhelpful	-	Disagree	Slightly Agree	Disagree	-
Co-operative	Agree	Slightly Agree	Agree	Agree	Slightly Agree
Polite	Slightly Agree	Agree	Agree	Agree	Agree
Annoyed	Agree	Slightly Agree	Agree	Agree	Agree

Table 4: Customer behaviour analysis results

6. Comparative Analysis of Human Behaviour Modelling Techniques

This section outlines the different techniques which can be used to model customer and CSA's behaviour within contact centre environment. The analysis briefly describes the techniques used for human behaviour modelling. To address these techniques the following criteria were used for the analysis which are (1) Customer Behaviour (mood before and after sales), (2) CSA interaction and (3) Customer satisfaction. The empty boxes shown within the chart suggests that the technique does not support the requirement.

Human Behaviour Modelling Technique	Description	Customer Behaviour	CSA Interaction	Customer Satisfaction	Reference
ETHOS	**Modelling Human Social Behaviour & Culture change** ▪ Ethos provides basic building blocks the kind of entities a modeller is likely to consider. ▪ Ethos uses a simple discrete time step scheme to trigger events. ▪ Limitations – It extends from the traditional features of MAS (Multi agent system). ▪ Currently in prototyping stage. ▪ Behavioural responses are triggered by stimulus generated by the physical or social environment.	●			(Suhm and Peterson, 2002) (Simao and Pereira, 2003)
Cognitive Process	**Modelling Human Behaviour** ▪ It describes the characteristics on cognitive psychological aspects and human interactions under collective behavioural situations. ▪ The crucial issues of treatments are: **1**. Physical, Physiological, psychological and informational interactions among persons. **2**. Vagueness, ambiguity, uncertainty of human inner states and knowledge. **3**. Flexible information processing in human cognitive processes ▪ The cognitive system performs the higher mental processes of understanding, evaluating, planning, deciding, and thinking, whereas affect refers to feeling responses. ▪ For modelling cognitive process of interpersonal interactions it has to embed existing qualitative knowledge on social psychological characteristics and to treat vague cognitive states. ▪ Limitations - It depends upon the kinds of experience that come from having a body with various capacities and embed in a more encompassing biological, psychological and cultural context.	●	●	●	(Fischer, Garbin and Gharakhanian, 1998) (IT Com , 2002)
Living Systems Theory	**Customer Behaviour** ▪ Elements, relations & wholes are expressed with different notion. ▪ Customers can be seen as such system, with the basic cognitive activities as the elements of the system. ▪ When a customer performed a basic cognitive activity and then followed by another basic cognitive activity, it will describe the relations between them. It will serve as descriptive tool of the model, describing how customer behaves based on what (s) he has done in the past. ▪ Limitations - Its philosophical approach to understand and model customer behaviour because of its ability to explain the behaviour of human beings as biological system.	●			(Anton, 2000) (Bernett and Gharakhanian, 1999) (Kurniawan, et al. 2003)

Human Behaviour Modelling Technique	Description	Customer Behaviour	CSA Interaction	Customer Satisfaction	Reference
Cubes Simulation Approach	**Customer Behaviour** ▪ Based on behavioural models concept. Software for simulating consumer behaviours. ▪ The customer cognitive functions are derived from generic behavioural components intrinsically related to the interaction aspect. ▪ Not targeted on a given population segment and a given type of product. ▪ It introduces stimuli based on promotional offers, brand loyalty, and innovation but does not consider the price as a determinant factor to the customer choice	●		●	(Ben Said et al, 2002)
Case Based Reasoning (CBR) Approach	**Discovery, Predictive modelling & Forensics Analysis**. ▪ CBR is both a paradigm for computer based problem solvers and a model of human cognition. ▪ GA- CBR is used to enhance the case matching process and to predict customer purchasing behaviour. ▪ Retrieving past cases that resemble the current problem. Adapting past solutions to the current situation. ▪ Better learning and testing performance. ▪ Difficult for mining customer purchasing insights that are complex, unstructured, and mixed with qualitative and quantitative information.			●	(Chaochang, 2002)
Multiple Classifier Combination Method	**Prediction of customer's purchase behaviour** ▪ Commonly used methods for combining classifiers majority voting, Bayesian, Borda Count. ▪ To enhance the accuracy in predicting the propensity of customer purchase by combining multiple classifiers based on genetic algorithms. ▪ Voting is most common method to combine more than one decision. ▪ Limitations: A method might override the others in classification performance on a specific problem, but in general, it is not possible that one method always outperforms all the other methods for every possible situation. This method is based on the fact that different classifiers potentially offer complementary information about the patterns to be classified.	●		●	(Kim et al, 2002)
CDM Method	**Categorise, Describing & Modelling Method** ▪ It allows the system to be customised to facilitate desired behaviour and optimise pre-existing behaviour. ▪ The CDM method has only applied to the sales negotiation telecommunication computer system. ▪ The purpose of CDM method is to build set of precise and accurate models that represent the interaction of diverse user behaviours.		●	●	(Bushey et al, 1999)
Valence Based Approach	**Customer Mood & Emotions** ▪ Entails a summation of positively and negativity of the different emotions that customer experience. ▪ Focus on mere valence has the disadvantage of ignoring all the specific elements that are present in the different emotions, which are not easily expressed by valence alone.	●	●	●	(Zeelenberg and Pieters, 2004)

