

Article

Service Quality Assessment of Smart Campus Dining Services: Combining SERVQUAL and IPA Models

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Abstract

This study evaluates the service quality of smart campus dining services as a core element of sustainable school meal governance and health-promoting campus environments. A structured questionnaire grounded in the five SERVQUAL dimensions—tangibles, reliability, responsiveness, assurance, and empathy—was administered to 375 users of a smart campus catering platform, including students, faculty and staff, and education administrators from 20 counties and cities in Taiwan. The data were analyzed using gap analysis, confirmatory factor analysis, multiple regression, and Importance–Performance Analysis (IPA) to identify major service quality gaps and sustainability-oriented improvement priorities. The results show that tangibles, reliability, responsiveness, and assurance significantly predict overall service quality, with assurance exerting the strongest effect, while empathy is highly correlated with the other dimensions. IPA further indicates that outdated or insufficient smart facilities fall into the high-importance/low-performance area and thus represent a critical weakness. These findings provide empirical evidence for data-driven and user-centered management of school meal services, supporting more efficient resource allocation, AI-assisted menu planning, and IoT-based food safety monitoring. By linking service quality assessment with sustainable campus governance, the study contributes to efforts to promote healthy eating, reduce food waste, and strengthen localized food supply collaboration, in line with Sustainable Development Goals related to health, education, and responsible consumption.

Keywords: SERVQUAL; IPA models; smart campus dining services

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1. Introduction

With the rapid development of information technology, AI-based recommendation systems and the Internet of Things (IoT) have become prominent topics in cross-disciplinary research and are increasingly applied in public health and nutrition, particularly within personalized service delivery systems. Trang et al. and Trattner and Elswailer analyzed existing food recommendation systems and found that they can be classified into four main categories: systems based on user preferences, systems based on nutritional requirements, systems that jointly consider user preferences and nutritional needs, and group-based recommendation systems [1–8]. The primary aim of such systems at the system level is to leverage data analytics to help users make healthier and more needs-oriented dietary choices by optimizing menu composition and aligning it with nutritional guidelines.

In school lunch services, the introduction of smart technologies has become a key strategy to enhance both service efficiency and nutritional quality. Shen et al. developed an Intelligent Menu Planning System based on multi-objective optimization, designed to address the time-consuming nature of traditional manually designed menus and the difficulty of ensuring nutritional balance [9]. By using “school lunch food content and nutritional standards” as core constraints and applying optimization algorithms (e.g., gradient descent), the system can flexibly adjust menus to specific school conditions while achieving nutritional balance, menu diversity, and a substantial reduction in the administrative burden on school lunch personnel. Building on this logic, Taiwan’s smart school lunch governance further integrates student health examination data, allergy information, ingredient prices, and supply chain constraints into AI-assisted menu planning, so that nutritional balance and menu diversity are primarily ensured upstream by the optimization-based menu recommendation subsystem and related regulations, before users actually experience the service. The implementation of this Optimization-Based Menu Recommendation Model (OMRM) represents a critical step in transforming campus catering services from traditional management to smart governance.

Despite substantial gains in operational efficiency from smart technologies, service quality remains a key indicator of public service performance, and its assessment within smart campus catering environments still presents a notable knowledge gap. Conventional service evaluation frameworks predominantly emphasize structural and process indicators while often overlooking the extent to which services meet end users’ expectations and perceptions, including faculty, staff, students, and their parents. In other words, while AI-based systems work in the background to design nutritionally adequate menus, there is still limited evidence on how users evaluate the quality of the service process and environment through which these menus are delivered. Consequently, there is a clear need to employ user-centered measurement tools to assess the quantitative quality of this innovative service model from the perspective of perceived service quality rather than nutritional intake alone.

Existing studies have applied service quality models and diagnostic tools such as SERVQUAL and Importance–Performance Analysis (IPA) in sectors including healthcare, tourism, and higher education; however, their application to smart campus dining services in primary and secondary school settings remains limited, particularly from the perspective of sustainable school meal governance. Few studies have simultaneously examined how different dimensions of perceived service quality shape users’ overall evaluations of smart school lunch services and how the resulting findings can inform sustainability-oriented decisions on resource allocation, food waste reduction, and local food sourcing. Moreover, prior work has seldom clarified how service quality assessments relate to, and are conceptually distinguished from, the upstream AI-driven menu planning and nutritional optimization subsystems.

To address this gap, the present study combines two evaluation tools that have been shown to be complementary: the SERVQUAL model and Importance–Performance Analysis (IPA). As a multidimensional service quality questionnaire, SERVQUAL allows for the objective quantification of discrepancies between customers’ service expectations and their perceived experiences [10,11]. IPA, by jointly examining the importance and performance of service attributes, can explicitly identify priority areas for resource allocation and has demonstrated strong effectiveness in service management applications [12–14]. Accordingly, this study integrates the SERVQUAL scale with the IPA framework to determine the magnitude of quality gaps across different dimensions of smart campus Dining services and to identify attributes requiring priority improvement. The empirical focus is on users’ perceptions of the service process and environment of smart campus dining—rather than on direct measurement of nutrient intake or menu composition, which are handled by the AI-

based menu planning subsystem—so that the findings provide an evidence-based basis for advancing smart governance of school lunch programs and establishing a student-oriented blueprint for the continuous optimization of service quality.

In line with this analytical strategy, confirmatory factor analysis (CFA) is employed to validate the five-dimensional SERVQUAL structure and the overall service quality construct, followed by stepwise multiple regression analysis to examine the associative relationships between these service quality dimensions and users' composite evaluations of smart campus dining services. Because the data are cross-sectional and self-reported, the regression results are interpreted as statistical associations rather than causal effects, while IPA is used to translate these associations into concrete managerial priorities for sustainable school meal governance.

Despite the rapid diffusion of smart campus catering platforms, prior research has predominantly focused on technical design, nutritional optimization, or system functionality, while offering limited evidence on how users across different stakeholder groups perceive service quality and where the largest gaps in expectations versus performance emerge in real-world school settings. Consequently, there remains a clear research gap regarding how integrated service quality frameworks can be used to support sustainable school meal governance and smart campus development. Building on this gap, this study pursues three core research questions: (1) Which dimensions of service quality most strongly influence overall satisfaction with smart campus dining services? (2) How do perceptions of service quality differ between frontline users (students, faculty, and staff) and education administrators within the implementation system? and (3) Which service attributes should be prioritized for improvement, from a sustainability-oriented resource-allocation perspective? By addressing these questions, the study contributes both theoretically, by extending SERVQUAL and IPA to the context of smart and sustainable campus catering, and practically, by providing evidence-based guidance for policy design and school-level decision-making.

