International Journal of Industrial Engineering & Management Science, Vol. 9, Issue 2, (2022) 1-10

University of Hormozgan

International Journal of Industrial Engineering & Management Science

journal homepage: www.ijiems.com

A Comprehensive Framework of Information Technology Service Quality Assessment in a Manufacturing Company

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ARTICLE INFO

Article history:
Received: 2022-10-17
Received in revised form: -
Accepted: 2023-10-09

Keywords:
Service Quality
SERVQUAL
Gap Analysis
ITSM
Data Mining
Machine Learning

ABSTRACT

With the advancement of technology, service quality has become strongly reliant on providing Information Technology (IT) services in all sections of an organization. Accordingly, a comprehensive framework is represented in this study to assess the quality of services supplied by the IT unit in a manufacturing company, which integrated the SERVQUAL model, the service quality gap, and IT service management metrics across the entire organization's supply chain. Regarding model reliability, a data-based decision model was designed in which big data analysis, including data mining and machine learning methods, was considered. Moreover, the essential analytical objectives for evaluating the IT unit, along with the data collection method and appropriate tools, were figured out. A steel production company was also used to express the efficiency and effectiveness of the proposed framework. The results determined SERVQUAL dimensions of reliability, responsiveness to tangible factors, sympathy, guarantee and the functional dimensions of problem-solving time, response time, and agreed service level are the most important, respectively.

1. Introduction

It is believed that Industry 4.0., as a business and technology integration, can significantly improve companies' process performance and innovation (Glogovac et al., 2020). Toward Industry 4.0, Information Technology (IT) plays a critical role in a company's entire supply chain and service quality (Peraković et al., 2020). Whereas, there is no specific model to assess all IT services in a manufactory (Alsaleh & Bageel, 2016; Herdiyanti et al., 2017). Based on this, a comprehensive model was designed and represented in this study, which integrated SERVQUAL and gap models, as well as IT Service Management (ITSM) metrics to obtain complete information from the entire supply chain of the company. Then, it exploited the big data analysis approach to discover the IT service quality situations.

The SERVQUAL model is a well-known, widely used, and critical technique for assessing service quality. It was firstly founded by Parasuraman, who identified five service quality attributes: tangible, responsiveness, reliability, assurance, and empathy (Parasuraman et al., 1985). In addition, it is a beneficial and valuable tool for gap analysis, where a gap is defined as the difference between customer expectations and customer perceptions (Parasuraman et al., 1988). ITIL is also a framework of best practices compiled from the private and public sectors of organizations worldwide that aims to deliver high-quality IT services based on ITSM (ITIL | IT Service Management | Axelos, n.d.). In the study of (Gacenga et al., 2011), the ITIL framework revealed a strong relationship between the coordinated performance framework and the clearly articulated ITSM metrics. Consequently, thorough features based on the SERVQUAL

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and gap model as well as ITSM metrics have been established for efficient assessment.

The IT unit also provides a variety of services to different suppliers, manufacturing workers, IT staff, and customers, the quality of which influences IT performance. As a result, this paper presents a developed model that allows a company to evaluate the IT service quality of all customers in the company's supply chain.

Another challenge is to examine performance indicators; because of big data of the entire supply chain, traditional analysis is insufficient. Data mining is a process that involves methods from machine learning, statistics, and database systems to extract and discover patterns in large data sets (Han et al., 2012). As a result, in this study, an inclusive data analysis approach is proposed to discover IT performance in service quality in terms of big data.

In the following section, a literature survey is discussed. Section 3 describes the proposed framework in detail, including steps taken, tools applied, and data used. Section 4 reports the results of applying the technique to a steel company. Section 4 also summarizes the conclusion.

2. Literature Review

SERVQUAL is a broadly employed tool for assessing and measurement of service quality. (Souri et al., 2018) proposed a framework for identifying consumer behavior toward green products by measuring the gaps between consumers' expectations and perceptions of LED bulbs. In another effort, (Ammar & Saleh, 2021) applied the grey relational analysis model to investigate the bulk water provision service in the Palestinian Water Authority-West Bank Water Department based on the SERVQUAL approach. (German et al., 2022) utilized the integrated pro-environmental planned behavior theory and SERVQUAL to analyze the impactful factors on the intention of consumers in the Philippines to choose a package delivery or carrying service during the COVID-19 pandemic. Additionally, the quality of educational services provided to dentistry and nursing students was assessed by (Aboubakr & Bayoumy, 2022) using the SERVQUAL model.

