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Predicting Customer Satisfaction Score (CSS) for Urban Company Utilizing the K-Nearest Neighbours (KNN) Algorithm: A Machine Learning Approach

N. Srividya*, B. Akila

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Abstract: Urban Company is one of the leading hyperlocal online home service providers connecting service providers with service seekers and relies heavily on customer satisfaction to maintain its reputation and competitiveness in the market. Understanding and predicting customer satisfaction levels are crucial for Urban Company to enhance its services and retain loyal customers. This study uses a machine learning approach using the K-Nearest Neighbors (KNN) algorithm to predict customer satisfaction on the Urban Company platform. The SERVQUAL model for assessing service quality based on five dimensions: Tangibles, Reliability, Responsiveness, Assurance, and Empathy acts as the input factor and the calculated Customer Satisfaction Score (CSS) using Root Mean Square (RMS) acts as the output parameter. A total of 514 survey data were collected, and its corresponding CSS value was calculated. From the survey, 80% of the data was used to train the model, and 20% was used for testing the model. The model underwent evaluation utilizing Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) metrics. Subsequently, the discrepancy between the actual and predicted CSS was assessed via the KNN algorithm, revealing a Root Mean Squared Error of 3.14 and a Mean Absolute Error of 1.92 which is beneficial for the Urban Company to understand its customer satisfaction level in various scenarios and to retain loyal customers.

Keywords: *Urban Company, Customer Satisfaction Score (CSS), SERVQUAL model, K-Nearest Neighbors (KNN) algorithm, Machine Learning*

1 Introduction

Urban Company, previously known as Urban Clap, is a technology platform that links customers with a variety of local service professionals. Founded in 2014 by Abhiraj Singh Bhal, Varun Khaitan, and Raghav Chandra, Urban Company provides a broad spectrum of services in categories like beauty and wellness, home repairs and maintenance, cleaning, appliance repairs, health and wellness, event planning, and more. The customers can book services through the Urban Company app or website, where they can browse through a list of verified professionals, read reviews, and book appointments based on their requirements (Jyani and Bansal, 2021). The platform aims to make it convenient for users to access reliable services while providing income opportunities for service professionals. Urban Company operates in several cities across India and has expanded its services to international markets such as Dubai, Saudi Arabia, USA. Overall, Urban Company has become a popular choice for individuals seeking various services, offering convenience, reliability, and quality assurance through its platform(Pathak, 2018).

Department of Commerce, Faculty of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur, Chengalpattu - 603 203, Tamilnadu, India
**Email Id – Srividyacommerce@gmail.com*

The Measuring Customer Satisfaction Score (CSS) in M/s Urban Company is crucial for its marketing efforts as every company strives to maintain high standards of service and customer satisfaction. It provides insights into customer expectations, Customer Retention, brand reputation, staying competitive advantage, Service Quality Improvement, Employee Satisfaction achieving long-term business success. However, it is challenging to measure it (Khan; and Tabassum, 2010) (Sultana, Islam, and Das, 2016) (Daniel and Lukong Beriny, 2010). CSS encompasses multiple dimensions, from product quality to service responsiveness, making it difficult to capture comprehensively in a single metric. Gathering reliable customer feedback, often through surveys or reviews, can be hindered by low response rates or biased responses. The dynamic nature of customer satisfaction requires continuous monitoring and adaptation of measurement strategies to capture evolving trends (Almugari *et al.*, 2022). Despite these obstacles, businesses persist in measuring CSS because it offers invaluable insights into customer preferences and drives improvements essential for retaining customer loyalty (Pathak, 2018)(Suchánek and Králová, 2019).

Advanced analytics techniques such as machine learning offer powerful tools for analyzing large volumes of data and uncovering meaningful patterns and trends. Machine learning is a branch of artificial intelligence (AI) that plays a significant role in enhancing various aspects of marketing, analyzing large volumes of data, extracting meaningful insights, automating decision-making processes, etc. Moreover, maintaining a customer-centric approach ensures that measurement efforts align with customer needs and preferences, enabling businesses to identify areas for improvement and drive meaningful change. By embracing these strategies, businesses can effectively measure CSS and take proactive steps to enhance customer satisfaction and loyalty. The K-Nearest Neighbors (KNN) algorithm is a commonly utilized technique in machine learning for both regression and classification. In KNN, the output value for a new observation is determined by averaging the values of the K nearest data points from the training set (Zhang, 2016).

