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ENHANCING CUSTOMER-INDUSTRY RELATIONSHIP USING HYBRID MULTI CRITERIA DECISION MAKING METHOD

Abstract: *This study explores the ways in which Customer Relationship Management (CRM) can be used to increase the effectiveness of the organizational interface toward customer satisfaction. The purpose of this study is to decrease the customer defection rate and increase overall customer satisfaction (customer-industry relationship), by developing software using a hybrid Multi Criteria Decision Making method (MCDM) for a company taken as a case study. In order to decrease the customer defection rate, the important criteria are ranked using the Fuzzy Analytical Hierarchy Process (FAHP) and their corresponding weights are found by constructing a pairwise comparison matrix and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). For improving product performance and service levels, a novel mathematical framework integrated with four different methods of normalization is also introduced. After implementing the software, the customer satisfaction rate substantially increased from 39% in January to 76% in February.*

Keywords: *CRM, MCDM, FAHP, TOPSIS*

1. Introduction

In a fast-growing world, businesses started flourishing and the industries grew in a very fast manner. As the industries grew, the competition in the big stages intensified leading to them focusing more on the market share. This led these industries to focus more on customers, thus moving towards CRM, which could optimise and increase effective communication with stakeholders. Customer Relationship Management is a unique term used to define the management of the relationship that exists between different industries and their valuable customers. (Datta et al., 2018) say that CRM is a complex and difficult way of doing business. Thus, creating a simple and value centralised CRM could increase the possibility for customers and manufacturers to understand the market well enough (Aiyer et al., 2019). CRM is an essential concept or a strategy that strengthens the relations with customers (AL-Shammari et al., 2021; Lv, 2021), and at the same time the cost is reduced, the productivity is enhanced and the profitability of the business is also enhanced. (Guerola-Navarro et al., 2021) and (Baashar et al., 2020) say an ideal and efficient CRM system is a combined collection of all the data sources which are then centralised under an organization and provide a real-time vision of information about the customer holistically. A CRM system is highly significant and vast, however, it can be definitely implemented for smaller businesses and large enterprises (Ngo & Hieu, 2021) since the goal is to assist the customers associated efficiently. This is where Strategic CRM comes to play. Strategic CRM is a concept that completely focuses on enhancing the development of a business culture that prioritizes its customers first i.e. a customer-centric approach is observed (Badwan et al., 2017). In this customer-centric culture, the available resources are totally allocated in a way to best enhance the value of a customer whilst providing rewards to promote employee behaviour for successfully satisfying the customer needs like mentioned in (Sigala, 2018; Teixeira, 2021) by collecting vital information about the customer expectation and sharing them for improving the nature of business (Witell et al., 2020). Consequently, businesses strive to keep the prices of the operation low and tend to develop low-cost routes to market (Neeraj et al., 2018). According to (van Doorn, 2017), this concept is applicable for CRMs in most of the developing economies or even in the segments of subsistence of the valuable economies that are developed. Still, in some cases like in (Guha et al., 2018), the different requirements of the

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customers that define their cause of buying are clearly not in line with the low-cost goal. Businesses cannot come out with a blanket strategy to predict customer expectations as they are prone to constant changes (Gil-Gomez et al., 2020). In most sales-oriented businesses, it is assumed that if enough investment is put into aspects such as advertising, marketing, dynamic public relations (PR) and different sales promotion, most customers will be tempted to actually buy the products (Gashi & Ahmeti, 2021). But it does not hold well in every case. From a larger-scale perspective, production orientation is followed by sales orientation (Ngo & Hieu, 2021).

Low-cost products are produced by the company and then a humongous effort is made to promote them in the market. (Paliouras & Siakas, 2017) argue that a company first develops better propositions of value for its customers by collecting and disseminating the available information on its customers for effective and competitive product delivery. According to (Capuano et al., 2021) customer-centric companies are always in the constant phase of learning. It keeps the company on its toes for adapting to the different requirements of the customer and different competitive market conditions. However, the market stages are different and other different orientations may have a very strong appeal in a particular stage. This brings us to OCRM (Operational Customer Relationship Management). OCRM genuinely focuses on the perfect automation of the individual customer touchpoints of different businesses (Boisvert & Khan, 2023). Touchpoints are the regions in the system where the customer and the company meet. Different CRM software enables the automation of various functions like marketing, selling, and service. Currently, Operational CRM, being the next generation of CRM, has created a major impact on industries thus attracting more and more industries to implement it. Android application based and web-based Operational CRM systems are being integrated with the business for providing a platform for data mining and data analysis (Anshari et al., 2019; Petrovic, 2020). However, Operational CRM is strategically developed with the intent of producing accurate results that could further enable industries to forecast the market, develop a strong bond with loyal customers (Makasi, 2014), create new relationships to value-adding customers and also to reduce the number of customer defections. At its core, customer relationship management is the foundation of all its service and technological advancements to retain its customers and develop new relationships with value-adding customers (Ullah & Narain, 2020). It helps the company to build its business by increasing the loyalty and satisfaction of the customer. (Wang & Lien, 2019) says by simply collecting data, a company can forecast the market and also keep track of customers for better communication. Also, the feedback from customers is stored for analyzing and improving the personalized customer service and to help attract more customers. At the start of the era of industrialization, relationships between the customers and the industries were one to one. The loyalty of customers was an important asset earned by companies. They were able to accurately address customer needs that led them on a successful journey. The increase in scaling up of industries has its own ups and downs. It led to an increase in the customer base but also resulted in a drastic decrease in the customer-industry relationship which in turn led to the increase in the customer defection rate owing to the gross customer mismanagement followed by many industries. Also, it had a significantly larger impact on customer retention which later became the immediate reason for the increase in customer defection rate.

