Service Quality Assessment Tool in a State University in Northern Mindanao

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ABSTRACT

Higher education institutions (HEIs) worldwide are increasingly being recognized as integral components of the service industry. However, established models for assessing service quality, such as SERVQUAL and HiEduQual, have primarily focused on foreign higher education systems. This study explored the unique context of a Philippine State University. It aims to localize existing quality assurance mechanisms by developing a tool to evaluate service quality from the viewpoint of undergraduate students. The results offer valuable insights into evolving service quality assessment practices within Philippine state universities and colleges (SUC), serving as a template for refinement and adaptation in similar contexts. 708 undergraduate students answered the initial 52-item questionnaire. After initial data analysis, only 630 cases were subjected to further analysis using Principal Component Analysis (PCA) and Confirmatory Factor Analysis (CFA). This resulted in a seven-factor model comprising 31 indicators, exhibiting favorable model fit indices (RMSEA = 0.039, CMIN/DF = 2.073, PCFA = 0.785, PNFI = 0.751, CFI = 0.951). These factors encompassed the following dimensions: ease of doing business, leadership quality, teacher quality, knowledge services, activities, e-governance, and continuous improvement. The findings demonstrated strong internal consistency and reliability across all scale factors. Convergent and discriminant validity were also confirmed. It is recommended that SUCs consider adopting the localized tool in their internal quality assessment procedures to complement existing service quality assessment mechanisms. As the tool is specifically tailored to students' perspectives as primary end users of SUC services, further research can focus on integrating the results of the study to develop a multi-stakeholder internal quality assessment tool or framework to meet evolving needs and expectations.

Keywords*: higher education; service quality; tool development; quality assurance; state universities and colleges*

Introduction

Academics and practitioners have devoted significant attention to the theory and implementation of service quality in recent decades. The impact of service quality on market share and customer satisfaction has been established by several studies (Anderson and Zeithaml, 1984; Buzzell and Gale, 1987; Parasuraman et al., 1985; Zeithaml, 2000). It is seen as a factor that allows customers to distinguish between different industries in a competitive market. Organizations are motivated to pursue quality services to ensure their survival and maintain a competitive edge. In the case of public sector organizations, they are obligated to provide great service and customer satisfaction not so much because of competitive advantage or profitability but because they are using the money of the people. Taxpayers' money and resources fund government service, and thus, government entities have to be accountable for impeccable service.

One important area of social service is education. Across the world, the public sector is crucial in delivering education services (Abrigo, 2021). Both governments and individuals invest a lot of money in education, as it is known to have many positive benefits, such as increasing income (Stryzhak, 2020; Abrigo, 2021), reducing the crime rate, and breaking the cycle of intergenerational poverty (Pohan, 2013). Currently, higher education institutions (HEIs) are increasingly being recognized as a component of the service industry (Galeeva, 2016). The evolving landscape of higher education, rising demand, and the rise and expansion of HEIs encourage institutions to step outside of their comfort zones and seriously consider how they can improve service quality aspects that various stakeholders deem valuable.

Several studies have examined service quality in higher education institutions (Latif et al., 2017; Pamatmat, 2018; Kinanti et al., 2020). Most of these studies were based on the SERVQUAL model by Parasuman et al. (1985), which states that customers should assess the quality of service on five different criteria: dependability, responsiveness, assurance, empathy, and tangibles. Although widely used, the SERVQUAL instrument has been subject to criticism and identified areas in need of enhancement. Galeeva (2016) has identified concerns regarding the dimensionality, validation, and applicability of SERVQUAL, despite its purported focus on customer-relevant aspects of service quality. Ladhari (2009) contends that the SERVQUAL scale lacks comprehensiveness and suggests the inclusion of additional characteristics to enhance the model's ability to measure service quality with greater accuracy. Clewes (2003) observed that modifications are necessary for the questionnaire used in research employing SERVQUAL, as there is a lack of consensus regarding the aspects of service quality and their relative significance in the context of Higher Education Institutions (HEIs). In 2017, Latif et al. created Higher Education Service Quality (HiEduQual) as a solution to address the deficiencies in SERVQUAL as a tool for evaluating the quality of services provided by Higher Education Institutions (HEIs). The study identified six characteristics that contribute to service quality in Higher Education Institutions (HEIs): teacher quality, administrative services, knowledge services, activities, continuous improvement, and leadership quality.

The majority of research utilizing SERVQUAL and HiEduQual has focused on evaluating the quality of service in international higher education systems, with less attention given to the Philippines. Philippine universities have a crucial role in education and are responsible for fostering the holistic growth of persons who possess professional competence, a service-oriented mindset, moral values, and productivity. The 1987 Philippine Constitution specifies that education receives the greatest budget allocation each year, highlighting its significant importance in the country. In the 2022 National Expenditure Program (NEP), the education sector, which encompasses the Department of Education (DepEd), State Universities and Colleges (SUCs), and the Commission on Higher Education (CHED), was allocated the largest amount of P773.6 billion. This represents a P21.9 billion or 2.9 percent increase compared to its share in the FY 2021 budget (Department of Budget and Management, 2021).

Philippine HEIs can be either colleges or universities and are typically categorized as either public or private. Private HEIs can either be "sectarian" or "non-sectarian" organizations. On the other hand, public HEIs are all non-sectarian organizations and fall under the State University and College (SUC) or Local College and University (LCU). Local government units are in charge of LUCs, while the Philippine Congress passes an Act creating SUCs. SUCs are fully subsidized by the national government and are also considered corporate bodies. State universities and colleges (SUCs) prioritize their primary roles as educational institutions at the tertiary level. The functions encompassed are instruction, research, community service, and production. Service quality among SUCs is therefore of particular interest because, as government agencies, they are expected to provide accessible and quality frontline services to meet the needs of clients.

According to RA 7722, also known as the Higher Education Act of 1994, one of the responsibilities of the Commission on Higher Education (CHED) is to monitor and evaluate the performance of service delivery by both public and private higher education institutions. Section 8 of this law states that CHED has the power and function to “monitor and evaluate the performance of programs and institutions of higher learning for appropriate incentives as well as the imposition of sanctions such as, but not limited to, diminution or withdrawal of subsidy, recommendation on the downgrading or withdrawal of accreditation, program termination, or school closure”.

The extent of service quality assessment mechanisms established by the Commission on Higher Education and other accrediting bodies is significant in the continual improvement of SUC. However, these measurements of service quality focus mostly on the management's opinions and attempts to provide quality education to their clients through the purview of third-party assessors. There is less emphasis on the perspectives of students as primary end-users of SUC services.