According to the literature, numerous attempts have been conducted to examine the quality of services in various organizations, such as teaching hospitals (Khan et al., 2020), social network services in the financial industry (Nam & Seong, 2021), hotel management (Rabiul et al., 2021), agro-food product factory (Okpala & Korzeniowska, 2021), and the airline (Parast & Golmohammadi, 2021). Meanwhile, there are a few cases where the IT quality service is examined in industries. In this era, (Badri et al., 2005) utilized SERVQUAL to determine gaps in the chain of services provided by IT resources in higher education institutions in the United Arab Emirates. (Brida et al., 2016) also evaluated service quality in an airport environment. Correspondingly, they examined how ICTs services affect passenger's perception of service quality at airport functional areas. Moreover, the quality gap of IT services from the perspective of service providers and consumers was assessed in another research (Herdiyanti et al., 2017). (Widjajarto et al., 2019) also described an IT Infrastructure architecture model based on service quality at government institutions to develop synergies between infrastructure service providers and service users (end-users).

Moreover, a large number of studies investigated the indicators using Structural Equation Modelling (SEM), statistical analysis, and Multiple Criteria Decision Making (MCDM). For example, (Yang et al., 2021) reported a sensory perception service quality model and applied the SEM to extract ten service characteristics for improving the industries' services. In addition, (Rahi et al., 2021) investigated patient behavior toward adopting telemedicine health services using three well-known theories and reported an 80.4% variance in patient attitude via SEM. (Afroj et al., 2021) revealed a common framework incorporating SERVQUAL, Analytical Hierarchy Process (AHP), and Citizen's Score Card to define the spatial and functional quality of municipal services based on citizen satisfaction. Additionally, (Tumsekcali et al., 2021) employed a SERVQUAL-based model to evaluate public transportation services via a multi-criteria decision making problem and a novel AHP integrated WASPAS (Weighted Aggregated Sum Product Assessment) under interval-valued intuitionistic fuzzy environment methodology. (Supriyanto et al., 2021) also employed path analysis and One-Way Analysis of Variance to figure out the effects of customer loyalty and satisfaction, as well as the simultaneous impacts of service quality and customer satisfaction on customer loyalty in a bank.

While some recent studies utilized data mining methods to achieve new findings in the field of service quality, such as (Lee et al., 2021) used clustering and classification methods to assess social perceptions of healthcare service quality and identify keywords for each SERVQUAL dimension. (Ram et al., 2021) also focused on the service quality of public transport attributes in urban tourist destinations by classification methods to determine which attributes are most significant for tourists prior to their arrival. In a study carried out by (Farazi et al., 2022), the impact of heterogeneity in users' perception of service quality on intercity train service was characterized by machine learning tools. During the COVID-19 outbreak, a method was represented for analyzing customer satisfaction that combined machine learning and survey-based approaches (Nilashi et al., 2022).

Table 1 summarizes the studies which have reviewed. According to the table, no research study presenting comprehensive features for evaluating the IT sector of any manufacturing company and entire supply chain was found. In addition, it was observed that some recent papers applied data mining and machine learning in the field of service quality assessment.

Table 1. Summary of recent relevant studies regarding

	SERVQUAL & Gap Model	ITSM Metrics	Supply Chain	Analysis Method	application
(Badri et al., 2005)	✓		Provider	Statistical analysis	Higher education institutions
(Brida et al., 2016)		✓	Provider	Statistical analysis	Airport
(Herdiyanti et al., 2017)	✓		Provider	Statistical analysis	University