Figure 1 depicts the KNN algorithm, with the X-axis denoting the independent variable and the Y-axis denoting the dependent variable. The distance between data points is generally calculated using Equation (1) i.e Euclidean distance formula, which involves summing the squared differences between corresponding data points and then taking the square root of the total, as illustrated below.

$$\mathbf{d(X, Y) = \sqrt{(X_1 - Y_1)^2 + (X_2 - Y_2)^2 + ... + (X_n - Y_n)^2} ....(1)}$$

Xn and Yn represent the nth feature in data points X and Y, respectively. The "k nearest neighbours" are selected as the smallest distances to the new data point and the data points in the training set. The predicted output value is then obtained by averaging the output values of these k nearest neighbours. (Imandoust and Bolandraftar, 2013).

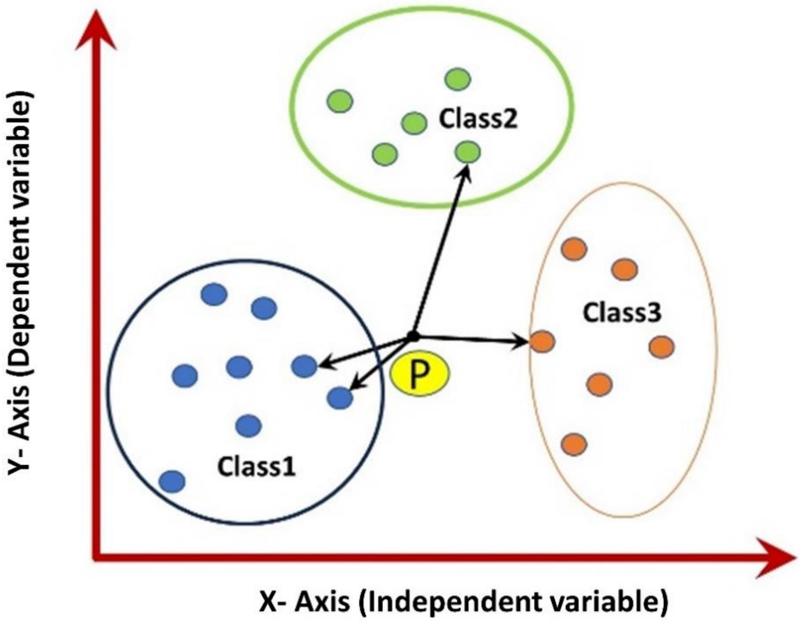

Fig 1 - Illustrative diagram of the K-nearest neighbour algorithm(Fan *et al.*, 2019)

The KNN algorithm boasts several advantages over other machine learning algorithms. In specific research areas such as customer satisfaction score (CSS), the K-Nearest Neighbors (KNN) algorithm has proven to be a valuable tool for analysis. Its utility lies in its ability to handle multi-dimensional data effectively, making it well-suited for the complex nature of CSS datasets.

The KNN algorithm only requires the "k" value of neighbors for making predictions and functions without any assumptions. It is capable of effectively managing non-linear data. Moreover, the algorithm utilizes experimental datasets for both training and testing, providing a simple and comprehensible approach. This simplicity facilitates easy adaptation and enables quicker real-time predictions compared to other algorithms(Kumar and Jain, 2022). Consequently, the KNN algorithm finds application across various research domains such as engineering, healthcare, finance, and more, owing to its ability to handle various types of data and tasks. For example, in healthcare, KNN is applied in tasks such as disease diagnosis, patient outcome prediction, and medical image analysis (Said Ibrahim and Saber, 2023). In finance, KNN is employed for tasks such as credit risk assessment, stock price prediction, and algorithmic trading strategies(Alkhatib *et al.*, 2013)(Imandoust and Bolandraftar, 2013). In engineering applications like fused deposition modeling (FDM), thermal time series data collected via thermocouples forms the foundation for training and testing with the K-nearest neighbors (KNN) algorithm. (Vincent and Natarajan, 2023)(Song *et al.*, 2020).