To complement the existing quality assurance mechanisms in SUCs, this study aims to develop a service quality assessment tool to measure service quality in SUCs from the perspective of students. It makes use of previous service quality assessment instruments as building blocks for a reformulated and locally constructed instrument. The assessment tool localizes HiEduQual factors in the Philippine setting, taking into account how things are now and what services are expected from SUCs. Furthermore, the study explored two other dimensions, ease of doing business and e-governance, in addition to the dimensions of the HiEduQual. These dimensions are anchored on the thrust of the Philippine government to improve services across government institutions by making processes simple, accessible, efficient, and transparent.

The resulting tool provides an array of factors and indicators that SUCs may use as an internal service quality assessment mechanism to monitor their operations and services. The localized tool complements existing service quality assessment mechanisms. It has the potential to offer a more comprehensive understanding of service quality and at the same time facilitate a more student-centric approach to evaluation.

Methodology

Tool Development Procedure

The development of the localized SUC service quality assessment tool included six phases, namely: 1) Tool Conceptualization and Item Construction; 2) Validity Testing; 3) Pilot and Reliability Testing; 4) Test Administration; 5)

Statistical Analysis; and 6) Finalization of the Tool. Figure 1 below illustrates the tool development process and is further discussed in the succeeding paragraphs.

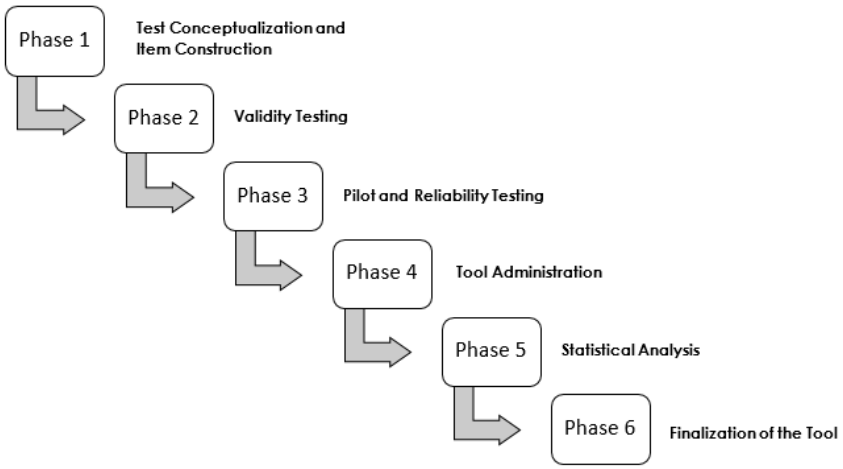

Figure 1: Tool development process

Phase 1: Tool Conceptualization and Item Construction

The dimensions and indicators of the SUC service quality assessment tool was developed based on a review of the literature, and the Higher Education Service Quality (HiEduQual) tool developed and published by Latif et al. (2017). Six dimensions were adopted from Latif's HiEduQual, namely: administrative services (AS); activities (AC); continuous improvement (CI); knowledge services (KS); leadership quality (LQ); and teacher quality (TQ). A total of thirty-seven (37) items were adapted from HiEduQual and modified to fit the context of an SUC and the purpose of the study. Permission to use and modify HiEduQual's content was obtained from the authors. Additionally, items related to ease of doing business were obtained from the implementing rules and regulations of Republic Act 11032 or the Ease of Doing Business and Efficient Government Service Delivery Act of 2018. In addition, five e-governance items were obtained from a literature review of e-governance in the Philippines.

Phase 2: Validity Testing

To establish validity, the Content Validity Index (CVI) approach was utilized. This is widely recognized as a robust method for assessing content validity in instrument development (Zamanzadeh et al., 2015). The CVI was computed using both the Item-level CVI (I-CVI) and the Scale-level CVI (S-CVI). To accomplish this, a panel of five subject matter experts (SMEs) was invited to participate in the study. The panel was composed of individuals with expertise in various relevant fields. It included a college dean, a senior researcher, a senior public administration faculty member, quality assurance officers, and a university administrator. The SMEs rated the initial 80-item questionnaire across eight dimensions to assess the relevance and representativeness of each item. The SMEs rated the IPS in terms of clarity and relevance to the constructs under study. A relevance rating on a 4-point scale was used. Based on the resulting CVI, 52 out of the 80 initial items were considered appropriate by the SMEs. Meanwhile, 28 items were eliminated. The scale-level CVI (S-CVI) of 0.855 indicates that the overall scale is acceptable. Among the dimensions, administrative services (AS) and e-governance (EG) had the highest number of eliminated items. Each of these dimensions had six items that were eliminated. On the other hand, Ease of Doing Business (EODB) had the highest number of retained items, with 9 items considered appropriate. Overall, only 52 items were retained in the first draft of the research instrument.

Phase 3: Reliability Pilot and Reliability Testing

After content validity, the 52-item SUC service quality assessment tool underwent pilot and reliability testing. The pilot test involved administering the instrument to 30 students who were not part of the study's sample. To evaluate the instrument's reliability, Cronbach's alpha was calculated. Cronbach's alpha values range from zero to one, with values over 0.70 indicating high internal consistency reliability (Todman & Dugard, 2007; Batican, 2011). Table 1 presents the results of the reliability test. It indicates that the instrument has high internal consistency reliability, with a Cronbach's alpha of 0.970.

Table 1: Reliability analysis

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.970	0.972	52

Phase 4: Tool Administration

After the validity and reliability of the instrument were established, the 52-item SUC service quality assessment tool was administered to the sampled population. This study emphasizes the importance of the student's perspective in developing a service quality assessment tool in SUC, given that students are considered the primary consumers of HEIs. Tool development studies by Latif et al. (2017) and Darawonga & Sandmaung (2019) assert that students are the main customers and direct recipients of services provided by HEIs and, therefore, are in the best position to evaluate the most critical aspects of service quality. As such, their perceptions and evaluations play a vital role in determining whether the services provided by the institutions align with the expectations of various stakeholders. The present study focused on the undergraduate student population enrolled in a state university in northern Mindanao for the second semester of SY 2022-2023. At the outset of test administration, the researcher initiated the process of securing permission from the university president to undertake the study. Once permission was granted, random sampling was utilized to identify the sample. Except for the College of Administration and the College of Nursing, both of which offered a single undergraduate program, all academic programs within the college were listed, and one program was randomly selected. For the College of Arts and Sciences, the selected program had three blocks. Hence, all three blocks of the identified program were considered in the sample frame. It was ensured that all year levels of the program were included and well represented. Table 2 shows the distribution of the 708 respondents who gave their consent to join the study. It can be surmised from the table that 28% of the respondents are in their fourth year; 25.71% are first-year students; 25.28% are second-year students; and 20.76% third-year students. There are no respondents from the fourth year of the College of Nursing and College of Education because, at the time of the administration of the instrument, the students were already deployed for their internship.