(Souri et al., 2018)	✓		Consumer	Statistical analysis	Consumers of LED bulbs
(Widjajarto et al., 2019)		✓	Supplier	Statistical analysis	Government institution
(Ammar & Saleh, 2021)	✓		Costumer	GRA model	Bulk water provision
(Afroj et al., 2021)	✓		Provider	MCDM	Municipal
(Tumsekcali et al., 2021)	✓		Provider	MCDM	Public transportation
(Yang et al., 2021)	✓		Provider	SEM	Service industries
(Rahi et al., 2021)			Provider	SEM	Telemedicine health services
(Supriyanto et al., 2021)			Customer	Statistical analysis	Bank
(Lee et al., 2021)	✓		Customer	Data mining	Social media
(Ram et al., 2021)			Customer	Data mining	Urban transportation
(German et al., 2022)	✓		Consumer	Statistical analysis	Package delivery
(Aboubakr & Bayoumy, 2022)	✓		Supplier	Statistical analysis	Educational services
(Farazi et al., 2022)			Consumer	Machine learning	Intercity train service
(Nilashi et al., 2022)			Consumer	Machine learning	Tourism
Proposed model	✓	✓	Entire chain	Data mining & Machine learning	Manufacturing company

3. Proposed Model

This paper presents a comprehensive quality evaluation framework based on the SERVQUAL model and the ITIL framework. The model could analyze big data using a data mining process and innovative machine learning tools to assess the specialized services of an IT unit to an organization's entire supply chain. The activities and tools used in each step are displayed in Figure 1.

Step 1: Clients Identification

As previously stated, the company's entire supply chain is the IT unit of service recipients; this unit can evaluate all clients electronically, without sampling, through developing services and the availability of intelligent mobile phones.

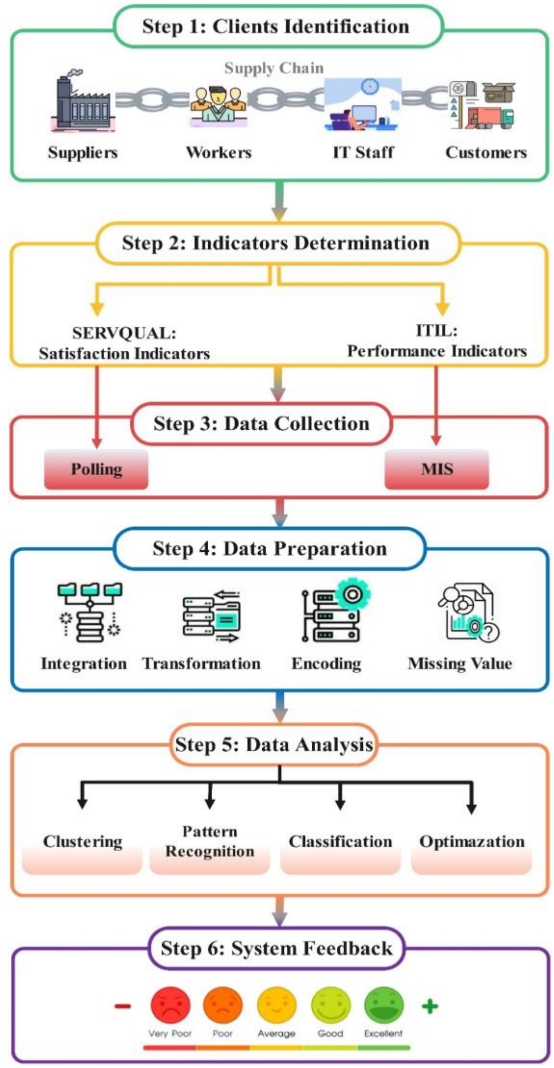

Figure 1. The proposed approach for service quality management

Step 2: Indicators Determination

According to the literature (Khamoushpour et al. 2021), there are two crucial types of indicators to evaluate IT: all indicators influencing service quality from the customer perception and the SERVQUAL model, and all described indicators affecting ITSM outlined in the system related to ITIL. Table 2 addresses the defined indicators based on the SERVQUAL quality dimensions.

