sciendo

ISMSME International Society for Manufacturing, Service and Management Engineering

received: 1 June 2023
accepted: 10 December 2023

pages: 65-76

Performance evaluation method of the service quality dimensions using Six Sigma metrics, the main components' quality indicator and the geometric capacity indicator

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ABSTRACT

This research aims to propose an evaluation and monitoring method with the Six Sigma performance metrics, the main component quality indicator, and the geometric capacity indicator to control service quality dimensions. The research was quantitative and evaluative. It was developed using primary historical information on the quality criteria of hotel service in twelve periods of 2019. It was possible to demonstrate that the geometric indicator was the most demanding capacity with a value of 0.91163, followed by the multivariate main components' indicator with a value of 0.9559, establishing as a relevant finding the integrality of the three performance criteria to evaluate a service. Topics of service quality, Six Sigma metrics, multivariate main component and geometric capacity indicators were addressed as a theoretical foundation. The research provides a unique contribution in the form of an innovative and efficient continuous improvement method, which makes services more reliable and accurate. Univariate and multivariate statistics were intensively used to evaluate and improve the dimensions of a service from different perspectives. This method has not been considered from the same approach despite its great usefulness in quality control.

KEY WORDS

service measurement, Six Sigma, multivariate capacity indicators

10.2478/emj-2024-0005

Introduction

With the globalisation of the economy and the global pandemic, the services sector finds itself in a new context where services must be more reliable and accurate (Fontalvo et al., 2022a; Fontalvo et al., 2022b) to respond to new customer demands and new forms of interaction. Therefore, intensive use of univariate and multivariate statistics is required to evaluate and improve service dimensions from different perspectives (Bagherian et al., 2022; Barreto & Herrera, 2022; Chia, 2023; De La Hoz et al., 2023).

Fontalvo Herrera, T. J., Herrera Acosta, R., & Banquez Maturana, A. G. (2024). Performance evaluation method of the service quality dimensions using Six Sigma metrics, the main components' quality indicator and the geometric capacity indicator. *Engineering Management in Production and Services, 16*(1), 65-76. doi: 10.2478/emj-2024-0005

This research analysed the best way to evaluate the performance of quality criteria or quality dimensions associated with service provision. As a result, it was necessary to evaluate different metrics to measure this type of economic activity through method articulation. In this sense, recent research shows the importance of using the Six Sigma methodology or its metrics to establish robust statistical criteria to generate improvements in the processes and services where they are implemented (Maged et al., 2019; Fontalvo & Banquez, 2023; Rana et al., 2018; Madhani, 2022; Najm et al., 2022; Sodhi et al., 2023). Consequently, this research seeks to establish a measurement structure that allows for evaluating quality dimensions through different metrics and multivariate quality capacity indicators associated with statistical quality control. It also compares which of these metrics allows evaluating the quality dimension's performance integrally and globally (Sharma et al., 2022; Sodhi, 2023; Banquez & Fontalvo, 2023). Recent research demonstrated the relevance of evaluating and monitoring processes from different multivariate statistical control tools. This research contributes to a deeper analysis of the quality dimensions, periodically and punctually considering nonconformity proportions. It is complemented with an analysis of two multivariate quality indicators to comprehensively assess a given service, which allows for evaluating the two proposed multivariate capacity indicators for better rigour when measuring the performance of a service from an integral perspective.

In general, this research aimed to propose a method to evaluate the performance of service quality criteria using the Six Sigma metrics, the multivariate indicator of principal components and the geometric capacity indicator. The following specific objectives were formulated: (i) evaluate service quality criteria with the Six Sigma metrics on time and periodically, (ii) evaluate the performance of service quality criteria using the multivariate indicator of the main component, (iii) evaluate the performance of service quality criteria using the multivariate geometric indicator, (iv) compare the performance evaluation of service quality criteria using the Six Sigma metrics, the multivariate indicator of the main component and the multivariate geometric indicator, (v) compare the three performance evaluation criteria for being more demanding and providing greater robustness in service measurement.

This research effort is extremely valuable for the scientific community and the service business sector as it provides a method integrating criteria for measuring service components or characteristics in a relevant way and facilitating decisions for service improvement.