Table 2: Distribution of respondents

YEAR LEVEL	COLLEGES								TOTAL	% Distribution
	CON	COT	COB	COE	CPAG	CAS				
						Block 1	Block 2	Block 3		
1st	27	18	34	12	35	23	22	11	**182**	**25.71%**
2nd	20	21	34	14	32	19	22	17	**179**	**25.28%**
3rd	17	25	36	18	23	12	7	9	**147**	**20.76%**
4th	-	28	65	-	28	27	24	28	**200**	**28.25%**
Total									**708**	**100%**

Note: CON - College of Nursing; COT - College of Technology; COB- College of Business; COE - College of Education; CPAG - College of Public Administration and Governance; CAS - College of Arts and Sciences

Phase 5: Statistical Analysis

After test administration, the resulting dataset was exported to IBM SPSS and AMOS. An Initial Data Analysis (IDA) was then conducted independently of the multivariate analysis needed to address the research questions. Huebner et al. (2016) argued that an IDA is an essential step to be carried out after the research plan and data collection have been finished but before formal statistical analyses. The purpose of IDA was to minimize the risk of incorrect or misleading results.

The first part of the IDA was the examination of missing data; this was done to avoid compromising the validity and reliability of the research findings (Schafer & Graham, 2002). To address the potential consequences of missing data, the study employed the Complete Case Approach, also known as the Listwise Deletion Approach. Prior studies have noted that this method is the most uncomplicated and straightforward approach for handling missing data, as it excludes cases with missing values from the data analysis process (Lang & Little, 2018; Black et al., 2019; Buuren, 2018). The use of this method ensures that only cases with complete data are considered in the subsequent statistical analysis, thereby minimizing the likelihood of biased results. In addition, the dataset was examined for extreme outliers, which were eliminated.

Multivariate normality (MVN) was also examined across the 52 indicators. Considering that the default parameter estimation method of the subsequent Confirmatory Factor Analysis was the maximum likelihood (ML) approach, which required the assumption of MVN to be held. This was a crucial step (Kline, 2016). When this assumption is violated,

parameter estimates become inaccurate (Kline, 2016). In this study, the skewness and kurtosis of each indicator were examined to evaluate MVN. Kline (2016) suggested that indicators with a skew index absolute value greater than 3.0 are considered "severely" skewed, whereas indicators with a kurtosis index absolute value between 8.00 and 20.00 are considered "severely" kurtic.

Moreover, principal component analysis (PCA) was performed before CFA. Alnaami et al., (2020) suggested that this step is vital before the conduct of CFA to verify the number of underlying factors, which loadings should be considered for the interpretation of the factors, and the pattern of observed variable-factor relationships. After finishing the first data analysis, a Confirmatory Factor Analysis (CFA) was performed to examine the factor structure of service quality in the SUC. CFA is a type of analysis that falls under the category of techniques called structural equation modeling (SEM). Hair et al. (2019) stated that Confirmatory Factor Analysis (CFA) should be employed when the researcher proposes links between the observed measures and the underlying factors and then tests this structure using statistical methods. The current study utilized the Confirmatory Factor Analysis (CFA) approach to assess if the proposed eight-factor structure of service quality in the SUC aligns with the data collected from the sample.

Several model-fit indices were analyzed to assess the overall fit of the measurement model. Fit indices such as Chi-square, Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Residual (SRMR), Parsimonious Comparative Fit Index (PCFI), Parsimonious Normed Fit Index (PNFI), and Comparative Fit Index (CFI) are included in this list. The fit indices indicate that the measurement model had a satisfactory fit to the data, as the values fell within the prescribed thresholds for each indicator.

To ensure the accuracy and dependability of the measurement model, the internal consistency reliability of the factors was evaluated using Cronbach's Alpha and Composite Reliability (CR). According to Hair et al. (2019), both Cronbach's alpha and CR are appropriate for assessing the internal consistency reliability of the measurement model. Both CR and Cronbach's alpha were evaluated in the present investigation. According to Hair et al. (2019), the least recommended level of dependability by CR is 0.70, except for exploratory investigations where the minimum is 0.60. Cronbach's alpha is a statistical measure that ranges from 0 to 1. To ensure reliability, the value of Cronbach's alpha should be larger than 0.70. However, a value of 0.60 can be acceptable for exploratory research purposes. The composite reliability (CR) of each factor is determined by calculating the sum of the squared factor loadings (Li) for each construct and the sum of the error variance terms for that construct. Its computational formula is:

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{n} L_i\right)^2}{\left(\sum_{i=1}^{n} L_i\right)^2 + \left(\sum_{i=1}^{n} e_i\right)}$$

Furthermore, the assessment of convergent and discriminant validity was conducted. Convergent validity assesses if the indicators of a particular construct should converge or exhibit a substantial amount of shared variance. Discriminant validity, in contrast, assesses the degree to which a concept or variable is genuinely separate from other constructs or variables (Hair et al., 2019). This study assesses the convergent validity by employing the Average Variance Extracted (AVE), which is determined by calculating the average amount of variance extracted from the items that measure a particular construct. The value can be computed by employing standardized loadings according to the following formula.

$$\mathrm{AVE} = \frac{\sum_{i=1}^{n} L_i^2}{n}$$

The completely normalized factor loading for the measured variable is represented by the squared sum of factor loadings (Li), where n is the number of item indicators for a construct. AVE is calculated by summing the squared standardized factor loadings (squared multiple correlations) and then dividing by the number of items. Finally, to determine whether there is a significant difference in the service quality score when grouped according to the year level of students in the SUC, a one-way analysis of variance (ANOVA) was utilized.

Phase 6: Finalization of the Tool

Upon conceptualizing the experimental version of the service quality assessment tool, subsequently constructing, piloting, and subjecting it to item analysis followed. This phase entailed the judicious assimilation of all gathered data, culminating in the refinement of the test into its final form.