2. Literature Review and Hypotheses Formulation

2.1. Service Quality (SERVQUAL)

SERVQUAL was proposed by Parasuraman, Zeithaml, and Berry in 1985 and has since become one of the most influential instruments in the study of service quality. Grounded in the “expectation–perception gap” (P–E gap) framework, the model conceptualizes service quality as the difference between customers' actual perceptions of a given service and their prior expectations of that service [15,16].

SERVQUAL has undergone several rounds of empirical refinement, ultimately converging on five core dimensions comprising 22 measurement items [16–18]. The dimensions are defined as follows: tangibles, referring to physical facilities, equipment, employee appearance, and associated communication materials; reliability, denoting the ability to perform the promised service dependably and accurately; responsiveness, referring to the willingness and promptness of service providers in helping customers and delivering service; Assurance, encompassing employees' knowledge and courtesy and their ability to inspire trust and confidence; and empathy, referring to the provision of caring, individualized attention to customers.

SERVQUAL is widely regarded as a benchmark instrument in service quality research because it can effectively capture the gap between customers' perceived service quality and actual service performance [19]. Its practical value lies in its strong applicability across industries. It has been adopted as a standard tool for assessing service quality in sectors such as healthcare, higher education, and retailing [20–22]. With advances in technology and the increasing complexity of service contexts, the original SERVQUAL model has

been extended and adapted to enhance its relevance in specific domains. Prominent derivatives include E-S-QUAL for electronic services, PubHosQual for public hospitals, and HEALTHQUAL for public health systems, as well as various modified applications in transport services such as bus, rail, and airline industries [23–25].

Empirical studies consistently indicate that service providers can effectively identify service gaps and determine priority areas for improvement by examining the quantified differences between customers' expectations and their perceptions of service performance. Moreover, as consumer behavior has shifted in diverse cultural contexts and in the post-pandemic era, and as emerging technologies such as smart catering environments have evolved, the applicability and explanatory power of each SERVQUAL dimension have been progressively extended and recalibrated. These developments underscore the model's high theoretical adaptability and substantial practical potential, confirming its suitability as the foundational framework for evaluating service quality in smart campus catering in the present study.

2.2. Importance–Performance Analysis (IPA)

Importance–Performance Analysis (IPA), first introduced by Martilla and James, is a key diagnostic tool for service quality assessment and strategic planning. It employs a two-dimensional matrix with “importance” on the horizontal axis and “performance” on the vertical axis to classify service attributes into four strategic quadrants, thereby helping managers identify strengths, weaknesses, and attributes that should receive priority in resource allocation [12,13,26].

The four quadrants of the IPA matrix and their strategic implications are as follows. Quadrant I, “Keep Up the Good Work” (high importance/high performance), contains attributes that customers highly value and that currently perform well; managers should continue to invest in these to maintain competitive advantage. Quadrant II, “Concentrate Here” (high importance/low performance), represents attributes that are crucial to customers but exhibit unsatisfactory performance; these constitute critical warning signals and priority areas for improvement, warranting intensive resource investment to enhance overall service performance and satisfaction. Quadrant III, “Low Priority” (low importance/low performance), includes attributes of relatively low importance and low performance. However, improvement is still desirable; these attributes should be addressed only after the issues in Quadrant II are resolved, to ensure efficient use of limited resources. Quadrant IV, “Possible Overkill” (low importance/high performance), comprises attributes whose performance exceeds the level of importance perceived by customers, suggesting potential overinvestment; managers may consider reallocating some resources from this quadrant—particularly toward Quadrant II—while merely maintaining current performance levels. Nevertheless, some scholars argue that in competitive environments, performance that exceeds expectations can still be strategically valuable and, in some cases, worth preserving [27].

Compared with traditional methods that rely solely on ranking attribute scores, Importance–Performance Analysis (IPA) offers a more structured basis for decision-making and serves as a practical strategic guide for service quality management. Empirical studies have widely applied IPA across sectors such as aviation, healthcare, education, and tourism to help managers allocate limited resources to enhance the most influential service attributes [28–31].

IPA's main advantages lie in its ease of implementation, relatively low cost, and the fact that it does not require complex statistical software, making it an attractive tool for practitioners tasked with evaluating service quality [32]. In addition, IPA applications highlight the importance of market segmentation, underscoring that conducting separate

analyses for different customer groups enables more precise marketing strategies and service positioning [33,34]. Recent research trends have increasingly emphasized the integrated use of IPA and SERVQUAL, arguing that this approach can address the limitations of relying on a single instrument for diagnosing service gaps: SERVQUAL quantifies the P–E gap, whereas IPA translates these gaps into an actionable strategic roadmap. Prior findings indicate that combining IPA with SERVQUAL not only facilitates a more comprehensive diagnosis of service quality but also enables more accurate determination of improvement priorities, thereby positively impacting customer satisfaction and loyalty [14].

Taken together, IPA supports managerial decision-making on resource allocation and service improvement by clarifying customer needs and pinpointing critical attributes for improvement, thereby providing a practical basis for enhancing both the customer experience and organizational performance [35,36]. Accordingly, this study adopts the integrated SERVQUAL–IPA model to conduct a comprehensive evaluation of smart campus Dining service quality and to derive concrete, strategy-oriented implications for service optimization.

2.3. Smart Campus Catering Service

In recent years, the quality of school meal provision has become a central concern in both public health and education. Through cross-departmental collaboration, the government has promoted a significant transformation of the school lunch service model, implemented in several stages. In the first phase (2019–2022), policy efforts focused on establishing a food safety governance framework, including integrating food safety resources, implementing joint inspection mechanisms, relaxing operational regulations, and encouraging joint procurement and innovative integration of certified agricultural supply chains, which together laid the groundwork for a smart school lunch service platform. The primary objective of this phase was to ensure basic food safety and regulatory compliance for school meals.