1. Literature review

1.1. Six Sigma or quality metrics to measure a service

Recent studies have shown the relevance of periodically and longitudinally monitoring different service quality criteria, which allows for the identification of criteria offering improvement opportunities and excellence criteria; this facilitates action towards service improvement (De La Hoz, et al., 2020; Fontalvo et al., 2022a; Sodhi et al., 2022). It is important to note that other research addressed the Six Sigma methodology application from other perspectives, i.e., its definition, measurement, analysis, improvement, and control in service organisations, focusing more on the method's application than the Six Sigma metrics (Adhyapak et al., 2019; Belcher, 2018). However, in contrast to this study type, other research focused more on the intensive use of the Six Sigma metrics than the DMAIC methodology. They evaluated and analysed the quality criteria performance on time and in different periods, combining the Six Sigma metrics with other univariate and multivariate statistical control techniques, such as the T-square control chart and multivariate capacity indicators. This showed the relevance of articulating this tool type to monitor service delivery processes complementarily (Fontalvo & Banquez, 2023). Other authors also used multivariate control charts and main components' indicators to analyse and improve a process with normal and non-quadratic variables as traditionally addressed by multivariate control charts, specifically the T-square control chart (García et al., 2020; Aldaihani et al., 2017).

1.2. Multidimensional capacity indicators

Many authors have used Multivariate capacity indicators. Herrera (2018) consolidated different multivariate capacity indicators and showed this solution's practical utility in different companies. Other authors (Fontalvo et al., 2021) highlighted the importance of its implementation in the service sector, where this tool type is rarely applied and practically contextualised. Recent studies showed the importance of addressing process improvement with a multivariate perspective (Das et al., 2017). This is aligned with results found in other research on a multivariate approach, additionally incorporating indicators of average multivariate capacity when evaluating service provision. In other words, they monitor the process with specific metrics and use multivariate quality capacity indicators to evaluate service quality criteria globally, holistically, and multidimensionally. This provides criteria and information for better quality management decision-making to meet client criteria and their growing expectations due to new market conditions (Fontalvo & Banquez, 2023; Sreedharan et al., 2020).

When analysing the use of multivariate capacity indicators, it is important to consider different multivariate capacity indicator types proposed by other researchers (Shinde & Khadse, 2009), highlighting: (i) the type proposed by Taam, Subbaiah and Liddy (1993), Castagliola et al. (2009), Bothe (1991) and Wierda (1994); (ii) the main component capacity indicator, established by Wang and Chen (1998) and Chan, Cheng and Spiring (1988); (iii) other approaches proposed by Shahriari and Abdollahzadeh (2009) and Cumea (2013); and (iv) the parametric and non-parametric capacity indicators applying functional data indicated by Clements (1989).

1.3. Multivariate geometric capacity indicator

Process capacity indicators are numerical estimates of the process or service capacity, i.e., they give an idea of how capable the service is of meeting quality criteria, which are highly useful given that they are easy to calculate and do not have measurement units, allowing different processes to be compared. The multivariate capacity indicator for evaluating characteristics stands out among the existing capacity indicators (Chen et al., 2003). It was modified to contextualise the indicator to the present investigation and adjust it to the guidelines required in the Six Sigma methodology.

$$\mathrm{MC_p(k)} = \frac{1}{3}\emptyset^{-1}\left\{\frac{\left[\prod_{j=1}^{k} p_j\right]^{1/k}+1}{2}\right\} \qquad (1)$$

This indicator measures the multivariate capacity considering the percentage of service compliance with respect to the quality criteria pj, where k can be the v criteria involved or the t periods evaluated.

1.4. Multidimensional main components' capacity indicator

The main component study is a quantitative methodology developed in 1901 by Karl Pearson, which provides information about the interdependence between analysed variables, finding their associations and reducing their number to facilitate their analysis. From this methodology, the following multivariate indicator emerges (Jackson, 1980; Wang & Du, 2000), presenting the formulations of the initial r components as follows:

$$\mathrm{MC_{PU}^{T}} = \left[\prod_{i=1}^{r}\left|\mathrm{C_{pu}}^{\mathrm{Yi}}\right|\right]^{\frac{1}{r}} \qquad (2)$$