Ethical Considerations

At the start of this research, permission was sought from all entities and offices concerned. This included getting the approval of the Xavier University Ethics Review Committee. Informed consent was obtained from the respondents, and they were assured that their participation in this study was voluntary, confidential, and had no repercussions on their

academic standing. The nature of the study and their participation were explained to the respondents. The use of the data, such as in research presentations and publications, was also indicated in the participation information sheet and informed consent.

Results and Discussions

Initial Data Analysis (IDA)

This study recognized the significance of IDA in ensuring the reliability and validity of the data collected. The IDA includes evaluating the following: (a) missing data; (b) normality of the data distribution; and (3) potential outliers that may impede the accuracy and interpretability of the research findings.

Treatment of Missing Data

Table 3 presents the count of initial cases, along with the numbers and percentages of complete and missing cases. The results indicate that the initial sample population of the research study comprised 708 respondents. Out of these, 698 respondents (98.59%) had complete data, while a small fraction of cases (10 cases) presented missing data, constituting 1.41% of the total sample size. After careful consideration of the number and proportion of missing data, this study adopted the Complete Case Approach (CCA), also known as the Listwise Deletion Technique. Following the application of the CCA, 10 cases were removed from the initial sample of 708 participants due to missing data, resulting in a sample size of 698 cases for subsequent data analysis.

Table 3: Number of cases with missing values

Initial cases	Number of cases with a valid response	%	Number of cases with missing values	%
708	698	98.59%	10	1.41%

Outliers

Before conducting confirmatory factor analysis (CFA), it is essential to address possible outliers in the dataset, as multivariate outliers can distort the covariance matrix and lead to biased estimates of factor loadings, variances, and covariances among factors (Verardi & Dehon, 2010; Peña & Prieto, 2001; Yuan & Bentler, 2001; Leys et al., 2018). The Mahalanobis distance method was utilized in this study to identify multivariate outliers in the data. This method measures the distance between a data point and the centroid of a distribution, considering the covariance between variables (De Maesschalck et al., 2000; Xiang et al., 2008; Ghorbani, 2019; Calenge et al., 2008).

In this study, the Mahalanobis distance was calculated after removing cases with missing data from the dataset, resulting in 68 cases identified as outliers and removed from the analysis based on the criterion of a distance that exceeded the critical value of $p<0.001$. Removal of multivariate outliers from the dataset is recommended to avoid violating the assumption of multivariate normality and to obtain accurate and reliable results from CFA (Leys et al., 2019; Tabachnick & Fidell, 2013). After removing the outliers, the final sample size for subsequent data analysis was 630 cases, down from the initial sample of 708.

Normality of the data distribution

Ensuring the assumption of multivariate normality (MVN) across the indicators was essential before conducting CFA and multivariate analysis of variance (MANOVA). Given that the default parameter estimation method for CFA is the maximum likelihood (ML) approach which requires the MVN assumption to be met, deviations from this assumption can result in inaccurate parameter estimates (Mindrila, 2010; Bera & Rao, 2011; and Kline, 2016). To address this, the present study examined the skewness and kurtosis of the 52 indicators of the research instrument. Table 4 presents the minimum and maximum scores, skewness, and kurtosis values per indicator. All indicators fell within the expected range of 1–5 for minimum and maximum scores. The skewness values ranged from -1.27 to -0.23, with the indicator KS1 having the lowest skewness value and the indicator EODB1 attaining the highest skewness value. The kurtosis values ranged from -0.64 to 1.66, with KS1 having the highest kurtosis value. Kline (2016) suggested that indicators with an absolute skewness value greater than 3.0 are considered "severely" skewed, while indicators with an absolute kurtosis value ranging from 8.00 to 20.00 are considered to have "severe" kurtosis. As all indicators in this study fall within acceptable ranges for these indices, the findings suggest that the data are normally distributed and can be used confidently for further analysis and modeling.

Suitability and Adequacy of Data for Factor Analysis

Before undertaking Confirmatory Factor Analysis (CFA), it was advised to evaluate the appropriateness and sufficiency of the data for factor analysis. This entails doing initial assessments, such as the Kaiser-Meyer-Olkin (KMO) measure to determine if the sample is sufficient, and Bartlett's test of sphericity. The KMO index has a range of values between 0 and 1.

Previous research has indicated that a Kaiser-Meyer-Olkin (KMO) value above 0.50 is deemed appropriate for conducting factor analysis, but a KMO value above 0.70 is considered highly acceptable for factor analysis (Netemeyer et al., 2003). For component analysis to be appropriate, Bartlett's Test of Sphericity must have a significant result ($p<.05$) (Tabachnick & Fidell, 2007). The KMO measure of sampling adequacy got a result of 0.962, suggesting a strong level of sampling adequacy. These findings indicate that there is a significant amount of common variation among the factors, which makes them very appropriate for factor analysis (Kaiser, 1974; Netemeyer et al., 2003). Furthermore, Bartlett's test of sphericity yielded a chi-square value of 1275 with a degree of freedom of 15647.726, indicating a high level of significance at $p < 0.001$. This suggests a strong correlation among the factors in the dataset, thereby providing support for the utilization of factor analysis techniques (Tabachnick & Fidell, 2007; Hair et al., 2018).