Table 2. The determined IT quality dimensions using the SERVQUAL approach

Dimension	Description	IT dimensions
Tangibles	The appearance of physical facilities, equipment, personnel, and communication	**The appearance of a software system from various aspects, e.g., color and page design**
Reliability	Ability to perform the promised service dependably and accurately	**Performance and reliability of systems**
Responsiveness	Willingness to help customers and provide prompt service	**The quick and correct response of experts to users' requested services**
Assurance	Knowledge and courtesy of employees and their ability to convey trust and confidence	**Trusting and technical knowledge of IT experts**
Empathy	Caring, individualized attention, the firm provides its customers	**Respecting users' particular needs**

Table 3 also introduces and defines the performance indicators associated with the ITIL-designed system.

Table 3. Performance indicators of the designed system defined by the ITIL framework

ITSM indicators	Description
Response Time	The time limit in which order reaches an IT expert, and he/she begins working on it.
Resolved Time	The time span between sending the order to the expert and completing the job.
Meeting SLA time	Orders are processed within the agreed-upon time frame.
Resolved rate	Determining whether or not the expert completed the task.
Meeting OLA times	Performing tasks across multiple working teams in a single order within an agreed time period.

Step 3: Data Collection

A questionnaire is essential to measure the difference between customers' expectations and perceptions of how services are delivered to extract the gaps in service delivery shown in Table 2. In addition, the company could request that a questionnaire be filled out via a specifically designed electronic system of Customer Satisfaction Management (CSM). In table 3, 44 features are proposed for assessing gaps in IT service quality by Delphi method.

Table 4. The features of the gap analysis based on the SERVQUAL model

Dimension	Feature
Tangibles (11)	Informing about the time of service provision. Informing about the methods of providing services. The amount of information supplied about the services that can be offered. Informing about new services that are possible to be availed. The ability of the user and the applicant to offer comments and suggestions. Information about the outcome of requesting services. The quality of service suppliers' dialect and verbal communication. The neatness and cleanliness of service providers. The apparent quality of the service portal. Continuous improvement in service portal design. The presence of software, hardware, and equipment used in the most recent and alternative network.
Reliability (9)	Quick response to requests. Speed in resolving system problems. Providing prescribed services at the promised time. The accuracy of the services provided. Uncertainty of the site. Standard rate of service delivery methods. Providing services in accordance with the provided obligations. Services and support of services provided. The degree of compatibility of the services given with the company's IT structure.
Responsiveness (6)	Presence of a sufficient number of service personnel. The ability to easily follow up and cancel service requests. Continuous response to applicants. The response rate to dissatisfactions. The willingness of service providers to respond to applicants' requests. The simplicity and convenience of the site.
Assurance (13)	The level of personal information protection. The performance quality of antivirus and security tools. The ability to access the information of previous requests. Providing services at the first opportunity. Ease of access to requested services. Adequacy of training courses related to service use. Providing services in accordance with the special requirments of customers. The degree of personalization in service provision. The level of conformity between the services committed and offered by the service providers. The level of knowledge and skills of the service suppliers. The proportion of service delivery methods to the applicant's conditions. The ability to change the characteristics of the required services after submitting the request. Creating satisfaction in the applicant through variety in the amount and type of services that can be availed.
Empathy (5)	Obtaining assistance from the applicant in providing services. Participation of service providers in errors occurred in the provision of services. Showing courtesy and respect to service providers. Having faith in service providers. The ability to determine the response time to a request.

The second type of indicator is service quality performance data, which could be obtained from the organization's Management Information System (MIS). All IT staff activities and performance are available in this system based on the recorded data. The extracted indicators according to each registered request are shown in Table 3.

In addition, the following nominal data relating to each request's specifications are required for further analysis:

- The request number;
- The applicant's name;
- The applicant's unit name;
- The group associated with the request type;
- The name of the relevant service expert;
- The service name related to the request;
- The name of the subservice associated with the request;
- The title and type of request;
- The subject of the request; and
- The request text (written by the user).

Step 4: Data Preparation

At this stage, polling and MIS datasets are first integrated into a database. Then, because data is extensive in both size and volume, outliers, missing values, incompatible cases, and data input errors must be identified and replaced. The data mining process employs various techniques to deal with noise (Han et al., 2012). Furthermore, descriptive statistical tools can be utilized to gain an initial understanding of variables and customer status.