2. Literature Survey

2.1 Customer Relationship Management

(Dewnarain et al., 2019) proposed a conceptual model which was well characterized that addresses the close relations between client relationship administration (CRM), innovations of social media, engagement of clients, devotion, etc., bringing critical commitments to the hypothesis of promoting communication in client relationship administration. (Srivastava et al., 2019) say that the appropriation of the procedure as proposed by the client-centric hypothesis has ended in commerce philosophy’s fundamental component within the benefits segment. The re-confirmation of the impacts on brand value due to the customer-centric community online was examined by (Chou, 2014) for improving the brand prevalence within markets. (González-Serrano et al., 2021) identified client profiles from an international hotel chain using Big Data with CRM where an analysis method was created for analyzing the behaviour of clients during Covid-19 involving bootstrap resampling techniques, kernel methods, and Multiple Correspondence Analysis. (Jaziri, 2019) pondered that Customer Experiential Knowledge Management (CEKM) is a different approach and this approach is propositioned well as a result of the building of the conceptual reflection. Through the integration of the live involvement and the encounter shared online the client’s experiential information is completely researched showing CEKM in the vital sense. The challenge presently is to discover a way that interfaces the framework known as the client information administration framework to the involvement of the client known as the client lived benefit experience. The information a client picks up through experience or client experiential information is drawn from the involvement picked up within the circumstance, both offline and online where this involvement is a beneficial encounter.

(Sánchez-Gutiérrez et al., 2019) evaluate the capabilities of client connections from an administration perspective and the path in which they change over information on the requirements of the client into choices which are particular within the showcase they have an influence on the creation of client esteem, as well as on execution within the money related sense, advancement of innovation utilization, all of which can serve as markers of the competitiveness in organizations. (Sanchez-Franco et al., 2019) analyze the terms' event to distinguish proof of the points that are important and to do an examination of the related services' zone that is associated with a really tall way with the quality of the relationship. This states that influence the visitors by assessment of all perspectives of the relationship between the visitors and the hotel in the situation of the hospitality sector. (Petzer & van Tonder, 2019) evaluate the impact of engagement of clients on the connections between relationship quality which is commitment, fulfilment, trust, and satisfaction of the client, and the dependability inside the industry's brief term insurance. (Feng et al., 2019) evaluated and escalated moderating impacts of client introduction on the execution of a firm based on the hypothesis of social learning and connections viewpoint, within the competitive sense and moral authority. (King & Burgess, 2008) proposes that CRM as a concept could be a well-researched region of showcasing hypotheses. Two distinguished CRM execution focuses can be recognized using the Delphi strategy: a prevailing "hard" execution of Customer Relationship Management (focusing on centralizing, analytics, and administration of campaign) and a "soft" usage of CRM (focusing on administration involving customers which are decentralized at the individual touchpoint (where customer and the industry product meet) level). (Kamakura et al., 2005) highlights that Customer Relationship Management (CRM) ordinarily includes following personal client behaviour over time, and utilizing this information to design arrangements absolutely custom-made to the vendors' and the customers' needs.

2.2. Multi Criteria Decision Making Models for Process and planning Control

(Çelen, 2014) assesses the impacts of normalization strategies on choice results of a given Multiple Attribute Decision Making (MADM) strategy. Utilizing these proper weights of an extra-large number of the properties calculated from the Fuzzy Analytical Hierarchy Process (FAHP) strategy, connected TOPSIS strategy in assessing budgetary execution of 13 Turkish store banks. (Sun, 2010), (Gitinavard et al., 2016) and (Thenarasu et al., 2019) state that MCDM (Multi criteria decision making) has grown in a rapid way and has also gotten to be in the primary stage of the research for the management of the choice issues which is quite complex. (Torlak et al., 2011) and (Jamali et al., 2021) employ fuzzy and TOPSIS combined leading to an approach which is multi methodological within the aircraft industry in Turkey. (Wang & Elhag, 2006) propose a strategy involving the fuzzy TOPSIS that is based on the level of alpha sets and (Amiri et al., 2021) present a strategy in nonlinear programming arrangement. In (Ghosh et al., 2022) data is collected from strategic, tactical, and operational levels and integrates it with an entropy method to determine the criteria and complex proportional assessment for choosing the order of preference in a manufacturing organisation. (Wang et al., 2021) used a hybrid method for evaluating the renewable energy production capabilities of 42 countries by combining Data Envelopment Analysis (DEA) and fuzzy TOPSIS. (Albayrak & Erensal, 2004) assess the worldwide economy and the cutting edge commercial and mechanical organization to create superior strategies for surveying the execution of the human asset than basically utilizing execution measures such as proficiency or viability. A survey technique called the Delphi method is followed to collect data from a company to understand the interaction between the clients and the company. Weightage for a set of criteria was found using Fuzzy AHP, and a Pseudocode was developed to find the weightage of any given set of criteria (Mohanavelu et al., 2020). (Ballı & Korukoğlu, 2009) created a choice model to properly select the actual and the most appropriate operating systems for computer systems in the firms by taking into consideration the subjective judgments of different makers of decisions. In (Jabbarzadeh, 2018) and (Thenarasu et al., 2022) the FAHP strategy is then utilized in deciding the proper weights of the different criteria by the creators of the decision and after that rankings of the actual working frameworks are decided by the TOPSIS strategy. (Kazerooni et al., 2021) proposes two novel frameworks, a hybrid feature selection model for identifying the most value-adding construction labour productivity (CLP) factors and combines it with a decision support model by introducing fuzzy multi criteria decision-making and fuzzy cognitive maps for ranking CLP strategies. (Mohanavelu et al., 2020) reviewed the selection of hybrid dispatching rules for JSSP using the TOPSIS approach to reduce lead time, waiting time and increase machine utilization. AHP based PDR was proposed by (Mohanavelu et al., 2017) considering real-time criteria such as production volume, due date and cycle time to minimize the lead-time of a large scale press-shop. Different PDRs were comparatively evaluated in their study. (Amiri, 2010) proposed a technique to supply a straightforward approach to survey elective ventures and also to help the makers of the decision to choose the best by the utilization of the six criteria of the comparison of the speculation choices as the criterion in the AHP and fluffy TOPSIS strategies.