The current study aims to bridge a critical gap in understanding customer satisfaction dynamics within the context of Urban Company, a leading hyperlocal online home service provider. Urban Company's success directly depends on its ability to consistently deliver satisfactory services and maintain a competitive edge in the market. However, the precise prediction of customer satisfaction levels remains an ongoing challenge for the company. So, our primary objective is to develop a robust predictive model that accurately anticipates customer satisfaction scores on the Urban Company platform. In this work, we investigate (i) the connection using the SERVQUAL model as a framework to evaluate different dimensions of service quality—such as reliability, assurance, tangibility, empathy, and responsiveness—and how they impact customers' perceptions of service quality, particularly within the context of Urban Company's services. (ii) We employ the K-nearest neighbours (KNN) algorithm to forecast the customer satisfaction score (CSS). This comprehensive analysis will enable Urban Company to make targeted improvements and adjustments to their services, ensuring that they are meeting the specific needs and expectations of diverse customer segments.

2.0 Material and method:

2.1 Data Collection:

Figure 2 depicts our study's location in Chennai, Tamil Nadu, India, which is situated at latitude 13.0827° N and longitude 80.2707° E (Malavikaa and Sreeya, 2019). The Chennai populations are taken into consideration for data collecting, due to its greater urban population with numerous manufacturing and software industries and increasing infrastructure, etc. The Census is an official survey or government count undertaken to determine the population. The Census conducted in 2011 shows the city's population was to be 4.6 million and it is predicted to reach 11.5 million in 2024. According to the Department of Economic and Social Affairs report (2019) (Electronics Corporation of Tamil Nadu limited, 2015), Chennai is the 30th largest metropolis in the world and the sixth most populous urban area in India. Geographically, Chennai has excellent access to all forms of transportation, including air, sea, and roads(Malavikaa and Sreeya, 2019).

Figure 2. Study area – South Chennai administrative boundaries.

Table 1: Questionnaire Parameters and Number of Questions

Description	No. of questions
Demographic profile of respondents	8
Respondent's awareness of urban company services	4
Respondents' usage of urban company services	3
Questions based on SERVQUAL factors:	
1) Reliability.	6
2) Assurance.	3
3) Tangibility.	5
4) Empathy.	5
5) Responsiveness	4
Respondents rating and Overall rating of urban company services	Rate using 1-5 scale from Excellent to poor.
Respondents' patronage of Urban company services	5

Firstly, we recorded the important control variables such as gender, age, nationality, educational level, job position, marital status, average salary, and frequency of usage of the M/s Urban company were recorded. Table 1 represents the breakdown of the questionnaire items along with their respective numbers of questions. This breakdown categorizes the questionnaire items into various sections, covering demographic information, awareness, usage, ratings based on SERVQUAL factors, overall satisfaction, and patronage of Urban Company services (Bhatt and Sahil Bhanawat, 2016)(K.Ravichandran, B.Tamil Mani, 2010). The Respondents were asked to rate their overall satisfaction on a 1-5 scale, ranging from Excellent to Poor. These variables serve as crucial factors in analyzing and interpreting the data, allowing for a more accurate assessment of the relationship between customer characteristics and their perceptions or experiences with the M/s Urban Company's services. Top of Form

The SERVQUAL service quality dimensions encompass the key service quality aspects essential for assessing and improving customer satisfaction. Table 2 consists of questionnaires based on SERVQUAL service quality dimensions such as Reliability, Assurance, Tangibility, Empathy, and Responsiveness, which can be used to assess each dimension. These questions are designed to measure customer perceptions and expectations regarding the quality of service provided. Respondents were asked to rate their overall expectations and perceptions score using a 1-5 scale ranging from Excellent to Poor. For each dimension, the gap between customers' expectations and perceptions is calculated by subtracting the mean perception score from the mean expectation score for each dimension. The formula for calculating the gap is shown in Eq (1):