In the second phase (2023–2026), policy efforts focus on the intensive application of smart technologies and information and communication technologies (ICT) to enhance service efficiency and transparency. The core of this phase lies in modernizing infrastructure—such as constructing modern central kitchens in selected areas (e.g., rural schools) and adopting a hub-and-spoke model in which these facilities supply meals to neighboring schools—and in strengthening logistics and food safety monitoring through a smart campus catering service platform that applies Internet of Things (IoT) technologies to cold-chain management. Concrete measures include using cloud-based GPS tracking and end-to-end temperature monitoring to ensure food safety during meal delivery while improving the efficiency of lunch operations and the accuracy of process data. In addition, schools annually upload student health examination data to the smart lunch platform, enabling the system to link health information with lunch operations in a standardized and scalable manner.

Building on this data infrastructure, this phase also promotes a more scientific approach to menu design by introducing an AI-based Menu System that is integrated with the Student Health Information System. By leveraging technological tools and student health data for joint analysis, this system provides an evidence-based foundation for optimizing school lunch menus and aligning them more closely with students' nutritional and health needs.

The core function of the smart campus menu planning system is to generate menus through multi-objective optimization. The system simultaneously incorporates multiple parameters, including nutritional standards, cost control, supply chain constraints, and student preferences and diversity. Specifically, it uses health data from the Student Health Information System (such as allergen information) and the minimum and maximum nutritional standards for each educational stage to redefine target ranges for different groups (e.g., lower and upper grades in elementary school, male and female students in junior

and senior high school). It also integrates market ingredient prices, regional food policies, and supply chain management functions to ensure the cost-effectiveness of menu design, while drawing on a menu database built in the first phase to estimate students' acceptance of different dishes and thereby maintain dietary variety and appeal. Through this AI-based multi-objective optimization process, nutritional balance and menu diversity are primarily achieved at the subsystem level, before meals are actually delivered to students. With AI support, dietitians and lunch administrators can rapidly design optimized, health-oriented menu combinations under simultaneous constraints of cost, nutrition, and taste, substantially improving both the efficiency and quality of menu planning and offering high scalability and practical value.

Overall, smart campus catering constitutes a complex socio-technical system. The quality of such services depends not only on the taste and nutritional value of the final meals but also on the accuracy of AI-driven decision-making at the front end and the reliability of IoT-based monitoring at the back end. It is therefore essential to conduct a systematic evaluation of service quality for this innovative service model. In this context, the AI menu planning subsystem is responsible for "nutritional and menu optimization" based on health data and regulatory standards, whereas the present study focuses on "users' perceived service quality" of smart campus dining services. The survey instrument therefore does not directly measure nutrient intake or local sourcing; instead, it captures how users experience the service process and environment built upon these upstream optimization mechanisms.

Accordingly, the integrated SERVQUAL–IPA model adopted in this study is grounded in two complementary theoretical perspectives. First, expectation–disconfirmation theory and the service gap model underlying SERVQUAL conceptualize service quality as the discrepancy between users' expectations and their perceived performance, emphasizing the roles of reliability, assurance, and empathy in shaping satisfaction and behavioral intentions. Second, importance–performance analysis is rooted in strategic management and value theory, positing that stakeholders' evaluations of service attributes are a function of both perceived performance and the subjective importance attached to each attribute. By combining these perspectives, the present model treats smart campus dining services as a socio-technical system in which infrastructural conditions, process reliability, and relational qualities jointly determine perceived service quality and sustainability-related outcomes.

2.4. Research Questions and Hypotheses

To guide the empirical analysis and strengthen the study's deductive logic, the following research questions (RQs) and hypotheses (Hs) were formulated based on the SERVQUAL framework and prior studies on smart public services.

RQ1: To what extent do the five SERVQUAL dimensions (tangibles, reliability, responsiveness, assurance, and empathy) predict users' overall perceptions of service quality in smart campus dining services?

RQ2: How do perceptions of expected service quality differ between frontline users (students, faculty, and staff) and education administrators with respect to the five SERVQUAL dimensions?

RQ3: Which service attributes should be prioritized for improvement, from a sustainability-oriented resource allocation perspective, based on the integrated SERVQUAL–IPA?

Drawing on the literature emphasizing the importance of tangible infrastructure and trust-related factors in education and health services, the following hypotheses were proposed:

H1: *Tangibles, reliability, responsiveness, assurance, and empathy each have a significant positive effect on overall perceived service quality in smart campus dining services.*

H2: *Among the SERVQUAL dimensions, assurance exerts the strongest positive effect on overall perceived service quality.*

H3: *Significant group differences exist between frontline users and education administrators in their expected service quality scores for reliability and empathy.*

3. Methodology

3.1. Research Design and Overview

The present study adopts a deductive, exploratory quantitative research design, employing the SERVQUAL scale as the core measurement instrument and supplementing it with the Importance–Performance Analysis (IPA) model to simultaneously evaluate service quality gaps and satisfaction in smart campus catering services, thereby identifying strategic priorities for service improvement. The integrated approach enables simultaneous assessment of perceived quality gaps and strategic service improvement priorities. Guided by a deductive research logic, this study is exploratory, using established service quality constructs to investigate how smart campus dining services are perceived and where new improvement opportunities arise in a sustainability-oriented governance context.

Importantly, this study's empirical focus is on users' perceived service quality in smart campus dining, rather than on direct measurement of nutritional intake or menu composition. The SERVQUAL-based instrument therefore captures how users evaluate the service process and environment built upon the upstream AI-driven nutritional and menu optimization subsystem, instead of attempting to replace specialized nutritional assessment tools.

3.2. Instrument Development and Localization

The core instrument is a localized questionnaire adapted from the SERVQUAL theoretical model, encompassing five service quality dimensions: tangibles, reliability, responsiveness, Assurance, and Empathy [16]. In line with the original SERVQUAL framework, the items were designed to reflect users' expectations and perceptions of smart campus dining service performance across five dimensions, rather than to collect dietary intake data or directly evaluate nutrient adequacy.