2.3. Normalization Methods

(Chakraborty & Yeh, 2009) say that the MADM utilizes a proper normalization method that is used to properly convert the execution evaluations with the diverse information estimation of units in the choice lattice into the consistent unit. The strategy for arranging similarities by closeness to the perfect arrangement (TOPSIS) is also one of the foremost prevalent and also broadly connected to the MCDM strategies. (Opricovic & Tzeng, 2004) outlined a proper comparative examination of VIKOR and TOPSIS is also outlined with a lot of numerical cases, appearing to show their closeness and also a few differences. (Hezer et al., 2021) analyzed and evaluated the safety levels of 100 regions with known data on COVID-19 using TOPSIS, VIKOR, and COPRAS (Complex Proportional Assessment) methods and compared their results. (Bakioglu & Atahan, 2021) addressed the risk prioritization in self-driving vehicles using a comparative analysis in TOPSIS combined with AHP and fuzzy VIKOR.

2.4. Objective

To decrease the customer defection rate and improve the relationship between the company and customers by developing software using hybrid MCDM (FAHP and TOPSIS) methods, for production planning and control which would take into account customer criteria for ranking orders, generating customer performance score.

3. Methodology

The methodology shown in Figure 1 has been followed to address the problem statement and achieve the objective.

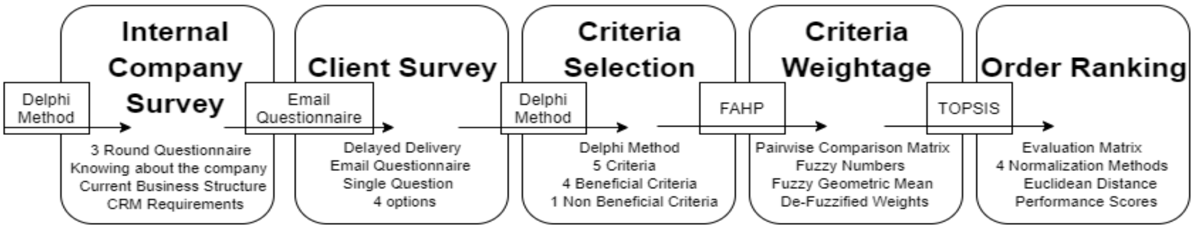

Figure 1. Pictorial representation of the Methodology

3.1. Internal Company Survey

Survey was conducted in the target company and the data was collected. The results of the survey are attached below. Delphi method is used to analyze the obtained information from the target company and this vital info serves as a building block for the creation of a novel system unique to the target company.

Implementation of Delphi Method

To get the cumulative opinion of the company's employees, three rounds of the survey were designed according to the Delphi method as shown in Figure 2 and the survey was distributed to selective employees of the company. The first round of the survey mainly concentrated on gaining knowledge about the company, the second round focussed more on knowing the work structure and the main problems faced by the existing CRMs in the company, and an intense data sweep was done in the third round for determining their extant CRM and the criteria for its successful implementation.

From the results of the survey conducted it is clearly visible from Figure 3 that "Delayed Delivery" was the major reason that contributed to customer defection, in fact, this survey was very useful because the company thought its service support level was the major reason for the customer defection rate, now the survey results will be used in developing software accordingly to decrease the delay in product delivery.

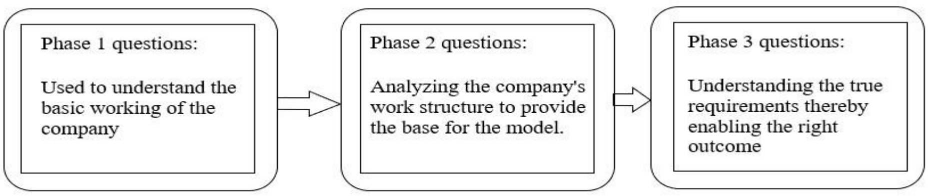

Figure 2. Pictorial representation of Delphi

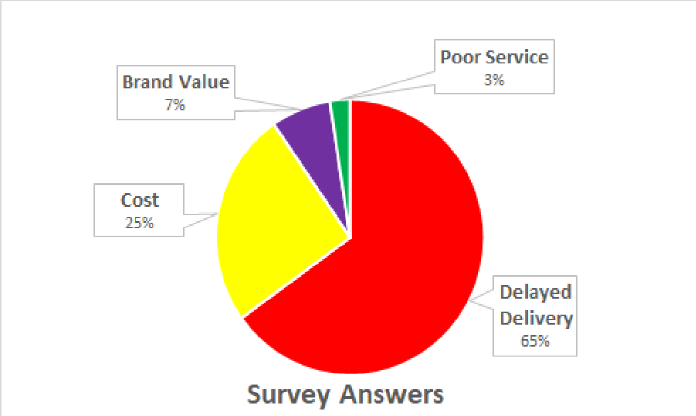

Figure 3. Pie chart of the Survey answers

Based on the series of surveys conducted within the company and clients it has been found that the increasing Customer Defection Rate was the major problem faced by the company and the major reason which was causing the Delay in Delivery, so a conceptual model is developed to rank the orders according to the customer value to decrease the delay in delivery, for this FAHP, TOPSIS, vector and linear normalization methods have been used, to check the consistency of different normalization methods some statistical tests like D-test, Correlation test have been used.

3.2. Criteria Selection

In order to rank orders using MCDM (Multi Criteria Decision Making) method some criteria are needed to be selected and weights should be given, by using the Delphi method following criteria are found to be important, the following criteria have been classified into two types beneficial and non-beneficial, More the value of the beneficial criteria the more importance will be given to the corresponding client, whereas for the non-beneficial criteria the lesser the value the more important it will get, out of five criteria selected there is one non-beneficial criterion and four of the beneficial criteria. For each of the criteria listed below in Table 1, a formula has been defined on how to measure the criteria for each order.