Gap = Perception Score - Expectation Score ………………………(1)

The average gap score for each dimension is calculated by measuring the average gap score for each dimension by averaging the gaps across all customers. Positive gap scores indicate that perceptions are lower than the expectations suggesting areas for improvement. Negative gap scores suggest that perceptions meet or exceed expectations, indicating strengths. The normalized gap score is used to assess the disparity between customer expectations and perceptions. It is calculated by dividing the actual gap score by the maximum possible gap score and multiplying it by 100 to express it as a percentage.

The Formula (2) for calculating the normalized gap score is as follows:

$$\textbf{Normalized gap score} = \left(\frac{\textit{Actual Gap score} - \textit{Maximum Possible Gap Score}}{\textit{Maximum Possible Gap Score} - \textit{Maximum Possible Gap Score}}\right) \boldsymbol{X}\ \mathbf{100} \text{ ………………………(2)}$$

The overall customer satisfaction score can be calculated by Root Mean Square (RMS) method which is sensitive to outliers in the data compared to the simple average method. The equal weightage was given to all the dimensions without using the Factor loading ensuring that no dimension is given undue importance, allowing for a fair assessment of satisfaction across all aspects of the customer experience. This method gives equal weight to each dimension and provides a way to summarize variations in satisfaction scores. The Formula (3) for calculating the overall customer satisfaction score using the RMS method is

$$\boldsymbol{Overall\ Customer\ Satisfaction\ Score} = \sqrt{\frac{\sum_{i=1}^{n}(\boldsymbol{Normalized\ Gap\ Score})^{\wedge}\mathbf{2}}{\boldsymbol{n}}} \text{……………………(3)}$$

Where n is the number of dimensions being considered and Normalized Gap Score is the normalized gap score for dimension$_{s.}$ This approach using the RMS method provides a balanced and unbiased measure of overall customer satisfaction, where each dimension contributes equally to the final score(Eid, 2011). It ensures that no dimension is given undue importance, allowing for a fair assessment of satisfaction across all aspects of the customer experience.

Based on Cochran's statistical formula, the sample size (n) can be calculated using the Formula (4):

$$\boldsymbol{n_0} = \frac{\boldsymbol{Z^2 * p * q}}{\boldsymbol{e^2}} \textbf{………………………(4)}$$

Z is the score determined using Z- the score table, p = proportion of the population, q = difference between 1 and p, and e is the margin of error.

Given that a 5% margin of error is used, and the Z-score is 1.96, the formula can be used to find the minimum required sample size (n_o). Substituting the given values into the Formula (5):

$$\boldsymbol{n_0} = \frac{\mathbf{(1.96)^2} * \boldsymbol{p * q}}{\mathbf{(0.05)^2}} \textbf{……………………… (5)}$$

Since the actual number of samples collected was 514, this exceeds the minimum required sample size **(n_o)** of 384, which was determined using Cochran's statistical formula. This indicates that the sample size collected for the study is sufficient to achieve the desired level of precision with a 5% margin of error.

Table 2: SERVQUAL service quality dimensions are listed.

Factor	Explanation	Dimension framed
Reliability	The business or service provider can supply the service in a precise, reliable, and timely manner as promised.	✓ The urban company provides services as promised. ✓ Urban company professionals arrive at the promised time. ✓ Urban company professionals show interest in the service they provide. ✓ Urban company professionals are well-trained and efficient.