Table 4: Skewness and Kurtosis Statistics

Factor	Indicator	Min	Max	Skew	Kurtosis	Factor	Indicator	Min	Max	Skew	Kurtosis
Administrative Services	AS 1	2	5	-1.05	0.51	E-Governance	EG 1	2	5	-0.57	-0.31
	AS 2	2	5	-0.86	0.20		EG 2	2	5	-0.75	-0.25
	AS 3	2	5	-0.76	-0.15		EG 3	2	5	-0.45	-0.64
	AS 4	2	5	-0.76	-0.05		EG 4	1	5	-0.42	0.37
Activities	A 1	1	5	-0.63	-0.31	Knowledge Services	KS 1	1	5	-1.27	1.66
	A 2	1	5	-0.72	0.11		KS 2	2	5	-0.66	-0.39
	A 3	1	5	-0.35	-0.20		KS 3	2	5	-0.87	0.27
	A 4	2	5	-0.81	-0.14		KS 4	2	5	-0.57	-0.22
	A 5	2	5	-0.66	-0.12		KS 5	2	5	-1.07	0.61
	A 6	2	5	-0.40	-0.43		KS 6	2	5	-1.14	0.73
	A 7	2	5	-0.50	-0.50		KS 7	2	5	-0.48	-0.43
Continuous Improvement	CI 1	2	5	-0.68	-0.34		KS 8	1	5	-1.20	1.04
	CI 2	2	5	-0.61	-0.45		LQ 1	2	5	-0.86	0.15
	CI 3	2	5	-0.83	-0.08		LQ 2	2	5	-0.65	-0.01
	CI 4	2	5	-0.61	-0.19		LQ 3	2	5	-0.46	-0.53
	CI 5	2	5	-0.68	-0.15	Leadership Quality	LQ 4	1	5	-0.63	0.37
Ease of Doing Business	EDB 1	2	5	-0.23	-0.38		LQ 5	2	5	-0.51	-0.09
	EDB 2	2	5	-0.34	-0.28		LQ 6	2	5	-0.45	-0.34
	EDB 3	2	5	-0.56	-0.41		LQ 7	2	5	-0.52	-0.39
	EDB 4	2	5	-0.38	-0.23		LQ 8	2	5	-0.61	-0.20
	EDB 5	2	5	-0.27	-0.34		TQ 1	2	5	-0.58	-0.53
	EDB 6	2	5	-0.54	-0.21		TQ 2	2	5	-0.71	-0.16
	EDB 7	2	5	-0.67	-0.36	Teacher Quality	TQ 3	2	5	-1.24	1.02
	EDB 8	1	5	-0.50	0.18		TQ 4	2	5	-1.10	0.69
	EDB 9	2	5	-0.70	-0.15		TQ 5	2	5	-0.59	-0.37
							TQ 6	2	5	-1.10	0.48
							TQ 7	2	5	-1.05	0.40

Table 5: Principal Component Analysis of the 8 Dimensions

Indicator	Component								Indicator	Component							
	1	2	3	4	5	6	7	8		1	2	3	4	5	6	7	8
EDB 4	0.667								KS 3				0.588				
EDB 5	0.661								KS 5				0.572				
EDB 8	0.592								KS 2				0.537				
EDB 6	0.568								KS 4				0.531				
EDB 2	0.561								KS 7				0.211				
EDB 3	0.521								LQ 1				0.529				
EDB 1	0.505								KS 6				0.505				0.449
EDB 7	0.444								A 3				0.407		0.4		
EDB 9	0.414								KS 8								
A6	0.402								KS 1								
LQ 5		0.686							A 2					0.696			
LQ 4		0.685							A 3					0.609			
LQ 6		0.632							A 1					0.575			
LQ 7		0.606							A 7					0.575			
LQ 3		0.546							A 5					0.463			
LQ 8		0.544							A 4								
LQ 2									EG 1						0.675		
TQ 1									EG 2						0.646		
TQ 7			0.699						EG 3						0.634		
TQ 4			0.659						AS 1						0.552		
TQ 6			0.657						EG 4						0.473		
TQ 5			0.646						AS 2						0.437		
TQ 3			0.58						AS 4						0.432		
TQ 2			0.434						CI 3							0.696	
									CI 2							0.690	
									CI 5							0.629	
									CI 4							0.540	
									CI 1							0.521	

Note: Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization

Principal Component Analysis

Principal Component Analysis (PCA) by Varimax Rotation was performed to test item loadings and determine if it was best to keep the indicators within the factors. Table 5 presents the result of the PCA performed on the items across eight factors. The results revealed that a seven-factor structure would better accommodate the item loadings. This is because, in the eighth factor, only one indicator was loaded (KS6) as opposed to a minimum of three indicators (Field, 2013; Hair et al., 2019). It is also noteworthy that KS6 displayed cross-loadings with the fourth factor, reinforcing the rationale for its exclusion from subsequent analysis.

The eliminated factor was Administrative Services (AS). Initially, this factor included indicators about the responsibility on the part of the administration of the state university. In the PCA, the initial indicators of administrative services were loaded under e-governance. It can be surmised that these indicators are related to digital governance.

The Total Variance Explained (TVE) in PCA is presented in Table 6 which provides valuable insights into the degree to which the retained principal components account for the overall variability in the dataset. In the current study, the Total Variance Explained (TVE) was calculated to be 53.041%. This suggests that the factors with Eigenvalues exceeding 1 collectively account for 53.041% of the total variance present in the data. Notably, the obtained TVE of 53.041% surpasses the advised threshold set forth by Streiner (1994), Hair et al. (1995), and Pett et al. (2003), who proposed a general guideline of achieving a minimum variance of 50%. This implies that the selected principal components successfully capture a substantial portion of the variability present in the dataset.

Table 6: Eigenvalues and Total Variance Explained

	Component								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Total**
Eigenvalues	16.907	2.433	1.677	1.403	1.265	1.169	1.129	1.068	
Total Variance Explained	33.151%	4.77%	3.29%	2.75%	2.48%	2.29%	2.21%	2.09%	53.0%

Confirmatory Factor Analysis

After the PCA, the CFA process was conducted using AMOS software to assess data fitness. This involved examining factor loadings and fit indices, which subsequently served as a guide for refining the factors and indicators.

Initial Model: Seven Factor-36 Indicator SUC Service Quality Model

The result of the PCA reveals that of the initial 52 indicators, only 36 indicators remained eligible for further analysis through CFA. Figure 2 illustrates the path diagram of the 36 indicators that aimed to measure the service quality of the SUC. The diagram showcases the relationships between various factors and their corresponding indicators. Specifically, Factor 1, consists of seven indicators; Factor 2, comprises six indicators; Factor 3, encompasses five indicators; and Factor 4 is five indicators. Factor 5 is represented by four indicators; Factor 6, four indicators; while Factor 7 includes five indicators.

As exhibited in Figure 2, the standardized factor loadings range between 0.542 and 0.744. Factor loadings refer to the correlation coefficient for the variable and factor; thus, they show the variance explained by the variable for that factor. According to Field (2005) and MacCallum et al. (1999, 2001), all items in a factor model should have loadings of at least 0.60. This study used the stricter cutoff that they suggested. Adhering to this guideline, indicators were excluded from further analysis out of the thirty-six indicators. These indicators are EODB8 (0.590), EODB3 (0.583), A1 (0.596), AS1 (0.542), and CI1 (0.583). Consequently, the remaining 31 indicators underwent a second round of CFA to ascertain whether the factor loadings had attained the minimum loading threshold.