Table 1. Criteria Description

C. No	Criteria	Criteria Type	Information
C1	Customer Segment Importance	Beneficial	Dividing a customer base into groups of individuals
C2	Profitability in order	Beneficial	Profitability = (Order cost-Basic cost)/(Basic cost)
C3	Customer Value	Beneficial	Customer Value = (No of Existing orders) + (No of predicted orders)
C4	No of Due Days Left	Non-Beneficial	No of days left as per the commitment
C5	Product Manufacturing Time	Beneficial	No of days required to complete the job for the respective client

Criteria Weightage

FAHP (Fuzzy Analytical Hierarchical Process) has been selected to calculate the weightage of each criterion, Analytical Hierarchical Process, and it is used generally with many Multi Criteria Decision Making (MCDM) Methods to find the weight of the criteria relative to others. It represents the criteria in hierarchical structures and the weights of all the alternatives are calculated by using the answers of the decision-maker given in a pair-wise comparison matrix. The conventional AHP is subjected to many controversies because it takes into account only fixed value judgments, as they consist of more ambiguity due to human error, to overcome this ambiguity a fuzzy version of the Analytical Hierarchical Process has been introduced to take into account the vagueness in the overall values, this process enables the decision-makers to give their answers in a range which rules out the human errors, there are many kinds of fuzzy numbers out of them Triangular and Trapezoidal function of the Fuzzy numbers are most used.

Step 1 – Construction of Pairwise comparison matrix

The first step of FAHP is constructing the pairwise comparison matrix; it is done by filling the relative weightage of each criterion with respect to the other one, on a scale of one to ten, for each level with reference to the aim of the best possible selection available. For constructing this matrix, the sides of the diagonal elements have to be filled, if the upper triangular matrix is filled lower triangular matrix can be found out or vice versa can also be done V_{ij}=V_{ji}, where

V_{ij}= Relative weightage of i^th^ criteria with respect to j^th^ criteria

V_{ji}= Relative weightage of j^th^ criteria with respect to i^th^ criteria

Using the rules of constructing a pairwise comparison matrix, Table 2 is prepared; the values of the diagonal elements are one since weightage of the criterion with respect to itself is one.

Table 2. Pairwise comparison matrix

Criteria	C1	C2	C3	C4	C5
C1	1	7	1/2	2	6
C2	1/7	1	1/8	1/4	1/2
C3	2	8	1	3	7
C4	1/2	4	1/3	1	4
C5	1/6	2	1/7	1/4	1

Step 2 – Converting to Fuzzy Numbers
After finding the pairwise comparison matrix using the fixed numbers, they are converted to triangular fuzzy numbers given the computational simplicity of TFNs (Triangular fuzzy number), many applications can make use of them efficiently. Also, they come in handy in a fuzzy environment for processing information and promoting presentation when applied successfully in several applications. A typical TFN has three values assigned to each real number, the lower number, middle number and upper number; they indicate the range of possible values for each fixed value number. Using these values, the fixed numbers are converted to their corresponding triangular fuzzy numbers.

Step 3 – Calculating the Fuzzy Geometric Mean
After finding the Fuzzy Pairwise comparison matrix the fuzzy geometric mean (r_i) is calculated for each criteria using Eqn. 1. Also the sum of all the geometric means (R) and its inverse (R^{-1}) is calculated as shown in Table 3

$$r_i = (x_{i1} * x_{i2} * x_{i3} * x_{i4} * x_{i5})^{1/5} \quad (1)$$

where x_{ij}= Relative Fuzzy weight of each criterion

Step 4 – Calculating the Fuzzy and Defuzzified Weights
After finding values of geometric means, fuzzy weights ($\widehat{w}_i$) are calculated using Eqn. 2, after that the fuzzy weights are defuzzified and defuzzified weights (w_i) are found using Eqn. 3 by taking the average of three numbers (l_i, m_i, u_i) as shown in Table 4, but w_i found here is not normalized which implies the sum of all defuzzified weights does not give answer one.

$$\widehat{w}_i = (r_i * (r_1 * r_2 * r_3 * r_4 * r_5))^{-1} \quad (2)$$

$$w_i = ((l_i + m_i + u_i)/3) \quad (3)$$

Table 3. Geometric mean calculation table

Criteria	C1			C2			C3			C4			C5			Geometric Mean		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
C1	1.00	1.00	1.00	6.00	7.00	8.00	0.33	0.50	1.00	1.00	2.00	3.00	5.00	6.00	7.00	1.58	2.11	2.79
C2	0.13	0.14	0.17	1.00	1.00	1.00	0.11	0.13	0.14	0.20	0.25	0.33	0.33	0.50	1.00	0.25	0.29	0.38
C3	1.00	2.00	3.00	7.00	8.00	9.00	1.00	1.00	1.00	2.00	3.00	4.00	6.00	7.00	8.00	2.43	3.20	3.87
C4	0.33	0.50	1.00	3.00	4.00	5.00	0.25	0.33	0.50	1.00	1.00	1.00	3.00	4.00	5.00	0.94	1.22	1.66
C5	0.14	0.17	0.20	1.00	2.00	3.00	0.13	0.14	0.17	0.20	0.25	0.33	1.00	1.00	1.00	0.32	0.41	0.51
													R			5.53	7.24	9.20
													R^{-1}			0.11	0.14	0.18

Table 4. Defuzzified weights calculation matrix

Criteria	Fuzzy Weights ($\widehat{w}_i$)			Defuzzified Weights (w_i)
	l	m	u	
C1	0.17	0.29	0.5	0.97
C2	0.03	0.04	0.07	0.14
C3	0.26	0.44	0.7	1.41
C4	0.1	0.17	0.3	0.57
C5	0.04	0.06	0.09	0.18
			Sum	3.27

Step 5 – Calculating the De-Fuzzified Normal Weights

The defuzzified weights (w_i) found in the previous step are normalized by using the formula as shown in Table 5.