$$\mathrm{MC_{PL}^{T}} = \left[\prod_{i=1}^{r}\left|\mathrm{C_{pl}}^{\mathrm{Yi}}\right|\right]^{\frac{1}{r}} \qquad (3)$$

where $\mathrm{C_{pu}}^{\mathrm{Yi}}$ y $\mathrm{C_{pl}}^{\mathrm{Yi}}$ are the values of the capacity indices for each of the main components. The calculations of the capacity indices $\mathrm{C_{pu}}$ y $\mathrm{C_{pl}}$ are defined as $\mathrm{C_{pu}} = (\mathrm{USL} - \mu)/3\sigma$ and $\mathrm{C_{pl}} = (\mu - \mathrm{lei})/3\sigma$.

Additionally, in this estimated point for each of the capacity indicators, it is necessary to perform, as a random variable, a global estimate of the criteria using confidence intervals, for which the following confidence interval is applied.

$$\widehat{\mathrm{MC}}_{\mathrm{PU}}^{\mathrm{T}} \pm t\alpha_{/2,n-1}\frac{s}{\sqrt{n}}, \qquad (4)$$

where $s = \left[\sum_{i=1}^{r}\lambda_i\right]^{1/2}$ is an estimate of the global variability of the criteria.

2. Research methods

For the development of this research, a rational positivist analysis was carried out, aiming to propose a method that integrates different performance criteria to evaluate service quality dimensions. To do this, it was necessary to collect service-related empirical information associated with its quality criteria. In the first phase, this allowed for the determination of the defect metrics in part per million DPMO, the Sigma Z level, and the performance of the quality criteria Y. Similarly, with the empirical information of the chosen service, the performance assessment of the service quality dimensions was calculated using the multivariate main component and geometric quality capacity indicators.

As an epistemological foundation for this research, a rational conception was used to propose an evaluation method that would allow for the integration of the three statistical quality control techniques. To evaluate service quality dimensions, a comparative analysis was also performed, which implied the understanding of the complementarity between the criteria and statistical methods to evaluate the quality criteria or dimensions punctually and multidimensionally. As a principle of explanation of the study object, a combined and integral approach was used, considering different measurement criteria.

The scientific origin of this research arises from the empirical researcher's analysis when quantifying empirical information of the evaluated service's quality criteria. Therefore, the essence of science is associated with the study object, i.e., the assessment of quality criteria with univariate and multivariate statistical quality control metrics. The truth conception is related to the reality construction supported by empiricism related to the measurement of service quality criteria of this research's object. As a truth criterion, this research is based on observing, verifying, and assessing the service quality dimensions with the service's empirical information. From the above, the method's logic is inductive, supported by quantifying the numerical information of the service criteria's quality, referring to twelve analysed periods. This facilitated a rational analysis, which made integrating and comparing the three service measurement criteria possible to establish the most robust and demanding one.

To assess the quality dimensions, a hotel was selected and the quality criteria it measures were identified to compare the assessment and performance of the three metrics subject to this research when these are applied to the studied service's quality dimensions. This way, it was possible to establish the level of demand for the three quality measurement criteria. To achieve this, the quality criteria identified in the selected service company were found and are presented in Table 1.

Tab. 1. Characterisation of the selected service criteria

Quality dimension	Dimension's description	Error opportunity
Customer support	Good customer service is verified upon arrival	2
Response time	It's verified that the attention is in the planned times	2
Amiability	The customer receives cordial attention during their stay	2
Customer satisfaction	It's verified that the service provided by the hotel meets the customers' needs	2
Customer exit	The customer exit protocol complies with what was proposed	2