The development process proceeded in two stages. In the first stage, expert consultation and item specification were conducted to ensure content validity and sectoral relevance. An initial item pool was constructed based on academic literature, followed by in-depth qualitative interviews with 11 professionals, including 10 school dietitians or school nurses and one section chief responsible for school lunch services in the local government. These expert interviews served to localize the SERVQUAL constructs to the context of smart campus catering, to identify sector-specific service attributes (e.g., facility conditions, information provision, problem-solving, and caring interactions), and to refine item wording for clarity and relevance. The interviews were thus used for content validation and contextual adaptation of the measurement instrument, rather than for constructing individual student health profiles. Drawing on expert feedback, the questionnaire's wording, format, and length were systematically revised, resulting in a finalized set of 22 items tailored to the context of campus catering services (see Table 1 and Appendix A for the full questionnaire items and their English translations, including detailed wording for each of the five SERVQUAL dimensions).

Given that the study sample covers 20 counties and cities in Taiwan (excluding Lienchiang County and Penghu County), the questionnaire was prepared in both Chinese and English. To ensure translational equivalence and meet cross-cultural research standards, a bilingual master's degree holder was commissioned to conduct forward–backward comparison and correction in accordance with recommended procedures [37].

Table 1. Item code and description of the questionnaire used in this survey.

Dimension	Item Code	Item Description
Tangibles	T1 to T4	Software and hardware facilities required for intelligent campus dining services, facility appearance, staff professional attire, and equipment compatibility.
Reliability	Rel5 to Rel9	Fulfillment of service commitments, enthusiasm for problem-solving, immediacy and timeliness of service, and stable operation of software and hardware facilities.
Responsiveness	Res10 to Res13	Information and notification during service provision, immediacy of service, willingness to assist at all times, and effective response to needs.
Assurance	A14 to A17	Instilling confidence and security in faculty and students, friendliness of service staff, and competence in professional knowledge.
Empathy	E18 to E22	Providing individualized attention to both teachers and students, delivering personalized services, striving for optimal benefits, accommodating special needs, and offering convenient meal times.

Note: Items were adapted from the SERVQUAL model developed by Parasuraman, Zeithaml, and Berry and contextualized for smart campus catering services based on expert interviews and sector-specific policy documents.

3.3. Pilot Study, Sampling, and Data Collection

In the second stage, a pre-test (pilot study) was conducted to assess the instrument's preliminary validity and item clarity. The pilot sample comprised 52 respondents: 17 professionals with more than 1 year of experience in campus catering services and 35 students from upper grades. The purpose of this stage was to verify the consistency of item interpretation across different respondent groups and to minimize potential comprehension biases prior to the formal large-scale survey. Based on feedback from the pilot respondents, minor revisions were made to improve the wording and ordering of several items, while preserving the five-dimensional SERVQUAL structure and the total of 22 service quality items.

The sampling and data collection strategy employed purposive sampling, a non-probability sampling technique, to target participants with substantial knowledge of or direct experience with smart campus catering services [38,39]. Data were collected between October 2023 and March 2024, following recommendations in prior research to clearly inform respondents of the study purpose and the nature of smart campus catering services before they completed the survey [40]; the survey was intentionally administered during the winter season to account for meal temperature as a potentially important determinant of satisfaction.

To reduce potential selection bias, respondents were recruited from both urban and rural areas, across different school levels, and from multiple stakeholder groups (students, faculty and staff, and education administrators). Participation was voluntary and anonymous, and respondents were clearly informed that their answers would be used solely for academic research, which helped mitigate social desirability bias. In addition, data screening procedures were applied to identify inconsistent or patterned responses, and no invalid questionnaires were detected, further supporting data quality.

The questionnaire was distributed via QR codes directing participants to a Google Forms survey and consisted of two sections: the first captured demographic information (gender, age, occupation, education level, residential area, and experience with campus catering services), while the second employed a five-point Likert scale (5 = strongly agree,

1 = strongly disagree) to measure 22 service quality items across the five SERVQUAL dimensions. Consistent with the conceptual focus of this study, these 22 items refer to users' perceptions of tangibles, reliability, responsiveness, assurance, and empathy in smart campus dining services, and do not contain items explicitly measuring nutritional balance, food diversity, or local sourcing; those aspects are addressed at the AI menu planning and policy levels rather than through this questionnaire. A total of 375 valid questionnaires were returned, with no invalid responses identified. The final sample comprised approximately 37.6% students, 35% faculty and staff, and 27.4% professionals. The gender distribution was roughly 1:1.3 (male-to-female). Regarding experience with campus catering services, 56% of respondents reported using them for less than 6 years, whereas 44% reported using them for 6 years or more (Table 2).

Table 2. Respondent Demographics from Smart Campus Dining Survey (N = 375).

Variable	Category	n	%
Gender	Male	162	43.2
	Female	213	56.8
Age (years old)	≤12	40	10.67
	13–20	101	26.93
	21–30	31	8.27
	31–40	81	21.6
	41–50	63	16.8
	≥51	59	15.73
Profession	Student	141	37.6
	Teacher	62	16.53
	Administrative staff	70	18.67
	Nutritionist/Nurse	102	27.2
Education	Elementary school	55	14.67
	Junior high	86	22.93
	High school	8	2.13
	College/University	171	45.6
	Graduate school	55	14.67
Experience (years)	≤6	210	56
	7–10	69	18.4
	11–20	63	16.8
	21–30	29	7.73
	≥31	4	1.07
Total		375	100

3.4. Measurement of SERVQUAL Dimensions and Overall Service Quality

Table 1 summarizes the item codes and descriptions for the five SERVQUAL dimensions used in this survey. Tangibles (T1–T4) capture software and hardware facilities required for intelligent campus dining services, facility appearance, staff professional attire, and equipment compatibility. Reliability (Rel5–Rel9) reflects fulfilment of service commitments, enthusiasm for problem-solving, immediacy and timeliness of service, and stable operation of software and hardware facilities. Responsiveness (Res10–Res13) measures information provision and notification during service, immediacy of assistance, willingness to help at all times, and effective responses to user needs. Assurance (A14–A17) focuses on instilling confidence and security in faculty and students, friendliness of service staff, and competence in professional knowledge. Empathy (E18–E22) assesses individualized attention to teachers and students, personalized services, striving for optimal benefits, accommodating special needs, and offering convenient meal times. Together, these dimensions provide a comprehensive picture of users' perceived service quality in smart campus

dining, while leaving the evaluation of nutrient content and menu design to the AI-based planning subsystem and existing nutritional regulations.