		✓ Bills/invoices provided by the urban company are error-free
Assurance	Skill, knowledge, and credibility of the staff, and their propensity to use this expertise to inspire confidence and trust.	✓ The urban company professionals are courteous and friendly. ✓ The urban company provides quality services. ✓ Urban company professionals show respect for the opinions that I give. ✓ Urban company professionals are experienced. ✓ As a customer, I, feel safe allowing urban company professionals into my place. ✓ Urban company service is good value for money
Tangibility	It is refers to the elements such as physical facilities, materials, and other physical features that are used to provide the service.	✓ Urban company has appropriate facilities for providing services. ✓ Urban company professionals have the required materials, equipment, and things for providing services. ✓ Urban company professionals have a neat and professional appearance.
Empathy	It is the skilfulness of the company or the service provider to understand the feelings, pain, or frustration of the customer	✓ The urban company understands the needs of the customer. ✓ Urban company professionals are punctual in attending the service requests. ✓ Urban company professionals give attention to the specific requests that I make. ✓ Urban company professionals give personal attention to my requests. ✓ I receive a spontaneous response to requests that I make in the Urban Company app
Responsiveness	It is the willingness of the company to help the customers by providing prompt services.	✓ Urban company professionals are quick at responding to customers' queries. ✓ Urban company professionals are always willing to help me. ✓ Urban company professionals are skilled enough. ✓ Urban company professionals always listen to my complaints. ✓ At times urban company app/website is too busy to respond

In summary, this study involved surveying 514 respondents from Chennai city, representing diverse demographics such as government employees, private employees, professionals, and self-employed individuals of all ages above 20. By collecting 514 survey respondents, we have surpassed the minimum required sample size determined by Cochran's formula to achieve a 5% margin of error, indicating that our sample size is sufficient. For purposive sampling collection, we have identified 82 apartment associations or complexes which include high-rise apartment buildings, and gated communities in four different zones (i.e Chennai Central, Chennai South, Chennai North, Chennai West) where residents are likely to have utilized Urban Company services. We reached out to all apartment secretaries and explained the purpose of our research study. With their assistance, we clearly instructed residents who are Urban Company users to participate in the field survey method, which involves completing an online survey, participating in an interview, and providing feedback. This field survey method adheres to ethical guidelines, including obtaining informed consent, protecting participant privacy, and maintaining confidentiality of participant information. We also implemented a rigorous questionnaire process to ensure that only respondents associated with Urban Company were included in our data collection. By filtering out data from respondents not associated with Urban Company, we obtained the most accurate results for our purposive sampling collection. The research model encompasses two sub-dimensions: one focusing on demographic information and the other on SERVQUAL service quality perceptions towards Urban Company(Moghadam and Saghih, 2021). The questionnaire includes questions related to respondents' demographics, such as age, gender, occupation, and education level. Additionally, it explores perceptions of service quality based on the SERVQUAL model's dimensions, including reliability, assurance, tangibility, empathy, and responsiveness, specifically tailored to Urban Company's services. This structured approach allows for a comprehensive assessment of both demographic factors and service quality perceptions, providing valuable insights into customer preferences and satisfaction levels. A structured questionnaire on a five-point Likert scale from strongly agree (1) to strongly disagree (5) was implemented to collect primary research data. The population mainly includes those respondents who are Urban Company users or who have already used urban company services.

2.2 Machine Learning and Model Development:

The study utilizes machine learning, particularly the K-nearest neighbors (KNN) algorithm, to predict customer satisfaction scores based on the SERVQUAL model, which evaluates service quality using factors like Reliability, Assurance, Tangibles, Responsiveness, and Empathy. Figure 3 demonstrates the sequential steps of the K-nearest neighbours (KNN) algorithm used to forecast customer satisfaction scores by utilizing input factors derived from the SERVQUAL model. The dataset used in the study consists of variations in input process parameters such as Reliability, Assurance, Tangibles, Responsiveness, and Empathy, along with corresponding Customer Satisfaction Scores (CSS). These parameters represent different aspects of service quality as per the SERVQUAL model. This dataset is then utilized to train and test the K-nearest neighbors (KNN) algorithm for predicting customer satisfaction scores based on the provided input factors. The dataset is split into 80% for training and 20% for testing. In the K-nearest neighbors (KNN) algorithm, determining the value of K is crucial as it affects the model's performance. One common heuristic for selecting K is to use the square root of the number of samples in the training dataset ($N^{1/2}$) (Kumar and Jain, 2022)(Vincent and Natarajan, 2023). In this case, K is determined as the square root of the number of samples in the training dataset (413), resulting in a value of K = 20.29. However, it's common to round this value to the nearest integer, which results in K=20. This value is used to determine the number of nearest neighbors considered when making predictions in the KNN algorithm. The trained model is then tested, and performance is evaluated using metrics like Mean Absolute Error, and Root Mean Squared Error. Smaller error values indicate higher accuracy of the KNN algorithm in predicting customer satisfaction. By analyzing these error metrics, we can assess the accuracy of the KNN algorithm in predicting customer satisfaction and make informed decisions to improve service quality across different levels. This systematic framework helps in understanding customer preferences and enhancing customer experiences, ultimately leading to higher satisfaction and loyalty.