Table 5. Calculation of Defuzzified normal weight

Criteria	Fuzzy Weights			Defuzzified Normal Weights (w_i)
	l	m	u	
C1	0.17	0.29	0.5	0.3
C2	0.03	0.04	0.07	0.04
C3	0.26	0.44	0.7	0.43
C4	0.1	0.17	0.3	0.17
C5	0.04	0.06	0.09	0.06
			Sum	1

3.3. Order Ranking and TOPSIS

To rank the orders according to their criteria values out of all the MCDM methods (ELECTRE, SAW, PROMETHEE, etc) TOPSIS method has been selected because of its analytical simplicity and efficiency in ranking. TOPSIS is a compensatory method that allows differences between criteria where a less value in one criterion compensates with the more value in other criteria, so it is better than non-compensatory methods. It compares the set of alternatives by identifying its distance from the positive and the negative ideal solution, the best alternative is ranked in such a way that it has a minimum of the Euclidean distance from the positive ideal solution and maximum of the Euclidean distance from the negative ideal solution, alternative with highest performance score is ranked first. To evaluate the consistency of the vector normalization method it has been compared with four different normalization methods. The following steps are followed for TOPSIS method

Step 1 – Creation of Evaluation Matrix

The evaluation matrix is constructed by finding each criteria value from Table 6 using the formulas for all the alternatives.

Table 6. Evaluation matrix

Criteria weights	0.3	0.04	0.43	0.17	0.06
Clients/Criteria	C1	C2	C3	C4	C5
Client 1	65	4	40	14	8
Client 2	45	12	50	24	3
Client 3	75	2	250	17	5
Client 4	85	3.5	120	8	3

Step 2 – Normalization of Evaluation Matrix

The table values are normalized using the vector normalization method. To evaluate the consistency of the vector normalization method it has been compared with 3 other scalar normalization methods: Linear Scale (Max-Min) Method, Linear Scale (Max) Method and Linear Scale (Sum) Method.

i) Vector Normalization

In this method, the performance value is divided by the root of power 2 of the sum of all squares of all the performance values. The formulas for beneficial criteria and non-beneficial criteria are mentioned in Eqns. 4 and 5 respectively.

For the Beneficial Criteria:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (4)$$

For Non-Beneficial Criteria:

$$r_{ij} = \frac{(1/x_{ij})}{\sqrt{\sum_{i=1}^{m} (1/x_{ij}^2)}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (5)$$

The obtained value is multiplied with criteria weight for normalizing the value and this is placed in the evaluation matrix accordingly.

Table 7. Normalized Evaluation Matrix for Vector Normalization Method

Criteria Weights	0.3	0.04	0.43	0.17	0.06		0.3	0.04	0.43	0.17	0.06				
Clients/Criteria	$C1^2$	$C2^2$	$C3^2$	$C4^2$	$C5^2$		R1*W1	R2*W2	R3*W3	R4*W4	R5*W5	S+	S-	Performance Score	Rank
Client 1	4225	16	1600	196	64		0.14	0.01	0.06	0.07	0.04	0.32	0.07	0.18	3
Client 2	2025	144	2500	576	9		0.1	0.04	0.08	0.13	0.02	0.33	0.03	0.1	4
Client 3	5625	4	62500	289	25		0.16	0.01	0.38	0.09	0.03	0.06	0.33	0.84	1
Client 4	7225	12.25	14400	64	9		0.18	0.01	0.18	0.04	0.02	0.2	0.17	0.46	2
$\sqrt{\sum x_{ij}^2}$	138.20	13.27	284.60	33.54	10.34	V+	0.18	0.04	0.38	0.04	0.04				
						V-	0.1	0.01	0.06	0.13	0.02				

ii) Linear Scale (Max-Min)

In this normalization method, both the maximum and the minimum performance values are used for calculation.

For Beneficial Criteria:

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (6)$$

For Non-Beneficial Criteria:

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (7)$$

The obtained value is multiplied with criteria weight for normalizing the value and this is placed in the evaluation matrix accordingly.

Table 8. Normalized Evaluation Matrix for Linear Scale (Max-Min) Method

Criteria Weights		0.3	0.04	0.43	0.17	0.06				
Clients/Criteria		R1*W1	R2*W2	R3*W3	R4*W4	R5*W5	S+	S-	Performance Score	Rank
Client 1		0.15	0.01	0	0.11	0.06	0.46	0.19	0.29	3
Client 2		0	0.04	0.02	0	0	0.54	0.05	0.08	4
Client 3		0.22	0	0.43	0.08	0.02	0.13	0.49	0.79	1
Client 4		0.3	0.01	0.16	0.17	0	0.27	0.38	0.58	2
	V+	0.3	0.04	0.43	0.17	0.06				
	V-	0	0	0	0	0				

Table 9. Normalized Evaluation Matrix for Linear Scale (Max) Method

Criteria Weights		0.3	0.04	0.43	0.17	0.06				
Clients/Criteria		R1*W1	R2*W2	R3*W3	R4*W4	R5*W5	S+	S-	Performance Score	Rank
Client 1		0.23	0.01	0.07	0.07	0.06	0.37	0.11	0.22	3
Client 2		0.16	0.04	0.09	0	0.02	0.39	0.04	0.09	4
Client 3		0.26	0.01	0.43	0.05	0.04	0.08	0.38	0.82	1
Client 4		0.3	0.01	0.21	0.12	0.02	0.23	0.23	0.5	2
	V+	0.3	0.04	0.43	0.12	0.06				
	V-	0.16	0.01	0.07	0	0.02				

Table 10. Normalized Evaluation Matrix for Linear Scale (Sum) Method

Criteria Weights		0.3	0.04	0.43	0.17	0.06				
Clients/Criteria		R1*W1	R2*W2	R3*W3	R4*W4	R5*W5	S+	S-	Performance Score	Rank
Client 1		0.07	0.01	0.04	0.04	0.02	0.2	0.03	0.14	4
Client 2		0.05	0.02	0.05	0.07	0.01	0.19	0.05	0.2	3
Client 3		0.08	0	0.23	0.05	0.01	0.03	0.2	0.87	1
Client 4		0.09	0.01	0.11	0.02	0.01	0.13	0.09	0.4	2
	V+	0.09	0.02	0.23	0.07	0.02				
	V-	0.05	0	0.04	0.02	0.01				

iii) Linear Scale (Max)