In addition to the five SERVQUAL dimensions, an overall service quality construct was included to capture respondents' global evaluations of smart campus dining services. Overall service quality was measured by three items (e.g., "Overall, I am satisfied with the service quality of smart campus dining services"; "The service quality of smart campus dining services meets my expectations"; "I would recommend smart campus dining services to others"), each rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The three items displayed satisfactory internal consistency (Cronbach's $\alpha = 0.82$), and their unidimensional structure is further supported by the confirmatory factor analysis reported in Section 4.1. The mean score of these items was therefore used as a composite index of overall service quality in the subsequent regression analyses.

4. Data Analysis and Results

4.1. Analysis of Reliability and Validity

This study employed SPSS 20 for descriptive statistics and regression analyses, and AMOS 17 for confirmatory factor analysis (CFA). The level of statistical significance for all analyses was set at $\alpha = 0.05$. The analysis first employed AMOS 17 to conduct a confirmatory factor analysis (CFA) on the initial set of 22 measurement items to assess the goodness-of-fit of the theoretical five-factor SERVQUAL model to the observed data. Model fit was evaluated using a combination of absolute and incremental fit indices, including χ^2/df , GFI, AGFI, NFI, NNFI, and CFI, and, following the recommendations of Hu and Bentler, at least one absolute index, one incremental index, and one residual-based index were reported to ensure a comprehensive model assessment [41].

Initial model evaluation indicated that several fit indices did not reach conventional benchmarks (see the "Initial Model" in Table 3). To improve model fit, seven items with non-significant or low factor loadings or problematic collinearity were removed (Rel8, Rel9, Res12, Res13, A16, E20, and E22). As shown in the comparison of fit indices (Table 3), all indices for the refined model met or exceeded accepted thresholds after item deletion; for example, χ^2/df decreased to 2.493 (≤ 3), the CFI increased to 0.972 (≥ 0.90), and the root mean square residual (RMS) was reduced to 0.0287 (≤ 0.10), indicating that the refined five-factor structure exhibited a good fit to the data.

Subsequently, CFA was used to further establish the construct reliability and convergent validity of the refined model, as summarized in Figure 1.

Reliability was assessed using composite reliability (CR), and validity was evaluated using the average variance extracted (AVE). In line with the criteria proposed by Fornell and Larcker, the CR values for all constructs ranged from 0.801 to 0.911, exceeding the recommended threshold of 0.70 (or 0.80), while the AVE values ranged from 0.664 to 0.720, all above the suggested cutoff of 0.50, indicating satisfactory convergent validity (see Table 4) [42]. In addition, Cronbach's α coefficients calculated with SPSS 20 (Tangibles: 0.893; Reliability: 0.898; Responsiveness: 0.846; Assurance: 0.870; Empathy: 0.900) were all greater than 0.70, further confirming the scale's strong internal consistency.

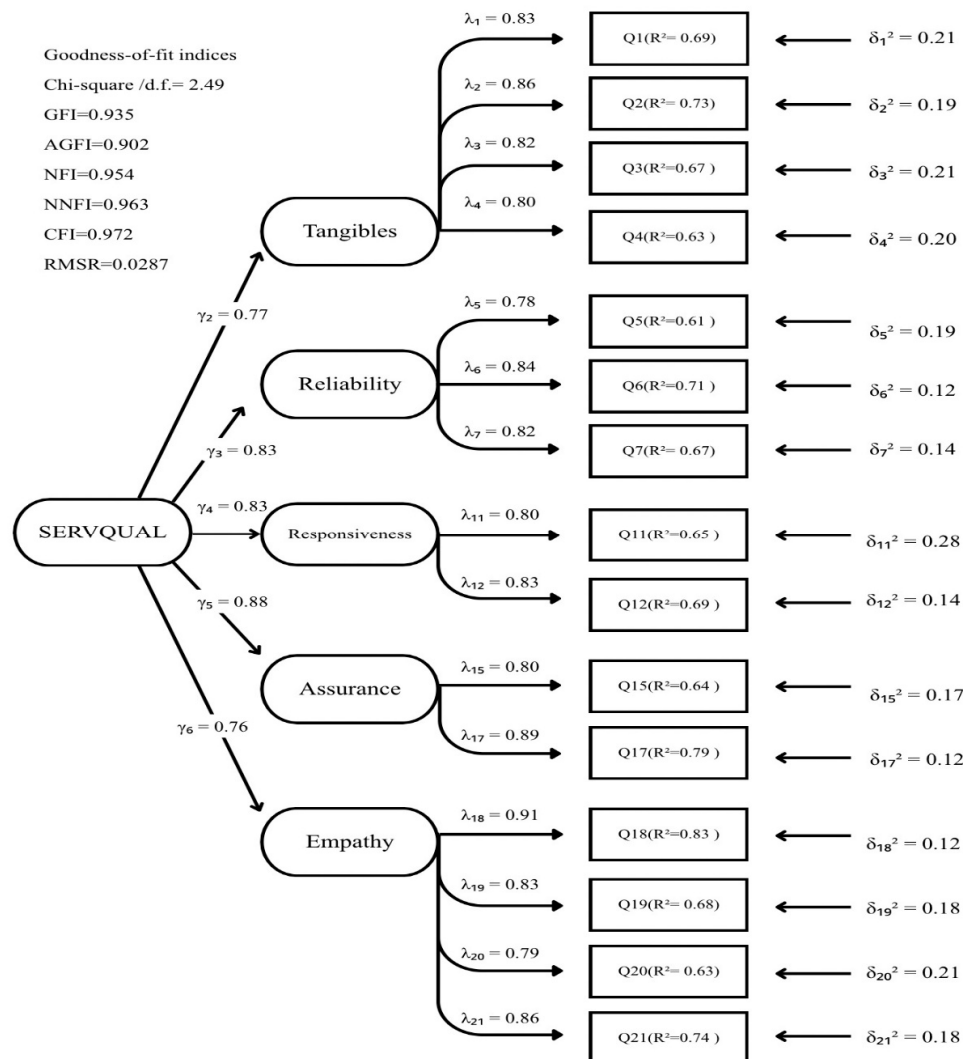


Figure 1. Testing results.

Table 3. Goodness-of-fit measures of the research model.