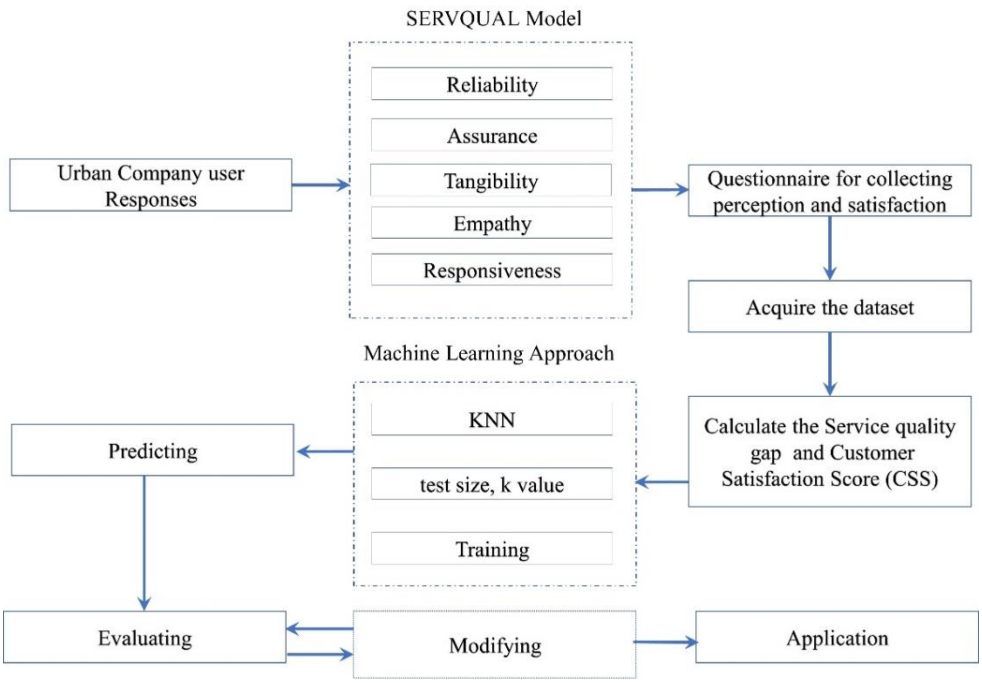

Fig 3: Illustrative Overview of the Steps in the KNN Algorithm for Projecting the Customer Satisfaction Score (CSS) Using Input Factors from the SERVQUAL Model.

3.0 Result and Discussion

The systematic experimental study involved varying input process parameters, such as Reliability, Assurance, Tangibles, Responsiveness, and Empathy, while recording the corresponding output value, which is the Customer Satisfaction Score (CSS). Table 3 presents these input values, including Normalized Reliability, Assurance, Tangibles, Responsiveness, and Empathy, alongside their corresponding Customer satisfaction score (CSS). Figure 4 illustrates the relationship between actual and predicted values of the Customer Satisfaction Score (CSS) concerning input parameters such as (a) Reliability, (b) Assurance, (c) Tangibles, (d) Responsiveness, and (e) Empathy, utilizing the K-nearest neighbour (KNN) machine learning algorithm. The plot features blue triangles representing predicted CSS values derived from the KNN algorithm using the input parameters, while red dots indicate the actual CSS values obtained from calculations.