Human Behaviour Modelling Technique	Description	Customer Behaviour	CSA Interaction	Customer Satisfaction	Reference
Specific Emotions Approach	**Customer Behaviour** ▪ Based on behavioural models concept. This approach leans heavily on the appraisal theory of emotions. ▪ Specific emotions are responses to specific situations	●		●	(Zeelenberg and Pieters, 2004)
Soft Computing					
Neural Networks	**Neural Networks (NN)** ▪ NN is quick in predicting new cases if it is properly trained. ▪ Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract complex patterns. ▪ NN is a powerful method to model human behaviour. ▪ NNs have been used for classification and recommendation in order to group together users with the same characteristics and create profiles. ▪ NNs have also been used for recommendation, which predicts the next step for a given user trajectory in a virtual environment.	●			(Hu and Tsoukalas, 2003) (Yasdi, 2000) (Fix and Amstrong, 1990) (Sas, Reilly, and O'Hare, 2003)
Fuzzy Logic System	**Fuzzy Cognitive Map** This technique gives more attention to human experience, rather than to the process being controlled. **Fuzzy Logic System** ▪ FL provides the ability of mixing different user preferences and profiles that are satisfied to a certain degree. ▪ Fuzzy systems reduce the complexity of a problem by refraining from unnecessarily discriminating very similar values. ▪ Because they are rule-based, fuzzy systems can easily make use of prior knowledge. ▪ FL provides a soft filtering process based on the degree of concordance between user preferences and the elements being filtered.	●	●	●	(Nasraoui and Petenes, 2003) (Vrettos and Stafylopatis, 2001) (Stylios and Groumpos, 2000b) (Stylios and Groumpos, 1999)

Human Behaviour Modelling Technique	Description	Customer Behaviour	CSA Interaction	Customer Satisfaction	Reference
Decision Trees Approach	**Tree Structure Approach** ▪ It is the easiest to understand. Tend to excel when a particular target attribute value is based on a complex, set of attributes with particular values. ▪ Decision tree algorithms tend to automate the entire process of hypothesis generation and then validation much more completely in a much more integrated way than any other data mining techniques. ▪ They produce models that are easy to understand and they are unaffected by missing values in data. ▪ Decision trees have been used to predict insolvencies in such a way that this prediction can be operationally useful for the decision support process of the telecommunications business handling customer insolvency. ▪ An example of decision-tree-based methodology to detect changes of customer behaviour automatically from customer profiles and sales data at different time snapshots was presented by (Kim, Song, Kim and Kim, 2005).	●		●	(Berson, Smith, and Thearling, 2000) (Daskalaki, Kopanas, Goudara and Avouris, 2002b) (Kim et al, 2005)
Genetic Algorithms	**Multiple Classifier System based on Genetic Algorithm** ▪ Integrated measurement level classification results generated by multiple classifiers into single result. Genetic Algorithms (GAs) are search algorithms based on the mechanics of natural selection. ▪ GA's are a search strategy that is tailored for vast, complex, multimodal search spaces. ▪ In general GAs have been used for Recommendation in the form of rules, which can capture user goals and preferences, because they perform a global search and cope better with attribute interaction than algorithms used in data mining, where the search is more local.	●	●		(Ishibuchi, Nozaki, Yamamoto and Tanaka, 1995) (Rees and Koehler, 2002)
Neuro – Fuzzy Systems Approach	**Neuro Fuzzy Systems** ▪ They have been proposed as advanced techniques in the modelling and control of real world problems that are usually imprecisely defined and require human intervention. ▪ Neuro-Fuzzy systems (NFS) use NNs to extract rules and/or membership functions from input-output data to be used in a Fuzzy Inference System. ▪ NFS are basically FL systems with an automatic learning process provided by NN. ▪ The combination of NN and fuzzy sets offers a powerful method to model human behaviour which allows NFS to be used for a variety of tasks. (George and Cardullo, 1999) represents a Neuro-fuzzy system for modelling human operator behaviour in computer generated forces.	●			(George and Cardullo, 1999) (Drigas, Kouremenos, Vrettos, Vrettaros and Kouremenos, 2004)
Fuzzy Clustering Technique	▪ The most widely used fuzzy clustering algorithm is the Fuzzy C-Means (FCM) Algorithm ▪ Fuzzy clustering can be regarded as an improved clustering technique, which has been used successfully in diverse fields for both data compression but and data categorization. ▪ Fuzzy clustering processes can be appropriate for grouping users in classes by navigational behaviour. ▪ Information in user profiles can be used to customise and identify a user with a social group, done by assigning a general profile related to preferences shown by the user.	●		●	(Lazzerini, Marcelloni, and Cococcioni, 2003) (Martin-Bautista, Kraft, Vila, Chen and Cruz, 2002)