In this normalization method, only maximum performance value is used for calculation

For Beneficial Criteria:

$$r_{ij} = \frac{x_{ij}}{x_j^{max}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (8)$$

For Non-Beneficial Criteria:

$$r_{ij} = 1 - \frac{x_{ij}}{x_j^{max}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (9)$$

Criteria weight is multiplied with this value to get the normalized value which is substituted in the evaluation matrix to get the normalized evaluation matrix.

iv) Linear Scale (Sum)

In this normalization method, the sum of all performance values is used for calculation:

For Beneficial Criteria:

$$r_{ij} = \frac{x_{ij}}{\sum_i^m x_{ij}} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (10)$$

For Non-Beneficial Criteria:

$$r_{ij} = \frac{(1/x_{ij})}{\sum_i^m (1/x_{ij})} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (11)$$

This value is then multiplied with criteria weights to obtain the normalized value and hence, the normalized evaluation matrix.

Step 3 – Calculation of Best and Worst Ideal Solution

After normalizing the evaluation matrix the best ideal solution (V_j^+) and the worst ideal solution (V_j^-) are found.

For Beneficial Criteria:

$$V_j^+ = \text{Max } (R_1{:}R_5) \quad (12)$$

$$V_j^- = \text{Min } (R_1{:}R_5) \quad (13)$$

For Non-Beneficial Criteria:

$$V_j^+ = \text{Min } (R_1{:}R_5) \quad (14)$$

$$V_j^- = \text{Max } (R_1{:}R_5) \quad (15)$$

For each normalization method, the best and worst ideal solutions are displayed in tables 7 to 10.

Step 4 –Calculation of Euclidean Distance

The Euclidean distance of each of the alternatives from the best (S_i^+) and worst (S_i^-) ideal solution is calculated using Eqns. 16 and 17:

$$S_i^+ = (\sum(V_{ij} - V_j^+)^2)^{0.5} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (16)$$

$$S_i^- = (\sum(V_{ij} - V_j^-)^2)^{0.5} \text{ i=1,2,3,...m; j=1,2,3,...n} \quad (17)$$

The tables 7 to 10 depict the Euclidean distances of best and worst ideal solution for each normalization method.

Step 5 – Calculation of Performance Score

The performance score (P_i) is calculated using Eqn. 18; the alternatives are ranked according to their performance scores in decreasing order.

$$P_i = ((S_i^-)/(S_i^+ + S_i^-)) \quad (18)$$

The performance score for the above given normalization methods are portrayed in tables 7 to 10.

3.4. Consistency Test

To evaluate the consistency of the vector normalization method it has been decided to compare it with other normalization methods, to compare analytically some tests have been selected, for the sake of test four sample clients have been selected and a test has been carried out on them. The performance score for the above-given normalization methods is portrayed in tables 11 to 16.

Consistency Search

The Consistency search consists of four conditions which evaluate four different normalization methods in different ways.

i) Condition 1, states that alternative models should generate performance measures that have quite similar distributional properties such as the mean, standard deviation, minimum and maximum values. Table 11 indicates that Vector Normalization, Linear Transformation (Max-Min), and Linear Transformation (Max) methods N1, N2, and N3 characteristics are very similar and have differences compared to the Linear Transformation (Sum) method.

Table 11. Consistency search 1

Clients/Methods	Vector Normalization	Linear Transformation (Min-Max)	Linear Transformation (Max)	Linear Transformation (Sum)	Mean	Standard Deviation
Client 1	0.18	0.29	0.22	0.14	0.38	0.02
Client 2	0.1	0.08	0.09	0.2	0.62	0.04
Client 3	0.84	0.79	0.82	0.87	0.44	0.03
Client 4	0.46	0.58	0.5	0.4	0.22	0.01

ii) Condition 2, states that alternate normalization methods should identify the same order as the ideal and non-ideal. Table 12 indicates that Vector Normalization, Linear Transformation (Max-Min), Linear Transformation (Max) methods rank the first and last orders similarly whereas the Linear Transformation (Sum) method does not match the other methods.

Table 12. Consistency search 2

Method/Rank	First	Last
Vector Normalization	Client 3	Client 2
Linear Transformation (Min-Max)	Client 3	Client 2
Linear Transformation (Max)	Client 3	Client 2
Linear Transformation (Sum)	Client 3	Client 1

iii) Condition 3, states that the alternative model should rank the customer orders mostly in similar order. Table 13 indicates that Vector Normalization, Linear Transformation (Max-Min), and Linear Transformation (Max) methods rank the others in the same pattern.

Table 13. Consistency Search 3

Orders/Method	Vector Normalization	Linear Transformation (Min-Max)	Linear Transformation (Max)	Linear Transformation (Sum)
Client 1	3	3	3	4
Client 2	4	4	4	3
Client 3	1	1	1	1
Client 4	2	2	2	2

iv) Condition 4, states that all four normalization methods should generate same or similar performance scores for all the alternatives. Table 14 indicates that Vector Normalization, Linear Transformation (Max-Min), and Linear Transformation (Max) methods' performance scores are nearer to each other compared to Linear Transformation (Sum) method.

Table 14. Consistency Search 4

Orders/ Method	Vector Normalization	Linear Transformation (Min-Max)	Linear Transformation (Max)	Linear Transformation (Sum)
Client 1	0.18	0.29	0.22	0.14
Client 2	0.1	0.08	0.09	0.2
Client 3	0.84	0.79	0.82	0.87
Client 4	0.46	0.58	0.5	0.4

Kolmogorov Smirnov Test

The Kolmogorov–Smirnov test is a non-parametric test of the equality of the continuous, one-dimensional distributions of the probabilities that can then be used to compare the sample with a reference probability distribution, or to compare the two samples. Healthy conclusions cannot be drawn from condition 1 alone; to test the condition statistically KS test is used. Table 15 indicates that all the D_{stat} values are less than D_{crit} so all the pairs have passed the test.