Table 3: Normalized Input dimensions using the SERQUAL model and and their Respective CSS Outputs.

S.No	Normalized Reliability Gap	Normalized Assurance Gap	Normalized Tangibility Gap	Normalized Empathy Gap	Normalized Responsiveness Gap	**Customer Satisfaction Score (CSS) using Root Mean Square (RMS)**
1	69.23	53.85	71.43	83.33	46.15	**60.92**
2	69.23	53.85	85.71	75.00	61.54	**66.01**
3	76.92	53.85	71.43	91.67	84.62	**71.69**
4	61.54	53.85	57.14	58.33	53.85	**58.75**
5	30.77	46.15	71.43	58.33	30.77	**53.82**
6	69.23	53.85	57.14	50.00	53.85	**55.41**
7	53.85	53.85	57.14	58.33	46.15	**55.65**
8	53.85	53.85	57.14	58.33	46.15	**52.59**
9	53.85	69.23	42.86	66.67	46.15	**58.29**
10	53.85	38.46	71.43	66.67	30.77	**54.54**
11	69.23	53.85	71.43	50.00	53.85	**55.73**
*	*	*	*	*	*	*
*	*	*	*	*	*	*
*	*	*	*	*	*	*
511	61.54	46.15	71.43	58.33	46.15	**54.58**
512	61.54	53.85	57.14	50.00	46.15	**54.00**
513	53.85	53.85	57.14	58.33	46.15	**52.59**
514	53.85	53.85	57.14	58.33	46.15	**55.65**

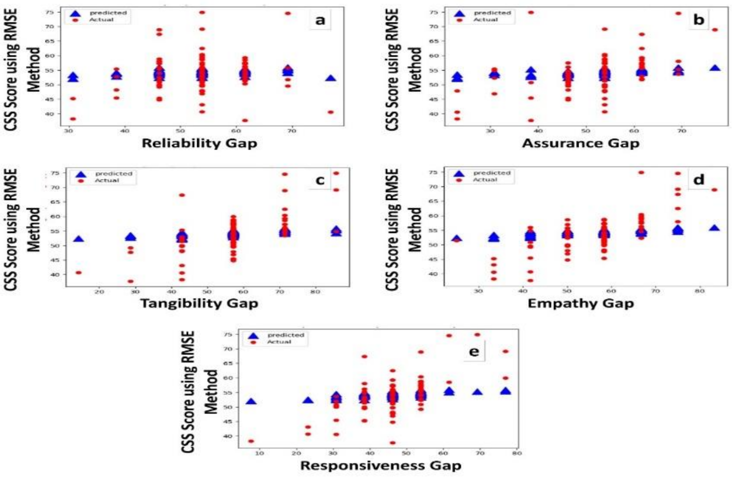

Fig 4: Actual and predicted Customer satisfaction score (CSS) by varying (a) Reliability gap (b) Assurance gap (c) Tangibles gap (d) Empathy and (e) Responsiveness gap.

Subsequently, the Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) values are computed using the following formulas:

$$\boldsymbol{Mean\ Absolute\ Error\ (MAE)}\ = \frac{\boldsymbol{1}}{\boldsymbol{n}} * \boldsymbol{\Sigma}(|\boldsymbol{y_a} - \boldsymbol{y_p}|) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

$$\boldsymbol{Root\ Mean\ Squared\ Error\ (RMSE)}\ = \sqrt{(}\frac{\boldsymbol{1}}{\boldsymbol{n}} * \boldsymbol{\Sigma}(\boldsymbol{y_a} - \boldsymbol{y_p})^{\boldsymbol{2}} \ldots\ldots\ldots\ldots (7)$$

In the given scenario, y_a denote the actual CSS values, y_p represents predicted CSS values and n is the no. of observations. Utilizing the KNN Machine Learning Model with a K value of 20, the Mean Squared Error is determined to be 3.14, while the Mean Absolute Error is calculated to be 1.92. These metrics quantify the average discrepancy between the predicted and actual values.