Step 5: Data Analysis

Despite the advancement and widespread use of data mining and big data analysis, unfortunately, they have received less attention in evaluating service quality. This step covers the fundamental concepts of data mining tools and metaheuristic algorithms and how they can be used in service quality assessments, as well as defining key terms and making critical distinctions.

Clustering: The main aim of cluster analysis is to classify data into groups (clusters) with similar characteristics, maximizing the similarity between in-cluster elements and the dissimilarity between inter-cluster elements (Fraley & Raftery, 1998). K-means clustering is a fundamental and widely used unsupervised machine learning algorithm that divides observations into k clusters, assigning each observation to the cluster with the closest mean (MacQueen, 1967). As a result, if all customer-measured indicators are clustered, they can be placed in a cluster based on the greatest similarity from the customer's perspective. Accordingly, the indicators can be classified into different clusters based on the most significant divergence between their centers. The cluster is then labelled according to the mean values of the indicators and the number of customers.

Pattern Recognition: Pattern recognition is concerned with the automatic detection of regularities in data using computer algorithms, as well as the application of these regularities to perform tasks such as data classification (Bishop, 2006). Supervised and non-supervised are defined as two types of recognition strategies. The presence of structured patterns is required for recognition in the former. The prediction of patterns of interest is carried out using this method. At this level, training is essential to determine the pattern's membership in a specific class. On the other hand, the latter strategy can predict data behaviors and relationships in order to identify a class's membership function (Chen et al., 1993). Hence, recognizing any pattern in the performance of experts and IT staff that leads to customer satisfaction and each labeled cluster could be beneficial.

Classification: Classification is a subcategory of supervised learning in which the goal is to predict the categorical class labels of new instances based on previous observations. You can employ several classification algorithms depending on the dataset (Coggeshall & Klinkenberg, 2014).

A classification can predict the quality of IT services based on gaps and performance indicators, allowing for a better understanding of the company's advantages and disadvantages. Another application is to forecast the gaps in the quality model using performance indicators of IT services so that the company can predict the quality of services without polling and knowing the gaps indicators.

Optimization: Optimization is selecting the best element from a set of available alternatives, which can be considered a minimization or maximization problem. The majority of real-world optimizations are highly nonlinear and multimodal, with a variety of complex constraints. Different objectives are often conflicting, and even for a single goal, sometimes, optimal solutions may not exist at all. In general, finding an optimal or even a sub-optimal solution is not easy (Shi et al., 2011). Metaheuristics are widely acknowledged as efficient approaches to many complex optimization problems (Boussaïd et al., 2013). To improve service quality, it is beneficial to understand how much service should be availed in order to achieve two goals: approaching a lower service quality gap from the service recipient, and making optimal use of the service infrastructure and not wasting service resources (avoiding a negative service quality gap). IT service providers would then be able to better manage service delivery times and results.

Step 6: System Feedback

The final but not least step is system feedback, which requires the IT unit to compile a list of the knowledge discovered during the data analysis phase. This data could assist ITSM in gaining a comprehensive understanding of the IT unit's entire situation and make better decisions to present superior services and prioritize service quality parameters. Moreover, these findings enable ITSM to receive feedback on revised actions even without the need for polling.

4. Case Study

The efficiency of the proposed method was examined by applying it to an IT unit of a steel company. In such production organizations, IT-quality services are key building blocks because the main production duty is supported by computers, information systems, and computer-related robots. All clients were from suppliers, staff and workers, IT staff, and customers (approximately 6000 individuals). We also considered all requests for a year in the first step, which amounted to about 9200 cases. Figure 2 depicts the supply chain relationship in a steel company.