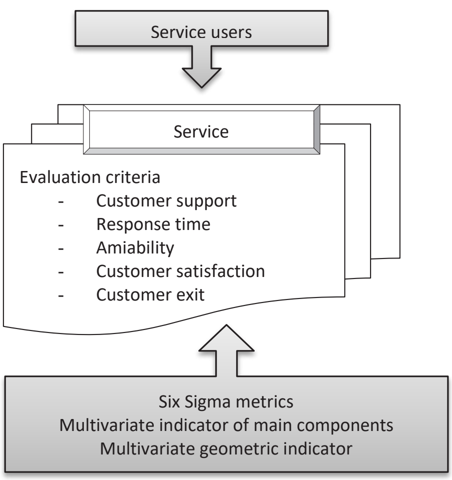

Fig. 1. Quality criteria to evaluate in the hotel service

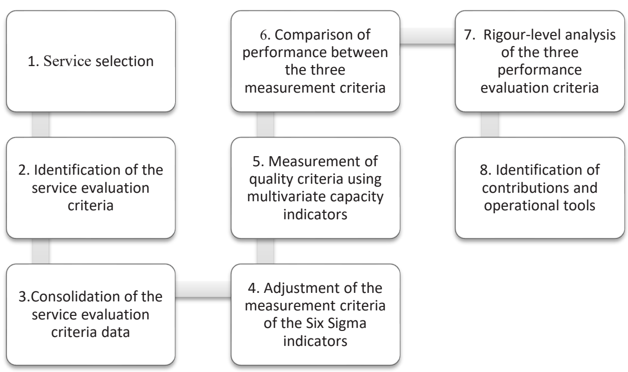

Fig. 2. Evaluation and comparison method of the service criteria performance evaluation

To develop this research, all the information was consolidated if associated with the quality dimensions established by the organisation to evaluate the service provided. Table 2 presents the information for the twelve periods of 2022. The information was used to calculate the metrics by months which allowed for the calculation of the quality capacity indicators of geometric and principal factors used.

A documentary review of the records associated with the service company's quality criteria and direct observation were carried out to collect empirical information on the quality criteria. The unstructured interview technique was used with the hotel's responsible personnel to collect information.

The consolidated empirical information of the service criteria for all the months or periods of 2019 was used to calculate the DPMO, the Sigma Z level, and the performance Y, as well as the multivariate main components and geometric capacity indicators.

Fig. 1 shows the relationship between the quality criteria and the univariate and multivariate statistical control techniques used in this research.

Fig. 2 shows the different activities of this research that support the evaluation method and comparison of the service quality criteria's performance using the Six Sigma metrics, the multivariate main components indicator and the geometric quality indicator.

3. Research results

To achieve the research objectives, the evaluation of the Six Sigma metrics of the service quality criteria was established as the first phase. In the second phase, the performance of the quality criteria was assessed using the geometric multivariate capacity indicator. In the third phase, the service quality criteria were assessed with the multivariate main component's capacity indicator, and finally, in the fourth phase, a comparative analysis of the performance evaluation of the service quality criteria was performed considering the measurement of the Six Sigma metrics and the two multivariate quality capacity indicators. This allowed for determining which of these three statistical criteria is more rigorous when evaluating quality criteria in the provision of a service.

Phase 1. Valuation of the service quality criteria using the Six Sigma metrics

Once the information related to the service quality criteria to be analysed was collected to determine which metric or capacity indicator is more rigorous, the information was consolidated on the quality criteria to be evaluated (Table 2).

Service quality results by Six Sigma

The historical information of the service company (Table 2) was then contextualised to the three measurement tools to determine the robustness and

Tab. 2. Information on service quality criteria

Quality criteria	Periods	Compliant services	Non-compliant services
Customer support	1	912	10
	2	593	13
	3	654	14
	4	638	10
	5	640	12
	6	715	9
	7	745	12
	8	662	9
	9	635	12
	10	798	9
	11	842	13
	12	976	14
Response time	1	912	12
	2	593	12
	3	654	14
	4	638	12
	5	640	11
	6	715	12
	7	745	8
	8	662	9
	9	635	8
	10	798	7
	11	842	15
	12	976	16
Amiability	1	912	10
	2	593	7
	3	654	6
	4	638	5
	5	640	9
	6	715	8
	7	745	4
	8	662	3
	9	635	4
	10	798	5
	11	842	2
	12	976	11

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Quality criteria	Periods	Compliant services	Non-compliant services
Customer satisfaction	1	912	12
	2	593	6
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	5	640	10
	6	715	6
	7	745	3
	8	662	2
	9	635	3
	10	798	4
	11	842	2
	12	976	10
Customer exit	1	912	14
	2	593	5
	3	654	4
	4	638	3
	5	640	11
	6	715	7
	7	745	4
	8	662	3
	9	635	2
	10	798	1
	11	842	3
	12	976	4

Source: information provided by the hotel service provider.

exigency and to proceed with the calculations of the performance criteria.