Goodness-of-Fit Measure	Threshold	Model	
		Initial	Refined
Chi-square/degree of freedom	≤ 3	5.023	2.493
Goodness-of-Fit Index (GFI)	≥ 0.90	0.787	0.935
Adjusted goodness-of-fit index (AGFI)	≥ 0.80	0.729	0.902
Normed fit index (NFI)	≥ 0.90	0.856	0.954
Non-normed fit index (NNFI)	≥ 0.90	0.861	0.963
Comparative Fit Index (CFI)	≥ 0.90	0.881	0.972
Root mean square residual (RMSR)	≤ 0.10	0.055	0.0287

Discriminant validity was examined following the criteria of Fornell and Larcker, whereby the square root of each construct's AVE exceeded its correlations with all other constructs (see Table 4), indicating adequate discriminant validity [42]. Based on these analyses, the refined SERVQUAL scale was deemed to possess satisfactory reliability, convergent validity, and discriminant validity and is therefore appropriate for measuring service quality in the context of smart campus catering services.

Table 4. Reliability, convergent validity, and discriminant validity of measurement models.

Construct	CR	AVE	$\sqrt{\text{AVE}}$	Correlation Coefficients Among Constructs				
				Tan	Rel	Res	Ass	Emp
Tan	0.81	0.46	0.796	1.00				
Rel	0.83	0.49	0.818	0.77	1.00			
Res	0.82	0.70	0.832	0.71	0.81	1.00		
Ass	0.75	0.50	0.889	0.73	0.79	0.78	1.00	
Emp	0.85	0.57	0.86	0.75	0.81	0.76	0.84	1.00

CR = composite reliability; AVE = average variance extracted.

In addition to the five SERVQUAL dimensions, an overall service quality construct was included to capture respondents' global evaluations of smart campus dining services. Overall service quality was measured by three items (e.g., "Overall, I am satisfied with the service quality of smart campus dining services"), each rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The three items demonstrated satisfactory internal consistency (Cronbach's $\alpha = 0.82$), and a single-factor confirmatory factor analysis indicated good model fit ($\chi^2 = 12.34$, $p = 0.002$; CFI = 0.989; RMSEA = 0.058), thereby supporting the use of their mean score as a composite index of overall service quality in subsequent regression analyses.

4.2. Descriptive Statistics

For preliminary analysis, descriptive statistics were computed for all SERVQUAL dimensions and the overall service quality composite score. Mean values for the five dimensions ranged from approximately 3.4 to 3.9 on a five-point Likert scale, indicating that respondents generally held moderately positive evaluations of smart campus dining services, with room for further improvement. Among the SERVQUAL dimensions, Assurance and Tangibles recorded comparatively higher mean scores, suggesting that respondents perceived staff professionalism, trustworthiness, and the physical environment as relatively satisfactory, whereas Responsiveness and Empathy showed slightly lower mean scores, reflecting opportunities to enhance promptness, communication, and personalized care.

Standard deviations across the SERVQUAL dimensions and overall service quality were all below 1.0, implying no severe response dispersion or extreme skewness in the data. Skewness and kurtosis statistics fell within conventional thresholds ($|\text{skewness}| < 2$, $|\text{kurtosis}| < 7$), supporting the assumption of approximate normality and justifying the use of parametric techniques such as multiple regression and independent-samples *t*-tests in subsequent analyses.

4.3. Multiple Regression Analysis

After confirming the reliability and validity of the measurement model, a stepwise multiple regression analysis was conducted to examine how the five SERVQUAL dimensions predict users' overall service quality evaluations. In this analysis, the composite score for overall service quality served as the dependent variable, while Tangibles, Reliability, Responsiveness, Assurance, and Empathy were entered as predictors. The level of statistical significance was set at $\alpha = 0.05$.

The regression results (summarized in Table 5) indicate that four dimensions—Tangibles, Reliability, Responsiveness, and Assurance—each exerted a significant positive effect on overall service quality ($p < 0.001$), with Assurance exhibiting the largest standardized coefficient (β), suggesting the strongest contribution to perceived service quality in the smart campus catering context. Empathy was excluded from the final model due to

relatively high collinearity with other predictors, and all retained predictors had VIF values below 3, indicating no serious multicollinearity concerns.

Table 5. Multiple regression analysis for SERVQUAL variables.

Construct	Parameter Estimate	VIF	t-Value
Tangibles	0.000 ***	2.142	4.289
Reliability	0.000 ***	2.654	5.819
Responsiveness	0.024 ***	2.157	2.265
Assurance	0.000 ***	2.187	9.573

Note: *** $p < 0.001$.

The final regression model was statistically significant, $F(4, 370) = 110.612$, $p < 0.001$, and explained 56% of the variance in overall service quality ($R^2 = 0.56$, adjusted $R^2 = 0.55$; Durbin–Watson = 1.579). As shown in Table 6, all five SERVQUAL dimensions exerted significant positive effects on overall service quality. Tangibles ($B = 0.14$, $SE = 0.06$, $\beta = 0.14$, $t = 2.33$, $p = 0.02$, 95% CI [0.020, 0.260]), Reliability ($B = 0.392$, $SE = 0.07$, $\beta = 0.316$, $t = 5.571$, $p < 0.001$, 95% CI [0.254, 0.530]), Empathy ($B = 0.264$, $SE = 0.062$, $\beta = 0.263$, $t = 4.289$, $p < 0.001$, 95% CI [0.143, 0.385]), Responsiveness ($B = 0.152$, $SE = 0.052$, $\beta = 0.148$, $t = 2.919$, $p = 0.004$, 95% CI [0.050, 0.254]), and Assurance ($B = 0.125$, $SE = 0.063$, $\beta = 0.113$, $t = 1.99$, $p = 0.047$, 95% CI [0.001, 0.249]) were all significant positive predictors of overall service quality.

Table 6. Stepwise multiple regression predicting overall service quality from SERVQUAL dimensions ($N = 375$).