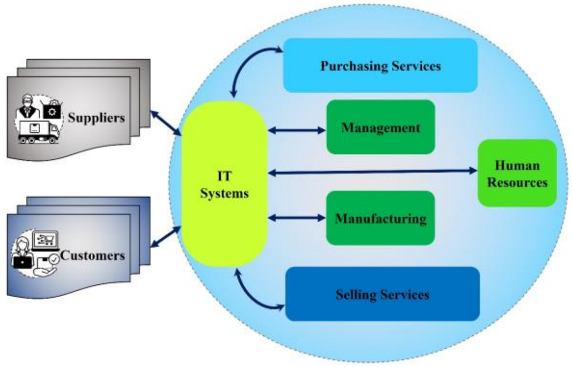

Figure 2. The relation of the IT unit with the supply chain of the steel company

In terms of data preparation, there were about 3% missing values in polling data, which were replaced by the mean of each feature, and approximately 5% outliers, which were deleted. Figure 3 displays the tools used in the data analysis stage of this study.

Figure 3. The applied methods for quality service analysis in steel company

The K-means algorithm was applied to cluster the quality of services provided by the IT unit. The Elbow method was also utilized to determine the optimal number of clusters, while the Silhouette indicator was used to evaluate the clustering model. Table 5 shows the clustering output after data normalization, displaying the cluster centers for all indicators for measuring service quality.

Table 5. The output of the cluster centers in the K-Means algorithm

Indicator	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Assurance	0.24	-0.66	1.77	0.94	2.81	0.73
Responsiveness	0.23	-0.69	1.75	0.92	2.66	0.74
Reliability	0.19	-0.65	1.65	0.90	2.64	0.67
Tangibles	0.28	-0.69	1.76	0.95	2.80	0.79
Empathy	0.33	-0.60	1.77	0.98	2.70	0.79
Response time	0.03	0.01	1.06	0.20	2.36	0.18
Resolved time	0.07	0.10	0.49	0.17	0.49	0.17
Meeting SLA time	0.05	0.06	1.03	0.18	2.38	0.16
Meeting OLA time	0.08	0.06	0.10	0.07	0.10	0.05
Resolved rate	5.00	5.00	5.00	5.00	0.11	0.00

In addition, Figure 4 depicts the results of cluster centers to understand the differences in the specifications of each cluster.

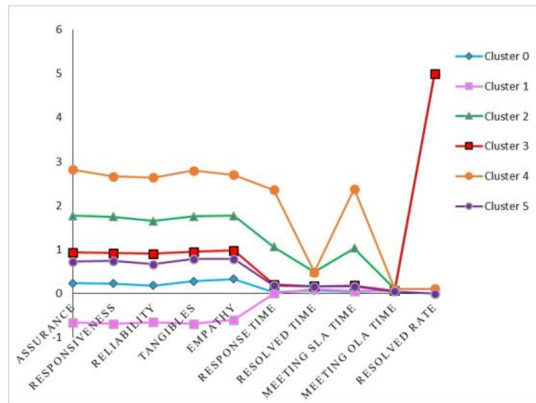

Figure 4. The cluster center specifications and their differences determined by the K-Means algorithm

Moreover, clusters have been labeled according to their specifications as well as changes in service quality indicators. These specifications and naming of each cluster, along with clustering output, were used as input in the rest analysis. Table 6 displays the clustering outputs and specifications.

Table 6. The clustering specifications and results

Cluster number	Number of people in each cluster	Cluster title	Specifications	Clusters' labels based on gap and fulfillment
1	102	GF1	The best service delivery performance and a negative gap, indicating high satisfaction	Very satisfied users
2	857	GF2	The most appropriate service delivery performance with the minimum gap	Satisfied users
3	197	GF3	Appropriate performance and gap, as well as proper service delivery	Relatively satisfied users
4	1462	GF4	Inappropriate service delivery performance, large gaps, and unresponsiveness	Relatively dissatisfied users
5	325	GF5	Unsuitable service delivery performance, large gap, and high dissatisfaction	Dissatisfied users
6	93	GF6	Highly inadequate service delivery performance, very large gap, and very high dissatisfaction	Very dissatisfied users

Herein, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which is based on association rules with reduced error pruning, was used For pattern recognition and assessing IT staff performance (Cohen, 1996). The RIPPER algorithm requires using all available data, which is composed of two parts: clustering output and request specification. This analysis was carried out on 9251 registered requests, and the accuracy of the rule learner model was 95.59% using the Cross-validation algorithm. Table 7 summarizes the results of RIPPER.