3.1 Validation of the model's accuracy:

Figure 5 provides a visual representation of the residuals, which are the errors made by the model in predicting the target variable. The x-axis represents the actual target values, while the y-axis represents the residuals, which are the differences between the actual and predicted values. A horizontal line at Y= 0 indicates perfect predictions. Points above the line indicate over-predictions, while points below the line indicate under-predictions. The equation Y= 0.154X − 8.316 represents a linear relationship between two variables and the coefficient 0.154 determines the slope of the line. The coefficient of determination R^2 = 0.99 signifies a robust and highly meaningful linear correlation between X and Y, implying an excellent fit of the model to the data. With a slope of 0.154, the model indicates minimal disparities between predicted and actual values. The model shows a Mean Squared Error of 3.14 and a Mean Absolute Error is 1.92.

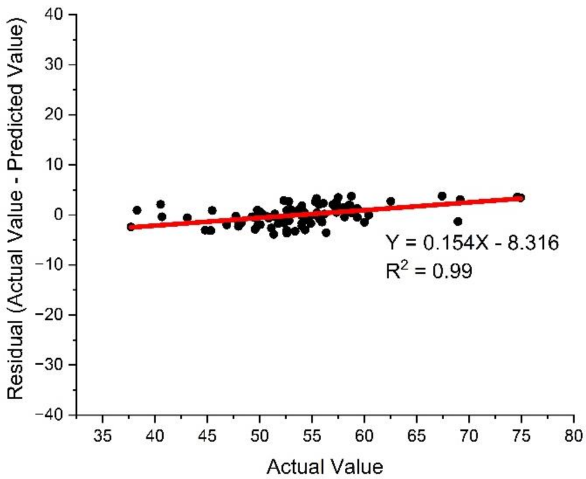

Fig 5: Variation of residual value by varying the actual values.

The study utilizes machine learning approach to provide valuable insights into customer satisfaction levels among Urban Company users based on the SERVQUAL model, there are some limitations which are not addressed are: (a) The study focuses exclusively on Urban Company users and the findings may not be directly applicable to other hyperlocal online service providers or industries (b) SERVQUAL model, while widely used, may not capture all relevant factors influencing customer satisfaction, other variables such as pricing, convenience, or customer service interactions could also play significant roles (c) Since the Urban company provide different services and catering to a diverse user base encompassing varying demographics and preferences, there is inherent variability in experiences across services and user groups. Although 514 survey responses were collected which is considered an adequate sample size, it is important to note that the sample size may vary in its ability to capture the full diversity of Urban Company users and their service experiences (d) K-Nearest Neighbours (KNN) algorithm can be used to predict customer satisfaction due to its simplicity, however, some more complex algorithms or models could potentially yield better results than KNN algorithm. Addressing these potential limitations and considering their implications can strengthen the applicability of the study's findings.

4.0 Conclusions:

This study investigates the significance of understanding and forecasting customer satisfaction levels for Urban Company, a prominent hyperlocal online home service provider for enhancing various aspects of marketing. Customer satisfaction is crucial for maintaining the company's reputation and competitiveness in the market. Here are the conclusions drawn from our work:

- Utilizing a machine learning approach with the K-Nearest Neighbors (KNN) algorithm proves to be a viable technique for predicting the customer satisfaction of the Urban Company platform and comparing it with the actual Customer Satisfaction Score (CSS) value. The SERVQUAL model, encompassing dimensions such as Tangibles, Reliability, Responsiveness, Assurance, and Empathy, serves as the input factors, while the calculated CSS score acts as the output factor.

- The model's effectiveness was assessed utilizing metrics like Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The results reveal a Root Mean Squared Error of 3.14 and a Mean Absolute Error of 1.92, indicating the model's ability to predict customer satisfaction levels of accuracy.

- The examination of residuals provides valuable insights into the model's accuracy and effectiveness in capturing the underlying relationships in the data. The equation $Y=0.154X-8.316$ represents a linear relationship between two variables. The slope of 0.154 indicates very small deviations between predicted and actual values.

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Declarations

Conflict of interest: The authors declare no Conflict of interest.

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