The refined model, hereafter referred to as Model 2, comprises seven distinct factors, each represented by a combination of thirty-one remaining indicators that make up the measurement of the service quality of the SUC. Factor 1 encompasses five indicators; Factor 2 comprises six indicators; Factors 3 and 4 are composed of five indicators each; while Factors 5 and 6 consist of three indicators each. Lastly, Factor 7 encompasses four indicators, completing the comprehensive structure of Model 2.

Figure 3 illustrates the path diagram of Model 2. For Factor 1, the standardized factor loadings range from 0.649 to 0.741. Similarly, Factor 2 exhibits factor loadings ranging from 0.663 to 0.740, while Factor 3 demonstrates factor loadings ranging from 0.642 to 0.717. Furthermore, Factor 5 displays factor loadings spanning from 0.662 to 0.765. Finally, Factors 6 and 7 have factor loadings ranging from 0.600 to 0.725 and 0.657 to 0.728, respectively.

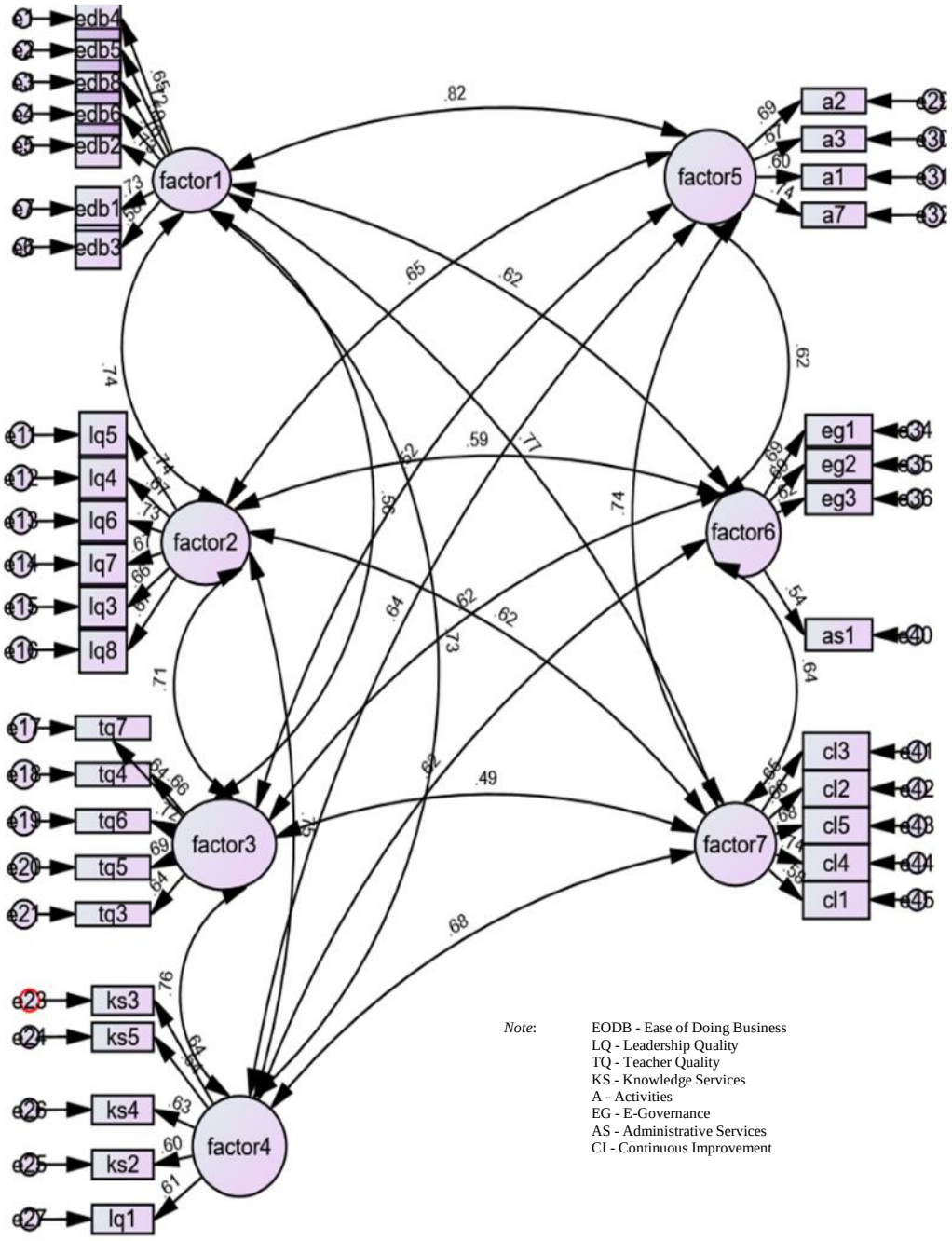

Figure 2: Initial Model Path Diagram

Final Model: Seven Factor-31 Indicator SUC Service Quality Model

According to Field (2005) and MacCallum et al. (1999, 2001), the results of Model 2 show that all indicators successfully meet the suggested threshold of 0.60. These findings show that the chosen indicators are reliable and that they can accurately measure the underlying constructs. The indicators' credibility and robustness are strengthened even more by consistently meeting the minimum threshold. This improves the overall quality and trustworthiness of the study's measurement model (Hair et al., 2019; Hooper et al., 2008; Hu & Bentler, 1999).