Table 7. Results and samples of the rule learner algorithm

Samples of the extracted rules		Results
IF, Condition	THEN, Conclusion	
Owner = Mr. XXXX and Sub-Service Name = Email and process	GF1, very good performance and satisfaction	Each expert's behavior and satisfaction were made out of this performance
Group Name = Planning and control of production system and Empathy < 2	GF6, least satisfaction, as well as very bad performance and service delivery interruption	The performance of each working group and the satisfaction were driven by the performance of this group's name
Service Name = Network and Tangibles > 3.5	GF4, low satisfaction, unsuitable performance, and long service processing time	The efficiency of each requested service and its sub-service names, as well as the satisfaction, were made out of this performance
Owner = Mr. ZZZZ	GF2, good performance, and satisfaction	Achieving general outcomes and rules

A decision tree was also used to classify the quality of services based on gap and performance. A decision tree is a popular classification tool that employs a tree-like model of decisions and their potential outcomes, including chance event outcomes, resource costs, and utility (Quinlan, 1987). If important indicators are available in the nodes and branches of the decision tree for the services provided, the service delivery ratio can be predicted; otherwise, other less important indicators cannot be measured and evaluated. We assumed all measured gaps and performance indicators as input variables and the clustering output as the target variable to build the tree. Figure 5 depicts the best tree as determined by tree evaluation performance. With three times of pre-pruning, the desired tree showed a confidence ratio of 0.5 and a maximum depth ratio of 8. This tree was assessed using the cross-credit multi-layer method, with automatic sampling and ten layers. It also exhibited a 98.12% accuracy and correctness ratio.

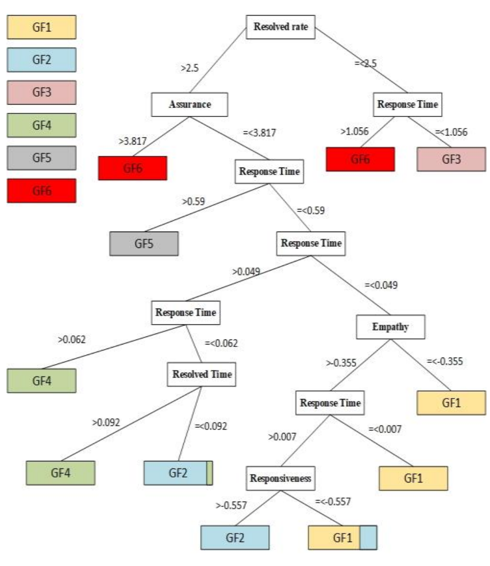

Figure 5. Proposed decision tree to predict service performance and gap ratio

The decision tree's results proposed the most important indicators for how services should be provided in the IT unit of this company, which are as follows: responsiveness time, guarantee, responsiveness ratio, problem solving time, empathy, and responsiveness.

Random forests were also applied in the next classification to predict service quality gaps based on performance indicators. Random forests are an ensemble learning method for classification in which the random forest output is the class selected by a majority of trees (Ho, 1995). The purpose of providing a prediction model by random forests is to use existing service performance data to predict service quality gaps. This assists in predicting the quality of services without conducting surveys or gap indicators and only by using performance indicators.

The final settings with the most negligible error in predicting the output were: 50 decision trees, the method of voting selection (the most commonly used method), a maximum depth of 12, and 5 times of pre-pruning. The output evaluation of this prediction's results was performed by the K-fold cross-validation method, which was sampled automatically, and the number of layers was set to ten. The accuracy and correctness of these results were 97.5%, as shown in Table 8.

Table 8. Confusion matrix of random forest prediction

	True GF2	True GF1	True GF4	True GF5	True GF3	True GF6	Class precision
Pred. GF2	849	50	3	0	0	0	94.12%
Pred. GF1	0	51	0	0	0	0	100%
Pred. GF4	7	0	1458	9	0	0	98.91%
Pred. GF5	1	1	1	316	2	0	98.44%
Pred. GF3	0	0	0	0	194	1	99.49%
Pred. GF6	0	0	0	0	1	92	98.92%
Class recall	99.07%	50.00%	99.73%	97.23%	98.48%	98.92%	
Accuracy: 97.5% ± 0.79% (Micro:97.5%)							

The random forest would then present more critical performance indicators to predict which services should be provided through voting from 50 trees.