7. Discussions and Future Research

This paper gives a brief overview of the techniques in modelling human behaviour within contact centre environment. The research provides understanding of the current techniques which are used for modelling customer and CSA (customer service advisor) behaviour, which helps managers optimise channels, improve customer acquisition, retention and add on selling particularly in CC context. Modelling and mapping customer relationships and behaviour of CSA's allows a better understanding of the way a company interacts with its customers. Modelling also helps managers formally define which customer segments they want to offer value, through which channels they want to do this and establishing what relationships. By using such an approach, customer communication becomes communicable, comparable, analysable and easily modifiable because of the building block like structures. On one hand this should improve communication between managers and CSA's and on the other hand it provides better customer satisfaction and retention. It was shown through the comparative analysis chart that these techniques have several limitations which led to the introduction of soft computing. The key findings from the research review are as:

The main aim and the purpose of this study was to identify the behavioural aspects of human in terms of customer and service advisor and how the previous research has been carried out to model these behavioural aspects within different environments. Understanding and adapting to changes of customer behaviour is an important aspect of surviving in a continuously changing environment (Chaochang, 2002). With effect to the changes in customer behaviour the authors has highlighted some of the important human behaviour modelling techniques within this section. The study of customer helps firms and organisations improve their marketing strategies by understanding issues such as: The psychology of how customers think, feels, reason, and select between different alternatives. The psychology of how the customer is influenced by his or her environment (e.g. culture, family, signs, media etc. The behaviour of customers while shopping or marking other marketing decisions (Zeelenberg and Pieters, 2004). Some of the modelling techniques discussed within this section are Fuzzy Cognitive Maps (Stylios and Groumpos, 2000), Living Systems Theory (Jurniawan, Tseng and So, 2003), Cognitive Process Modelling (Dolen et al, 2004) (Nakamura, 2001), Case Based Reasoning Approach (Chaochang, 2002), Cubes Simulation (Ben Said et al, 2002), Ethos (Simao and Pereira, 2003) and other Soft Computing Techniques. One method to improve the user's performance is to categorise the system users into groups, describe and model each group's behaviours and the incorporate this information in the design and operational processes which is also called the CDM (Categorising – Describing – Modelling) method (Bushey, Mauney, and Deelman, 1999). Valence Based Approach is used to model the impact of emotions on satisfaction through summation of the positively and negativity of the different emotions that customers experience to arrive at an overall judgment of (dis)satisfaction ((Zeelenberg and Pieters, 2004).

Based on this study the authors have highlighted the importance of customer and advisor categorisation on the basis of demographic, experience and behavioural variables. A prototype model can be developed with the use of soft computing which would identify the type of customer and advisor within the contact centre scenario and on the basis of this identification; it would enable the managers within the centre to distribute the right kind of person for each customer call. Soft computing is already a major area of academic research.

While the methodological evolution is taking place, the number of successful soft computing based products is increasing concurrently. In the majority of such products, SC is hidden inside systems or subsystems, and the end user does not necessarily know that soft computing methods are used in control, diagnosis, pattern recognition, signal processing, etc. This is the case when SC is mainly used for improving the performance of conventional hard computing algorithms or even replacing them. However, soft computing is very effective when it is applied to real world problems that are not able to be solved by traditional hard computing. Future research work should place emphasis on proposing advanced soft computing methods, for example, new neural network models and learning algorithms, which can make use of the data to predict the type of customer and advisor behaviour within contact centre domain. Besides the further study on soft computing methods themselves, comprehensive comparisons including performance criterion, algorithm complexity, and implementation cost should be made before actually applying soft computing into engineering area. In fact, the components of soft computing have been individually explored for more than a decade, although the term ‘soft computing’ is quite new. The fusion among these techniques, on the other hand, is still not well developed and can be next steps for the research community.

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