Initially, the Six Sigma criteria and metrics were used to evaluate the performance of the service quality criteria with the following quantitative expressions.

U: Quantity of services provided

O: Opportunity for error

n: Number of non-compliant services

Y: Performance of the service quality dimension

DPMO: Defects Per Million Opportunities

The mathematical expressions for assessing the quality criteria performance are presented below: Defects in Parts per Million Opportunity (DPMO), the Sigma level (Z), and the performance (Y) and the equations for their calculation (4), (5), and (6).

$$\mathrm{DPMO} = \frac{n}{t} * 1.000.000 = \frac{n}{u \times o} * 1.000.000 \qquad (4)$$

$$Z = \sqrt{(29.3 - 2.221 * \ln(\mathrm{DPMO}))} + 0.8406 \qquad (5)$$

$$y = 1 - \frac{n}{u * o}. \qquad (6)$$

The quantitative assessment of the quality criteria of the hotel service is presented below in Tables 3 and 4.

Tab. 3. Assessment of the Six Sigma metrics DPMO, Z and Y

Customer support			
Period	DPMO	Z	Y
1	3113.325031	4.233	99.69 %
2	1184.834123	4.535	99.88 %
3	5572.441743	4.036	99.44 %
4	6493.506494	3.983	99.35 %
5	5008.347245	4.073	99.50 %
6	3793.626707	4.167	99.62 %
7	3115.264798	4.232	99.69 %
8	7692.307692	3.922	99.23 %
9	4160.887656	4.136	99.58 %
10	2005.347594	4.374	99.80 %
11	1506.024096	4.463	99.85 %
12	2351.097179	4.323	99.76 %
Response time			
Period	DPMO	Z	Y
1	6493.506494	3.983	99.35 %
2	9917.355372	3.829	99.01 %
3	10479.04192	3.809	98.95 %
4	9230.769231	3.856	99.08 %
5	8448.540707	3.888	99.16 %
6	8253.094911	3.897	99.17 %
7	5312.084993	4.053	99.47 %
8	6706.408346	3.971	99.33 %
9	6220.839813	3.998	99.38 %
10	4347.826087	4.121	99.57 %
11	8751.458576	3.875	99.12 %
12	8064.516129	3.905	99.19 %
Amiability			
Period	DPMO	Z	Y
1	5422.993492	4.046	99.46 %
2	5833.333333	4.020	99.42 %
3	4545.454545	4.106	99.55 %
4	3888.024883	4.159	99.61 %
5	6933.744222	3.959	99.31 %
6	5532.503458	4.039	99.45 %
7	2670.226969	4.282	99.73 %
8	2255.639098	4.336	99.77 %

Tab. 3. Assessment of the Six Sigma metrics DPMO, Z and Y

Customer support			
Period	DPMO	Z	Y
8	2255.639098	4.336	99.77 %
9	3129.890454	4.231	99.69 %
10	3113.325031	4.233	99.69 %
11	1184.834123	4.535	99.88 %
12	5572.441743	4.036	99.44 %
Customer satisfaction			
Period	DPMO	Z	Y
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7	2005.347594	4.374	99.80 %
8	1506.024096	4.463	99.85 %
9	2351.097179	4.323	99.76 %
10	5070.993915	4.069	99.49 %
Customer exit			
Period	DPMO	Z	Y
1	7559.395248	3.929	99.24 %
2	4180.602007	4.135	99.58 %
3	3039.513678	4.240	99.70 %
4	2340.093604	4.325	99.77 %
5	8448.540707	3.888	99.16 %
6	4847.645429	4.084	99.52 %
7	2670.226969	4.282	99.73 %
8	2255.639098	4.336	99.77 %
9	1569.858713	4.450	99.84 %
10	625.7822278	4.722	99.94 %
11	1775.147929	4.412	99.82 %
12	2040.816327	4.368	99.80 %

Table 3 shows the performance evaluation of all the quality dimensions punctually and periodically. All the specifically evaluated service dimensions show good performance in general when measured with the Six Sigma metrics.