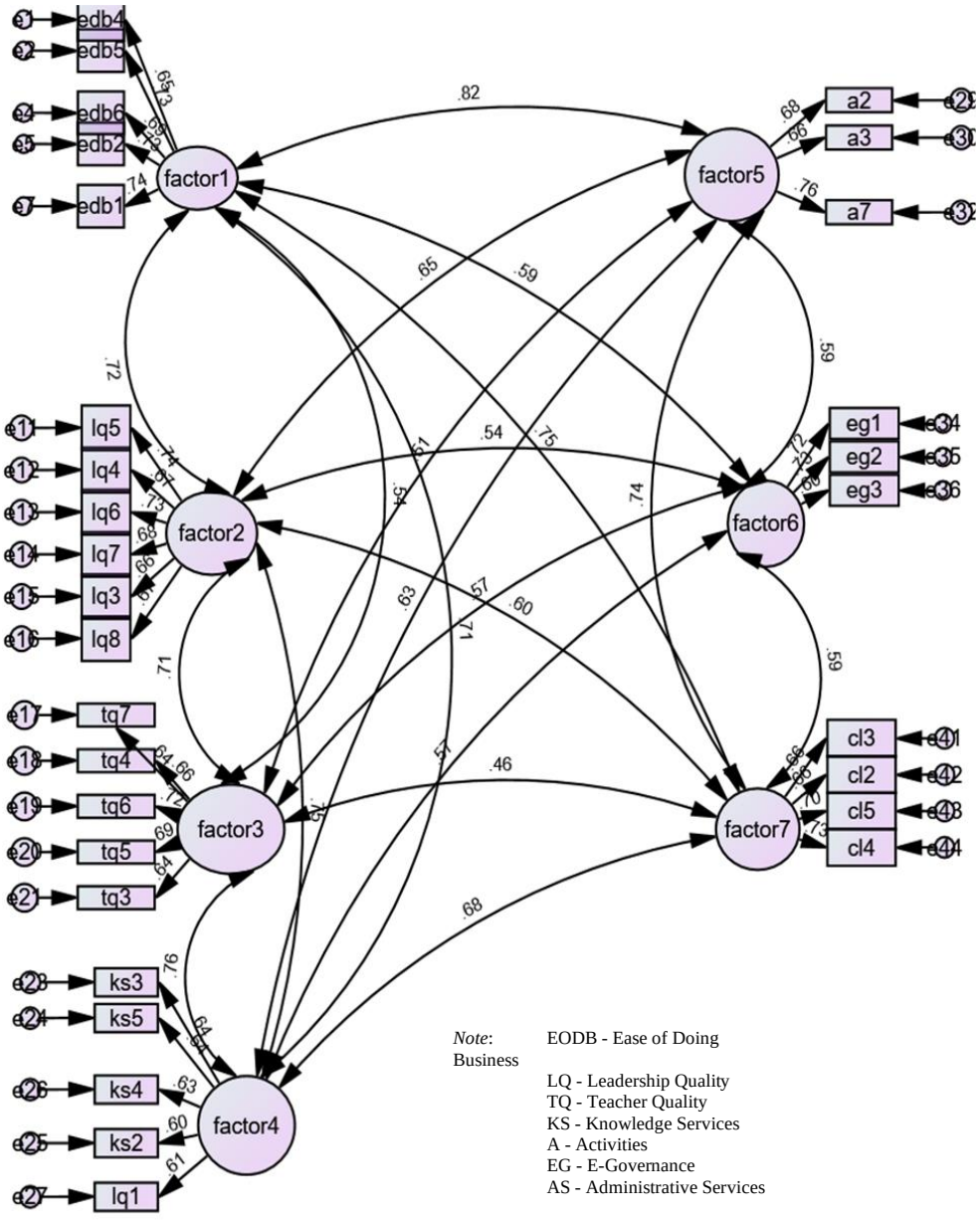

Figure 3: Final Model Path Diagram

Evaluating Model Fit of the Measurement Tool

In this study, different model fit indices were used as guides to assess the adequacy of the measurement model. Table 7 presents a summary of the degree to which Model 2 fits the data. The Root Mean Square Error Approximation (RMSEA) was used as an indicator in the absolute fit category. The model has an RMSEA score of 0.039, signifying an optimal fit. As to the findings of Hair et al. (2019), it is advised that the RMSEA value should be less than 0.08. However, Hu and Bentler (1999) proposed that RMSEA values should be below 0.06. By meeting the recommended threshold for RMSEA, the measurement model in this study demonstrates a strong fit for the observed data. These results align with established guidelines and affirm the model's suitability for accurately representing the underlying constructs of interest.

In evaluating the parsimonious fit category, several indices were utilized to assess the fit of the measurement model. The Minimum Discrepancy Function divided by Degrees of Freedom (CMIN/DF), Parsimonious Comparative Fit

Index (PCFI), and Parsimonious Normed Fit Index (PNFI) were employed for this purpose. The CMIN/DF yielded a value of 2.073, indicating a good fit. Kline (2016) has suggested that a CMIN/DF value of ≤ 3 is acceptable. The PCFI yielded a value of 0.785, while the PNFI yielded a value of 0.751, both of which are considered indicative of a good fit. Although Hooper et al. (2008) did not provide specific cut-off values, they stated that a value greater than 0.5 is generally considered satisfactory.

Table 7: Model Fit Indices

Category	Model Fit Criteria	Recommended Value	Obtained Value	Interpretation
Absolute Fit	RMSEA	≤ 0.06	0.039	Best fit
Parsimonious Fit	CMIN/DF	≤ 3-5	2.073	Good fit
	PCFI	> 0.5	0.785	Good fit
	PNFI	> 0.5	0.751	Good fit
Incremental Fit	CFI	≥ 0.90	0.951	Best fit

Turning to the Incremental Fit category, the Comparative Fit Index (CFI) was employed. The study found a CFI value of 0.951, which is in line with what Hair et al. (2019) and Bentler (1990) said should be seen as signs of a good fit: values higher than 0.92 and 0.90, respectively.

Taken together, the results of the Absolute Fit, Parsimonious Fit, and Incremental Fit categories indicate that the measurement model exhibits a favorable fit with the observed data. These findings provide support for the appropriateness and adequacy of the model in accurately capturing the underlying constructs of interest. The summary of the factors that were confirmed to measure service quality in the SUC is presented in Table 8.

Table 8: Summary of factors and indicators confirmed to measure service quality in the SUC

Factor	Name of Factor	Indicator	
Factor 1	**Ease of Doing Business**	EODB 1	The university adopts simplified procedures to expedite transactions.
		EODB 2	The university complies with the prescribed processing time of frontline services as indicated in their published service charters.
		EODB 4	The university has an updated Citizen's Charter which indicates the person(s) responsible for each step and the amount of fees in each service or transaction.
		EODB 5	The university's Citizen's Charter is accessible and visible to stakeholders.
		EODB 6	The university procedures for obtaining/accessing university frontline services are easy to understand and follow.
Factor 2	**Leadership Quality**	LQ 3	The university leaders are responsive to the needs of the students.
		LQ 4	The University leaders are visible in student activities.
		LQ 5	The university leaders are involved in monitoring and evaluating the extent of quality in its mandated services
		LQ 6	The university leaders are continuously checking the quality of delivery of instruction and other services.
		LQ 7	The university leaders involve students in the governance of the university.