SERVQUAL Dimension	B (Unstd.)	SE	β (Std.)	t	p	95% CI
Tangibles	0.140	0.06	0.14	2.330	0.020 *	[0.020, 0.260]
Reliability	0.392	0.07	0.316	5.571	<0.001 ***	[0.254, 0.530]
Empathy	0.264	0.062	0.263	4.289	<0.001 ***	[0.143, 0.385]
Responsiveness	0.152	0.052	0.148	2.919	0.004 **	[0.050, 0.254]
Assurance	0.125	0.063	0.113	1.99	0.047 *	[0.001, 0.249]
Constant	−0.091	0.028	—	−3.186	0.002 **	[−0.147, −0.035]
Model Statistics	R^2	Adj. R^2	F	df	p	Durbin-Watson
	0.560	0.550	110.612	4.370	<0.001 **	1.579

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Among these dimensions, Reliability and Empathy showed the largest standardized coefficients, indicating that fulfilment of commitments and staff understanding and care are particularly influential for users' global evaluations of smart campus dining services. Tangibles and Assurance, while having relatively smaller coefficients, still contributed significantly to perceived overall service quality, highlighting the importance of both physical facilities and perceived professionalism and trust in shaping users' holistic judgments.

Given the cross-sectional, self-reported design and the exploratory nature of the stepwise procedure, these regression results are interpreted as statistical associations rather than causal effects. Future longitudinal or experimental research using multi-source data is needed to establish causal pathways between service quality dimensions and overall service evaluations.

4.4. Group Differences Analysis

To examine group differences in perceptions of service quality, independent-samples t tests were conducted. The sample was divided into a faculty–staff–student group ($n_3 = 201$) and an education administrators' group ($n_4 = 174$), and their mean scores on expected service levels were compared. Reliability ($t = -2.85$, $p = 0.005$) and empathy ($t = -2.22$,

$p = 0.028$) showed statistically significant differences between the two groups ($p < 0.05$), with Cohen's d values of 0.57 and 0.46, respectively, both indicating medium effect sizes; in both dimensions, mean scores for faculty, staff, and students were significantly lower than those for administrators, highlighting perceptual gaps between service users and policy implementers regarding Reliability and Empathy. Although the p -value for responsiveness slightly exceeded 0.05, the corresponding Cohen's d was 0.46, indicating a medium effect size and warranting managerial attention. In contrast, no significant differences were observed between the two groups for Tangibles, Assurance, or the overall SERVQUAL score, and the associated effect sizes were small, suggesting relatively similar perceptions across these dimensions (See Table 7).

Table 7. Results of Independent Samples t -tests and Effect Sizes for SERVQUAL Dimensions.

Construct	Levene F (Sig.)	t -Test Used	t (df)	p (Two-Tailed)	MD	Cohen's d
SERVQUAL (total)	8.88 (0.003)	Welch's	−0.99 (8.22)	0.349	−0.33	0.40
Tangibles	0.00 (0.977)	Student's	0.19 (223)	0.850	0.05	0.06
Reliability	19.14 (<0.001)	Welch's t	−2.85 (223)	0.005	−0.61	0.57
Responsiveness	3.59 (0.059)	Student's t -test	−1.74 (223)	0.83	−0.41	0.46
Assurance	1.66 (0.198)	Student's t -test	−0.67 (223)	0.505	−0.14	0.20
Empathy	16.92 (<0.001)	Welch's t	−2.22 (223)	0.028	−0.56	0.46

Within the education administrator group ($n = 174$), respondents were further classified into agency personnel ($n = 70$) and school administrative staff ($n = 104$) to compare perceived service quality performance levels (Table 8). As shown in Table 8, significant differences were observed between the two groups across the overall SERVQUAL construct and all five sub-dimensions ($p < 0.001$). The independent samples t -test indicated a mean difference of 0.66 for overall SERVQUAL, with a large effect size (Cohen's $d = 1.04$), suggesting a substantial difference in perceived service quality between the groups.

Table 8. Independent Samples t -test Results and Effect Sizes for SERVQUAL Constructs.

Construct	Levene F (Sig.)	t (df)	MD	Cohen's d
SERVQUAL (total)	14.25 (<0.001)	6.99 (373)	0.66	1.04
Tangibles	45.48 (<0.001)	0.19 (223)	0.89	1.18
Reliability	19.14 (<0.001)	3.98 (373)	0.38	0.60
Responsiveness	30.93 (<0.001)	4.08 (373)	0.48	0.62
Assurance	45.73 (<0.001)	6.53 (373)	0.69	0.97
Empathy	14.38 (<0.001)	6.08 (373)	0.70	0.93

Note. Cohen's d interpreted as 0.2 = small, 0.5 = medium, 0.8 = large. $p < 0.05$.

Among the five dimensions, Tangibles demonstrated the largest difference (mean difference = 0.89, $d = 1.18$), representing a large effect size and indicating that physical facilities and visible service attributes were key differentiating factors. Assurance and empathy also exhibited significant and large effect sizes ($d = 0.97$ and 0.93 , respectively), highlighting the critical role of professional competence, trust, and caring attitudes in service quality evaluation.

In contrast, Responsiveness and Reliability, although statistically significant, showed moderate-to-large effect sizes ($d = 0.62$ and 0.60 , respectively), indicating a comparatively smaller but still meaningful contribution to group differences. Overall, the findings demonstrate not only statistical significance but also practical significance, providing strong empirical support for the explanatory power of the SERVQUAL model in assessing service quality differences.

Parasuraman, Zeithaml, and Berry originally developed the SERVQUAL model, emphasizing Reliability and Empathy as core dimensions of service quality, and cross-cultural studies have similarly shown that groups from different backgrounds often exhibit significant differences on these two dimensions [11,16]. In health care and education, professional background has been found to shape perceptions of reliability; for example, Mohebifar et al. reported significant discrepancies in Reliability scores across different hospital departments, suggesting that organizational role and training shape how “fulfilment of commitments” is evaluated, while Jonkisz et al. identified empathy as the dimension most strongly differentiating levels of user satisfaction, particularly in public and health services [43,44]. Consistent with this theoretical and empirical evidence, the present findings show that education administrators report significantly higher scores than faculty, staff, and students on both Reliability and Empathy, indicating a potential need to strengthen service orientation and interpersonal engagement among frontline personnel. These group differences suggest that professional development for education.

Among education administrators, agency personnel scored significantly higher than school administrative staff across all service quality dimensions, indicating substantial gaps in service consistency, trustworthiness, professionalism, and empathy between different levels of the implementation system. This pattern aligns with SERVQUAL theory and prior cross-organizational comparisons: Parasuraman, Zeithaml, and Berry identify Reliability and Empathy as core determinants of service quality, and subsequent work has shown that organizational type and managerial level can lead to marked differences in performance on these dimensions. Higher scores among education administrators may stem from greater standardization of procedures, more stable resource allocation, and higher process consistency at the institutional level, structural advantages that enhance perceived Reliability and Assurance and, in turn, foster higher trust in their services [11,16,45].