Table 4 also shows the "average" measurement of all quality criteria or dimensions by the evaluated period, associated with the Six Sigma metrics DPMO, Z and Y. This shows the average performance per period, i.e., the service presents a good performance when the quality dimensions are measured with the Six Sigma metrics.

Tab. 4. Average performances per period

Period	Average DPMO	Average Z	Average Y
1	6278.479044	3.997	99.37 %
2	7133.142113	3.972	99.29 %
3	6467.335753	4.026	99.35 %
4	5258.04038	4.099	99.47 %
5	8145.117463	3.903	99.19 %
6	5801.920213	4.031	99.42 %
7	4116.782061	4.181	99.59 %
8	3886.023797	4.216	99.61 %
9	4509.051297	4.171	99.55 %
10	3231.381422	4.283	99.68 %
11	4099.722787	4.257	99.59 %
12	5563.895037	4.066	99.44 %

Phase 2. Assessing the performance of service quality criteria using the geometric multidimensional capacity indicator

Considering equation (1), the overall and global performance of the service's geometric multidimensional capacity indicator was assessed, which was:

$$\mathrm{MC_p}(\mathrm{v}) = \frac{1}{3}\emptyset^{-1}\left\{\frac{[0.9922\times\ldots\times 0.9922]^{1/5}+1}{2}\right\} = 0.91163.$$

This measurement is made for each dimension for the case of customer support; the geometric multidimensional indicator for the twelve evaluated periods presents the following value,

$$\mathrm{MC_p}(\mathrm{t}) = \frac{1}{3}\emptyset^{-1}\left\{\frac{[0.9939\times\ldots\times 0.9932]^{\frac{1}{12}}+1}{2}\right\} = 0.88647$$

The values of the capacity indicators evaluated both in the criteria and in the periods generated similar values, which implies that the variability within (intrinsic) and between (extrinsic) the criteria behaviour in the accommodation service has been homogeneous.

Phase 3. Assessing the performance of the service quality criteria using the main components' capacity indicator

Fig. 3 clearly shows that the first component is focused on the criteria of customer support and response time, and the second dimensional component focuses on the treatment given to the customer,

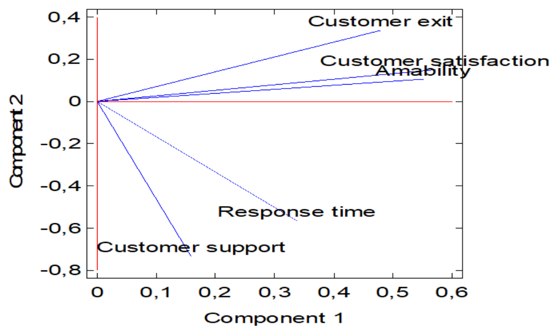

Fig. 3. Main components

Tab. 5. Eigenvalues of each of the main components

Component number	Eigenvalue	Variance percentage	Accumulated percentage
1	3.07655	51.276	51.276
2	1.55845	25.974	77.250
3	0.740425	12.340	89.590
4	0.385624	6.427	96.017
5	0.221078	3.685	99.702
6	0.0178766	0.298	100.000

Tab. 6. Main components

Quality criteria	Component 1	Component 2	Component 3
Customer support	0.157812	-0.731113	0.613679
Response time	0.337513	-0.56406	-0.753221
Amiability	0.551234	0.104538	0.158041
Customer satisfaction	0.572348	0.151477	0.167864
Customer exit	0.47931	0.336804	-0.0538652

Tab. 7. Natural specifications of each of the criteria

	Customer support	Response time	Amiability	Customer satisfaction	Customer exit
USL	10	12	10	10	10
LSL	8	7	3	2	2

Tab. 8. Comparative table of performance metrics

Quality metric	Average DPMO	Average Sigma level (Z)	Average yield (Y)	Geometric capacity indicator	PCA indicator	Confidence interval	
						Lower limit	Upper limit
Customer support	7826.44	3.92	99.22 %	0.88647			
Response time	7685.45	3.93	99.23 %	0.88850			
Amiability	4173.53	4.17	99.58 %	0.95488	0.9559	0.4891	1.4226
Customer satisfaction	3739.67	4.22	99.63 %	0.96639			
Customer exit	7756.39	3.93	99.22 %	0.88747			
Global indicator				0.91163			

in this case, amiability and satisfaction in the care of the service.