Factor	Name of Factor	Indicator	
		LQ 8	The university leaders are dedicated to increasing students' satisfaction with university services.
Factor 3	**Teacher Quality**	TQ 3	During classes, instructors/professors encourage student participation.
		TQ 4	Instructors/professors regularly administer quizzes and assignments to evaluate our learning competencies.
		TQ 5	Instructors/professors have class lectures that are easy to follow and understand.
		TQ 6	Instructors/professors give requirements as indicated in the course syllabus.
		TQ 7	Instructors/professors regularly come to class prepared.
Factor 4	**Knowledge Services**	KS 2	I believe that the contents of my subjects cover the needs of local and international industries.
		KS 3	I believe that the university is equipping me with academic knowledge that is current and up-to-date.
		KS 4	The university offers in-demand and priority programs
		KS 5	I believe that subjects in my curriculum help me have a strong theoretical foundation in my chosen field of specialization
		LQ 1	The university leaders prioritize the need for quality education.
Factor 5	**Activities**	A 2	The university regularly arranges Seminars/workshops/pieces of training for its students.
		A 3	The university regularly arranges Job Fairs to improve students' job prospects.
		A 7	The university conducts leadership training for students.
Factor 6	**E-Governance**	EG 1	The information provided by the online systems of the university is up-to-date.
		EG 2	The information provided by the online systems of the university is relevant and helpful.
		EG 3	Procedures of the online processes of the university are easy to read, understand, and follow.
Factor 7	**Continuous Improvement**	CI 2	Throughout my stay at the university, I have observed an increase in the number of students who can attend local, national, and international opportunities.
		CI 3	Throughout my stay at the university, the university has attained awards at the local, regional, and national levels.
		CI 4	Throughout my stay at the university, improvement in the accreditation status of the university is evident.
		CI 5	Throughout my stay at the university, the ranking of the university has continued to improve.

Internal Consistency, Composite Reliability, and Average Variance Extracted

The findings indicate that both Cronbach's Alpha and Composite Reliability values surpassed the suggested threshold of 0.70 (Nunnally, 1978), thereby confirming the presence of internal consistency in the measurement model. This study assessed the convergent validity of a measurement model by employing composite reliability (CR) and average variance extracted (AVE). According to Fornell and Larcker (1981), if the average variance extracted (AVE) is below 0.50 but the composite reliability is over 0.60, the construct still demonstrates sufficient convergent validity. Convergent validity was established while comparing the values of CR to the values of AVE, which exceeded 0.60 and were higher than the AVE values.

Table 9: Internal Consistency, Composite Reliability, and Average Variance Extracted

Factor	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Factor 1: Ease of Doing Business	0.836	0.836	0.505
Factor 2: Leadership Quality	0.844	0.799	0.500
Factor 3: Teaching Quality	0.803	0.803	0.450
Factor 4: Knowledge Services	0.758	0.761	0.389
Factor 5: Activities	0.743	0.745	0.494
Factor 6: E-Governance	0.714	0.712	0.553
Factor 7: Continuous Improvement	0.782	0.781	0.472
Model	0.940		

Discriminant Validity

To evaluate the discriminant validity of the measurement model, this study utilized the Heterotrait-monotrait ratio of the correlations (HTMT) approach, as suggested by Henseler et al. (2015). Henseler et al. (2015) proposed a threshold of 0.90 for structural models that involve constructs that are highly comparable in terms of their conceptual nature. The data presented in Table 10 indicates that all ratios were below the threshold of 0.85, as reported by Henseler et al. (2015) and Kline (2011). Therefore, it was determined that the constructs also demonstrated discriminant validity.

Table 10: Discriminant Validity

	E_Gov	Con_Imp	Actv	Ease_D_Bus	Know_Serv	Lead_Qual	Teach_Qual
E_Gov							
Con_Imp	0.61						
Actv	0.55	0.84					
Ease_D_Bus	0.54	0.84	0.81				
Know_Serv	0.52	0.75	0.62	0.68			
Lead_Qual	0.52	0.72	0.66	0.74	0.79		
Teach_Qual	0.54	0.52	0.50	0.54	0.75	0.74	

Conclusions

Based on the results of this study, it was established that undergraduate students consider seven important dimensions of service quality in the SUC which are: (1) ease of doing business, (2) leadership quality, (3) teacher quality, (4) knowledge services, (5) activities, (6) e-governance, and (7) continuous improvement. These dimensions are the anchorage of the developed localized SUC Service Quality Assessment Tool. The tool was developed through a customer-focused approach, a principle of TQM, wherein the perspective of students as key clients of an SUC was considered. Moreover, one important dimension of the tool is continuous improvement which corresponds to the TQM principle of continuous quality improvement. These findings underscore the fundamental importance of integrating these principles into the operational framework of SUCs, thereby reinforcing the commitment of government service to delivering excellence and value to clients while fostering a culture of perpetual enhancement. The results also indicated that the developed tool possessed good internal consistency and established convergent and discriminant validity.

Based on the findings and conclusions presented in the study, the following recommendations are offered to the following:

- The SUC management should ensure that services in the SUC are maintained and always enhanced. The SUCs may consider adopting the localized tool in their internal quality assessment procedures to complement existing service quality assessment mechanisms. This initiative not only enhances their service quality assessment but also has the potential to lead to data-driven and student-centric policy formulation.
- The Commission on Higher Education, which has regulatory power over all higher education institutions in the country, may explore the potential benefits of this tool and consider its formal integration into their assessment protocols. The utilization of this tool within the framework of the Commission's monitoring power over SUCs and its quality assessment mechanisms, as provided for in the Higher Education Act, will not only offer a more comprehensive understanding of service quality but also facilitate a more student-centric approach to evaluation. By focusing on the experiences and perceptions of students, HEIs can better align their goals and priorities with the needs and expectations of their primary beneficiaries. This initiative aligns with CHED's commitment to ensuring the highest standards of education and promoting student-centered approaches in higher education institutions across the country.
- Future research may consider utilizing the derived model in another SUC to check whether the dimensions and its indicators yield the same results on internal consistency, convergent validity, and discriminant validity. As the tool is specifically tailored to undergraduate students' perspectives as primary end users of SUC services, further research can focus on integrating the results of the study to develop a multi-stakeholder internal quality assessment tool or framework to meet evolving needs and expectations. This research can look into the perspectives of graduate students and other stakeholders such as the teaching and non-teaching personnel, alumni, top management, and partner agencies to validate the service quality dimensions and make the developed instrument more comprehensive.

Contributions of Authors

The authors confirm the equal contribution in each part of this work. All authors reviewed and approved the final version of this work.

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Conflict of Interests

All authors declare that they have no conflicts of interest

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