Table 15. Kolmogorov Smirnov Test

Model	D_{stat}	D_{crit}	Status
1-2	0.0801	1.2586	Pass
1-3	0.0298	1.2587	Pass
1-4	0.0658	1.2588	Pass
2-3	0.0502	1.2589	Pass
2-4	0.0891	1.2590	Pass
3-4	0.0716	1.2591	Pass

Pearson Correlation Test

This test is used to examine the correlation of performance scores of orders of different normalization methods, the value of the correlation coefficient ranges from zero to one where one indicates the highest similarity between two models whereas zero indicates no similarity between two models. Table 16 indicates that the correlation is nearly perfect for all the models present and none of them is irrelevant.

Table 16. Pearson Correlation Test

Normalization Method	N1	N2	N3	N4
N1	1	0.9645	0.996	0.9725
N2	0.9645	1	0.984	0.8777
N3	0.996	0.984	1	0.9483
N4	0.9725	0.8777	0.9483	1

4. Software Development

As per the requirement of company executives, cloud-based software is developed using the latest web technologies. PHP (Hypertext Pre-processor) and HTML (HyperText Mark-up Language) stack are used to develop the software as it is the oldest and most popular stack and open-source. The novelty of the software is that it deals with a cloud-based software hosted on an internal server in the company. This software can be accessed through a web browser to access customer satisfaction and can be used in the areas of quality assurance, conducting surveys, and ensuring collaboration between stakeholders. It can also be applied to small and medium businesses that want to automate their workflow structure, customer management, business performance reporting, and more.
A predefined Software Development Life Cycle (SDLC) known as Waterfall Method has been followed to develop the software according to the industry standards in order to avoid run-time bugs and gaps between the expectation and actual output, the main building blocks of the waterfall method are

1. Requirement Collection
2. Design Specification
3. Software Development
4. Verification
5. Implementation and Maintenance

4.1. Software Algorithm

Software algorithm is basically a logic-based diagram drawn to know the flow of the software, it serves the purpose of supporting documents in designing the software architecture, by understanding the flow of the methodology this algorithm displayed in Figure 4 has been designed.

4.2. Software Architecture

Software Architecture as shown in Figure 5 has been decided on and designed after thoroughly evaluating software available in the market and an activity diagram has been constructed.

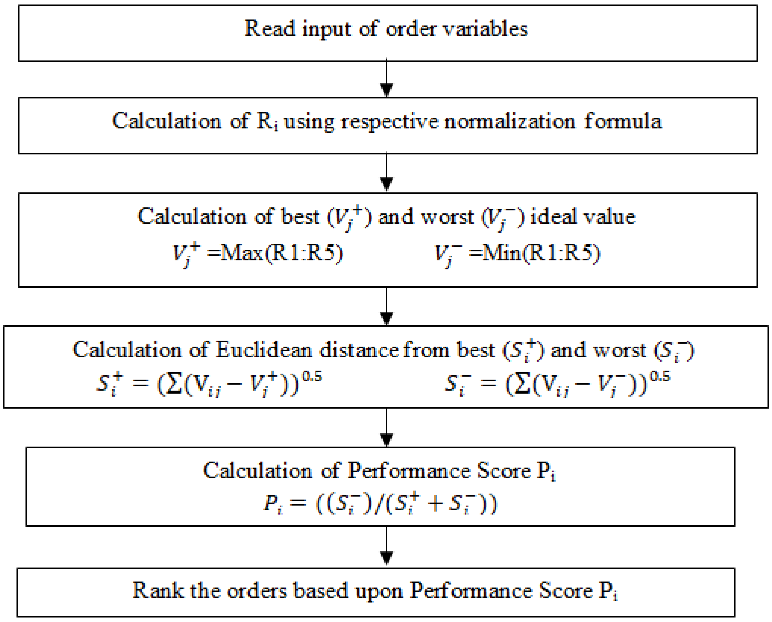

Figure 4. Pictorial Depiction of the algorithm

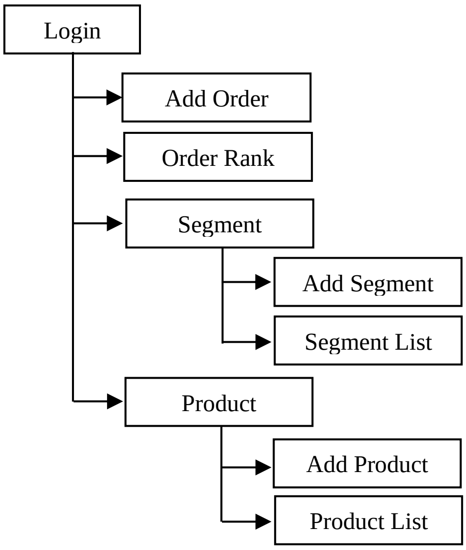

Figure 5. Software Architecture

4.3. ER (Entity Relationship) Diagram

According to the software architecture, the Database Structure has been designed by following Normalization Rules. The structure has been designed in such a way that it occupies minimum space in the server. The following Figure 6 depicts the relation between three tables

1. Orders: stores all order data, here product_id and segment_id are foreign keys.
2. Customer_segment_master: stores master data for each segment, like name and segment importance.
3. Product_master: stores master data for each product like name manufacturing time and realized basic price.

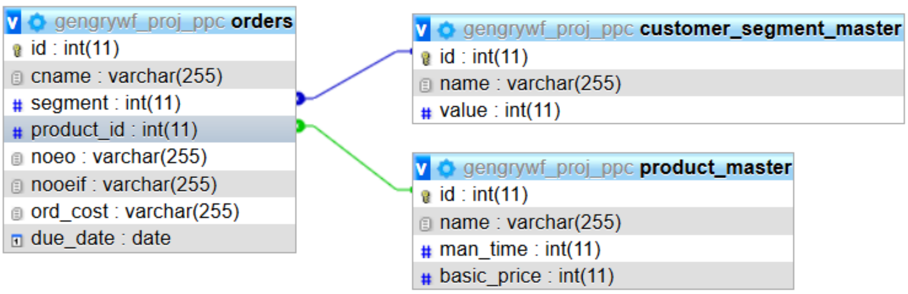

Figure 6. Entity relationship diagram

4.4. Software Testing

After developing the software in line with the design specifications, integrated testing was done to make the software bug free. For testing, five sample clients are chosen to check whether the actual results are matching the expected results. Some minor bugs were found from the testing and were resolved.