The first main component is defined as follows, standardising each of the criteria:

$$z_1 = 0.157812 \times \text{Customer support} + 0.337513 \times \\ \times \text{Response time} + 0.551234 \times \text{Amiability} + 0.572348 \times \\ \times \text{Customer satisfaction} + 0.47931 \times \text{Customer exit}$$

This component allows estimating the specifications of the main component's indicator based on the values specified as service quality criteria, as presented in Table 7.

Performing the linear combination calculations of the mean vector and the specification vector with the coefficients of the normalised vectors, the following results were received for the first component:

$$\text{PCA } L_{Y_1} = (8 \times 0.157812 + \cdots + 2 \times 0.47931) = 9.169$$

And the superior specification

$$U_{Y_1} = (10 \times 0.157812 + \ldots + 10 \times 0.47931) = 21.94079.$$

The result of the global capacity index is based on the main components; equations (2) and (3) present the following results:

$$MC_p^T = [1.2587 \times 0.4665 \times 1.4983]^{\frac{1}{3}} = 0.9559.$$

where the indicators of the first two components are

$$C_p^{Y_1} = \left[{|21.9407 - 9.169|}/{6 \times 1.691}\right] = 1.2587$$

$$C_p^{Y_2} = \left[{|-6.3499 - (-3.000)|}/{6 \times 1.1964}\right] = 0.4665.$$

y

$$C_p^{Y_3} = \left[{|1.21724 - (-4.3656)|}/{6 \times 0.62099}\right] = 1.49837.$$

The global value of 0.9559 of the multivariate dimensional capacity index shows a process that requires improvement. An estimate using a confidence interval is necessary, with a probability of 95 %; equation (4) presents the following results,

$$\widehat{MC}_{PU}^T \pm t_{\alpha/2, n-1} \frac{S}{\sqrt{n}} = 0.9559 \pm 2.59 \frac{2.1625}{12} = [0.4891; 1.4226].$$

This is an extremely wide confidence interval. Based on the data of the periods, the index could be less than one, 0.4891 (a situation where it is necessary to make improvements in the service) or an estimated value of 1.4226, which would imply a desired situation in the service.

Phase 4. Comparative analysis of the performance of the Six Sigma metrics, the multidimensional geometric quality capacity indicator and the multidimensional main components capacity indicator.

Based on the different equations proposed in this research, all metrics and indicators of multidimensional capacity were calculated, which are presented in Table 8.

Based on Table 7 and Phases 1, 2 and 3, the multivariate geometric capacity indicator is the most robust as it presents the lowest evaluation of the service. The indicators reach the highest values.

The multivariate geometric capacity indicator presents improvement actions in the dimension of service relevance with a value of 0.91168. The global geometric indicator obtained a performance value of 0.91163. Consequently, it is more robust and demanding than the multivariate main components indicator that obtained a value of 0.9559. Table 7 shows that the least demanding indicator is the Six Sigma metrics that obtained values above 0.99 when analysing the hotel service under study in this research.

It can be asserted that the service provision is good, considering that the Six Sigma metrics, the geometric quality capacity indicator, and the multivariate main components indicator show that the performance of the quality criteria is good. In addition to empirical evidence, it can be pointed out that the geometric quality capacity indicator is the most robust and demanding, evaluating the quality of service criteria with a value of 0.911. It is followed by the multivariate main component's quality capacity indicator with a value of 0.9559, and the Six Sigma metrics, such as DPMO, Sigma level and Yield levels, with the lowest level of rigour, as shown in Table 8 for each evaluated criterion. This is a novel and significant finding as it showed other indicators being much more rigorous and useful than the Six Sigma metrics. They can be applied to assess the service quality criteria multidimensionally to measure performance and have a greater margin for improvement. That is, to the extent that the performance level obtains a lower value, service improvement actions will have to be

Tab. 8. Comparative table of performance metrics

Quality metric	Average DPMO	Average Sigma level (Z)	Average yield (Y)	Geometric capacity indicator	PCA indicator	Confidence interval	
						Lower limit	Upper limit
Customer support	7826.44	3.92	99.22 %	0.88647	0.9559	0.4891	1.4226
Response time	7685.45	3.93	99.23 %	0.88850			
Amiability	4173.53	4.17	99.58 %	0.95488			
Customer satisfaction	3739.67	4.22	99.63 %	0.96639			
Customer exit	7756.39	3.93	99.22 %	0.88747			
Global indicator				0.91163			

taken to contribute to increasing the performance value. On the contrary, to the extent that the value of the indicator is greater, the margin or gap to improve will be less when improvement actions are taken.