The final novel analysis was the use of meta-heuristic algorithms to select and optimize indicators to minimize the service quality gap. The desired optimization would be required to minimize the service quality gap and avoid the service resource loss, i.e., the negative service quality gap. Two well-known meta-heuristic algorithms were applied to achieve the objectives. The Genetic Algorithm (GA) is a metaheuristic inspired by the natural selection process that is part of the larger class of evolutionary algorithms. GA is frequently used to generate high-quality optimization and search problems by utilizing biologically inspired operators such as mutation, crossover, and selection (Mitchell, 1996). PSO is also a computational method for optimizing a problem by attempting to improve a candidate solution in relation to a given measure of quality. It solves a problem via a population of candidate solutions, dubbed particles in this context, and moving them around in the search space using a simple mathematical formula based on the particle's position and velocity (Kennedy & Eberhart, 1995). Table 9 shows how the parameters for the GA and PSO algorithms were set.

Table 9. Parameters of the GA and PSO selected by the analyst

GA parameters		PSO parameters	
Population	100	Population	70
Maximum production rate	12	Maximum production rate	30
Maximum fit	Unlimited	Inertial weight	1
Type of selection	Roulette wheel	The best local weight	1
Type of intersection	Single point	The best global weight	1
Probability of intersection	0.5		
Probability of mutation	0.5		

The GA result is represented in Table 10, in which the final time to perform the service level and response rate were not significant enough to minimize the gap.

Table 10. The results of selected effective indicators in minimizing the service quality gap

The results of quality performance indicators		The results of quality gap indicators	
Response time	1	Reliability	1
Problem-solving time	1	Responsiveness	1
Time to perform the agreed service level	1	Guarantee	1
The final time to perform the service level	0	Tangible factors	1
Response rate	0	Sympathy	1

The PSO result with the aim of minimizing the service quality gap is listed in Table 11.

Table 11. The results of effective indicators in minimizing service quality gap

Quality performance indicator outcomes		Quality gap indicator implications	
Response time	0.62	Reliability	0.91
Problem-solving time	0.86	Responsiveness	0.86
Time to perform the agreed service level	0.56	Guarantee	0.76
The final time to perform the service level	0.06	Tangible factors	0.82
Response rate	0.22	Sympathy	0.79

The PSO consequence not only confirmed the GA result, but it could also be used to prioritize the indicators that had the most influence on service quality.

5. Conclusion

Herein, an evaluation framework was developed for all manufacturing companies that require IT units to perform their services. In this structure, thorough features for IT unit of manufacturing companies were established based on SERVQUAL and gap analysis, as well as ITSM indicators via Delphi assessment. The model then incorporated a database related to online electronic survey data aggregation and the IT unit's requests and performances from MIS, since the MIS platform is present in all companies. Of note, after gathering the opinions of the entire supply chain, this model confronted a big data problem. Accordingly, the data mining process was applied to extract knowledge about the company's current and future situations through data preparation, elementary recognition, and data analysis using machine learning methods. The proposed model was also validated by employing clustering tools, association rules, decision trees, random forests, GA, and PSO on a steel company. According to findings, the two performance indicators of the final time of performing the service level and response rate showed less importance. Also, the research results of SERVQUAL dimensions of reliability, responsiveness to tangible factors, sympathy, and guarantee, plus the functional dimensions of problem-solving time, response time, and agreed service level, were the most important, respectively. However, in order to minimize service quality gaps, it is possible to ultimately determine the importance of each indicator and the optimal state of service delivery. In general, the implementation achievements indicated that the feedback from the results could be extremely useful in improving performance and providing the expected quality services to customers.

In the future, various types of relevant indicators affecting service quality, whose data is recorded in various systems, can be analysed to improve and promote the service quality level; other types of data mining methods with different applications are also suggested to be applied; and various or several organizations can also be used to increase the volume of data and compare sectors, with the aim of analysing this model.

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