5. Results and Discussion

The software was developed and tested thoroughly and the required training was given to the company people for its usability. The company people started using the software in February–2020 and also planned the production schedule according to the rankings of orders obtained from the software as shown in Table 17 after implementing the software a notable increase in customer satisfaction was observed compared to previous months.

Customer satisfaction was measured using the satisfaction survey link which was sent to the client immediately after dispatch of the product through mail and SMS, the survey conducted mainly four Multiple Choice Single Answer Questions and three descriptive questions, the answers of the survey were converted to measurable form with the zero being the least and three being the maximum marks for each question.

Since there were four objective questions the maximum marks possible for the whole survey was twelve and the minimum mark possible was zero, the marks obtained (C_{sa}) were then multiplied with Normalized customer value (C_{vn}) to obtain individual customer satisfaction

Table 17. February - 2020 Data Results

S.No	Customer Name	Performance Score	Rank
1	Client 1	0.054	65
2	Client 2	0.0176	92
3	Client 3	0.0973	6
4	Client 4	0.0661	57
5	Client 5	0.0263	78
6	Client 6	0.0106	104
7	Client 7	0.0907	22
8	Client 8	0.0886	24
9	Client 9	0.093	20
10	Client 10	0.0714	33
	…...		
110	Client 110	0.057	62

Normalized Customer Value (C_{vn}) = (C_{vi}) / Max(C_v) (19)

Customer Value (C_{vi}) = (Customer Segment Importance + Number of Existing Orders Given + Number of orders expected in future) (20)

Customer Satisfaction $(C_s) = \sum C_{vn} * C_{sa} / \sum C_{vn} * 12$ (21)

Using Eqns. 19 to 21, the customer satisfaction of the last five months' data was measured and plotted in a bar graph.

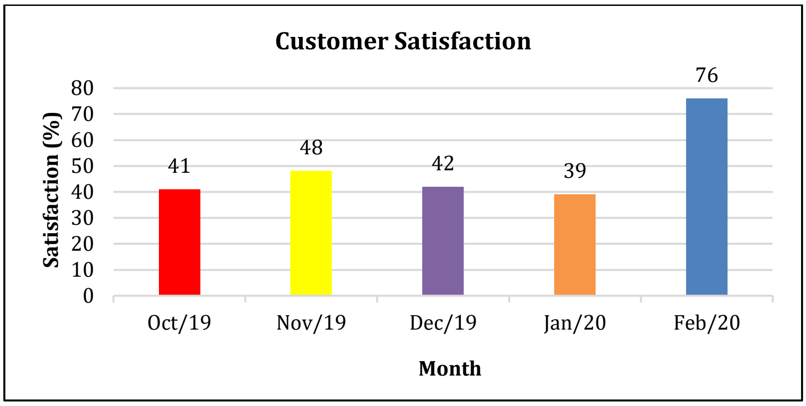

Figure 4. Customer Satisfaction Graph

The objective function customer defection rate was not measured directly because it would take a longer time to measure the results because changes cannot be seen immediately as the time period gap between each purchase from the same customer is around 3 months, therefore its substitute function Customer satisfaction in percentage has been measured which will affect the customer defection rate. So the increased customer satisfaction rate ultimately will result in a decrease in customer defection rate, which is the main objective of the project.

The company was having trouble satisfying its customers prior to the implementation of the software because it was using a manual database management system that took time to update customer information and process customer inquiries. Due to inefficiency in monitoring customer complaints about the company's products and services, the rate of customer defection began to rise. The delivery time of the product was also affected. The developed software software improved the salesforce's productivity by streamlining the company's workflow structure. The company was able to track product sales, changing customer interests, and customer complaints remotely from any location with the help of automated systems. The ability to access existing customer data shortened the time it took to respond to customer inquiries. The sales team collaborated more effectively as a result of the increased mobility.

However, the software limitations are complex because extensive documentation during the development phase makes the processing time consuming, and the software finishes compiling only after the last sequence of the program thus making it nearly impossible for making any changes in between, especially in projects containing large datasets.

6. Conclusion

This study dealt with customer relationship management to understand the reasons behind the defection of a company's service and product by its customers. The aim was to reduce the customer defection rate by heightening the service levels and product performance levels of the company. Using internal company surveys and customer feedback, the existing problems faced in the company's workflow structure on a daily basis were analysed. Using the data collected, criteria were derived to determine the performance of the company. FAHP was used to weigh the criteria and a pairwise comparison matrix was formed. The weights were normalised after fuzzification and customer prioritisation was done using the known weights. To calculate performance scores various normalisation methods were employed using TOPSIS. The consistency of each of the normalization methods was tested based on 4 constraints and vector normalisation was found to be more consistent. Pseudocode was written for deciding the architecture of the software. Using Hypertext Pre-processor (PHP) and Hypertext Mark-up Language (HTML), the software was developed. This software was used by the company for the month of February 2020.

From the data collected, a notable difference in customer satisfaction i.e., from 39% in January to 76% in February, was observed. The company's profitability increased, a loyal customer base was established, and existing customers began referring the company's services and products to their business partners. The information gathered through customer feedback surveys assisted the company in identifying and correcting flaws in product deliverables, such as quality and performance level. In the future, the software can be developed to a more optimized and personalized version of the current process with respect to future situations. There are also ways to set up these algorithms in a centralised software connected with the base cloud system and also to develop a mobile application for easy portability and accessibility.

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