4. Discussion of the results

Other investigations (Fontalvo et al., 2021) using the Six Sigma metrics and similar multicomponent quality capacity indicators have shown their relevance in measuring service quality criteria. Additionally, they show a complementary approach to monitoring and controlling a service punctually and individually with a multidimensional approach, and globally and holistically, using a different perspective for the measurement and decision-making to improve the service quality criteria (Sikder et al., 2019).

The contrasting method of using different measurement approaches has also been addressed by other researchers when monitoring processes with different multivariate statistical control tools, such as the multivariate capacity indicators proposed in this research and the multivariate control charts. This shows the relevance of the ability to identify which indicator or metric is more demanding to articulate them with the multidimensional control charts and, thus, establish more robust monitoring and control methods that guarantee decision-making for sustainable improvement of service quality (Fontalvo et al., 2022c). In contrast to this type of quality tools, Tamminen et al. (2019) also used tools to monitor quality from other quality perspectives and approaches.

Notwithstanding the quantitative findings of this research, it is important to point out that in production or service processes, when the monitored variables are presented as fractions or proportions, there are few proposals of capacity indicators for univariate fractions. This inconvenience is even greater in the multivariate field, i.e., the proportions come from p variables. It is complex to evaluate them as a whole and to evidence it in a single indicator as done and contributed by this research. Therefore, this study provides a new methodology that allows using multivariate indicators to obtain another measure to evaluate a new metric within the Six Sigma methodology that facilitates the analysis of the results of compliance proportions of different dimensions associated with a service evaluated holistically.

Conclusions

The proposed methodology shows the usefulness of articulating the Six Sigma metrics to evaluate the performance of the service on time and specifically. In addition, as another benefit, the multivariate capacity indicators allow for a holistic, integral, and global perspective, which is a benefit for those responsible for service improvement processes, considering that it allows the service quality dimensions to be evaluated independently. The multidimensional indicator of main factors allows the quality dimensions to be assessed integrally. The main factors that affect the provision of the service under study are established.

Likewise, the multivariate capacity indicator for the measurements of joint conforming proportions allows using a tool in the evaluation of fractions of conformities that occur in areas, dimensions and stages of a production or service process, which generally present different types of variables. This is an innovative contribution of this research.

As a contribution to this research work, a valuation method is proposed that integrates different criteria for measuring the quality dimensions of a service. In addition, it was possible to demonstrate that the multivariate geometric capacity indicator is much more demanding and robust to evaluate the service quality criteria when compared with the multivariate main component capacity indicator and the Six Sigma performance indicators Y, DPMO, and the Sigma Z level in the point estimates evaluated in this research. This finding is important for service organisations that require robust and demanding criteria to assess the quality criteria of a service and act for improvement according to its performance.

As a theoretical contribution, this research articulates, contrasts, and compares theories and measurement techniques of statistical control related to the Six Sigma metrics and the concept of the multivariate main component and geometric quality capacity indicators. The evidence indicates that the latter two are more demanding than the Six Sigma metrics. Likewise, the complementarity between the different indicators to measure and improve service is evident, considering the diverse approach of each measure.

As a practical and operational contribution to service measurement, it can be noted that while the

Six Sigma metrics allow the performance of the service quality criteria to be evaluated individually, punctually and periodically, the geometric and main component indicators of multivariate quality capacity allow for the evaluation of the service quality criteria multidimensionally, globally and holistically. Therefore, the two approaches can be used complementarily to monitor the service and its criteria. Therefore, the proposed method allows for having different, more robust control and monitoring criteria that affect the improvement of a service or process.

The estimation using the confidence interval shows the capacities of the service under extreme conditions; the service can obtain very low-quality indicators as well as optimal performance. In this case, it is evident that the analysed hotel service must be improved to reduce the variability of the service dimensions.

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