Lower ratings among school administrative staff may be attributable to constraints such as limited workforce and resources, inconsistent implementation standards, or discrepancies in service training. Evidence from healthcare research similarly shows that inadequate organizational support and restricted managerial autonomy are associated with significantly lower scores on Reliability and Empathy [43]. Empathy and Assurance both exhibited large effect sizes in this study, indicating that users place particular importance on staff understanding, care, and perceived professional credibility. Jonkisz et al. confirm that these two dimensions are among the most critical determinants of satisfaction in public sector and healthcare institutions, while Alfatafta et al. argue that when organizations balance managerial empowerment with sufficient resource support, service quality across all five SERVQUAL dimensions improves markedly [44,46].

4.5. Implications for Practice and Policy

The findings highlight the critical need to strengthen standardized operational procedures and reinforce staff training among educational administrators to ensure consistency, reliability, and quality in service implementation. Administrators should develop cross-level mechanisms for feedback and collaboration that promote effective communication between administrative departments and schools. Such mechanisms can facilitate the systematic transfer and internalization of administrative knowledge, professional values, and best practices, thereby bridging the gap between policymaking and on-site implementation and fostering a coherent service culture across educational hierarchies.

From a policy standpoint, education authorities are advised to institutionalize professional development initiatives through ongoing training, performance evaluations, and quality assurance systems. These strategies can enhance the empathy, service professionalism, and responsiveness of school administrative personnel to meet the diverse needs

of teachers and students. Embedding these practices within long-term governance frameworks will enable educational institutions to improve administrative efficiency and service quality, fostering sustained progress in smart campus governance and advancing equitable, high-quality public education services.

4.6. Importance–Performance Analysis, IPA

This study calculated gap scores for each service item by comparing the mean scores of expected service levels (importance) and perceived performance. Following the approach proposed by Martilla and James, an Importance–Performance Analysis (IPA) strategic matrix was constructed using SPSS 20, as illustrated in Figure 2. The cutoff values for the two axes of the IPA map were set to the grand means of importance and performance, respectively; that is, the mean of all expectation scores across all items defined the vertical (importance) boundary, and the mean of all performance scores defined the horizontal (performance) boundary, thereby positioning all service attributes within a two-dimensional space and facilitating the identification of managerial priorities and strategic improvement areas [12].

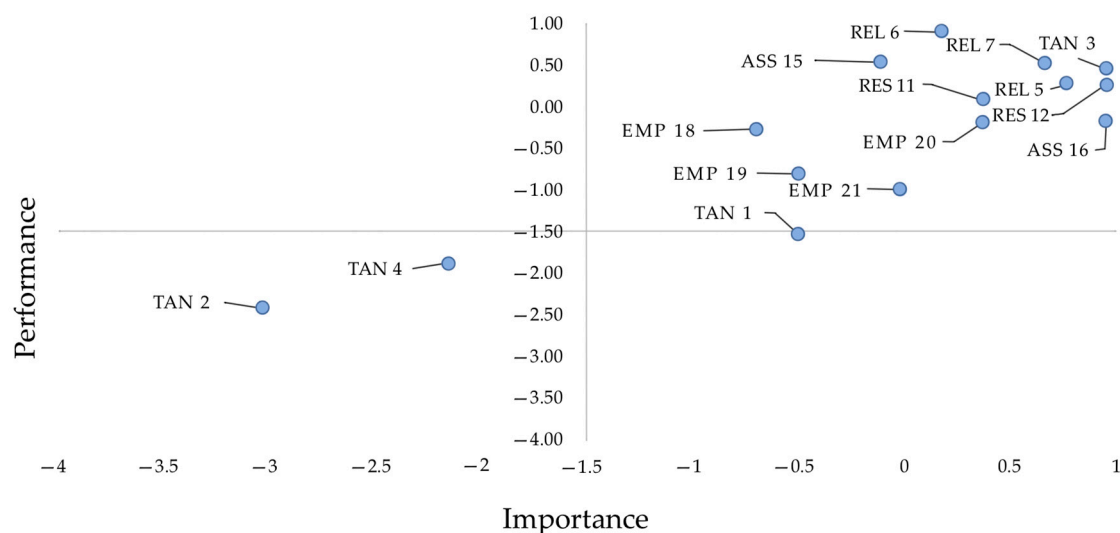


Figure 2. Results of IPA for facility management. (Note: See Table 1 “Item code and description of the questionnaire used in this survey.”).

The results indicate that item T1 under the Tangibles dimension (“having up-to-date hardware and software facilities”) was positioned in the “Concentrate Here” quadrant (high importance/low performance). This finding suggests that respondents attach high importance to the modernization of facilities, while perceiving current performance as insufficient, thereby identifying this attribute as an urgent target for improvement. From a managerial perspective, outdated or unstable smart facilities not only reduce perceived service quality but may also hinder the reliable execution of AI-assisted menu planning, data transmission, and cold-chain monitoring, thereby weakening the effectiveness of the overall smart lunch system.

Most service items within the Reliability, Responsiveness, Assurance, and Empathy dimensions were located in the “Keep Up the Good Work” quadrant (high importance/high performance). This distribution indicates that these attributes are not only highly valued by users but are also delivered effectively, serving as key drivers of overall satisfaction with facility management services. Maintaining high performance in these dimensions is crucial for ensuring that AI-generated, nutritionally optimized menus and standardized procurement procedures are translated into trustworthy, timely, and user-friendly services for students, teachers, and administrators.

No service items fell into the “Possible Overkill” quadrant (low importance/high performance), suggesting that there is no evidence of excessive resource allocation to attributes that are of relatively low importance to users.

In the “Low Priority” quadrant (low importance/low performance), two Tangibles items -T2 (“attractive appearance of facilities”) and T4 (“equipment and services are well matched”)-were identified. These attributes received comparatively lower ratings in both importance and performance and may therefore be considered secondary targets for improvement. Nevertheless, gradual enhancement of these attributes may still support the long-term visibility and user acceptance of smart campus catering infrastructure, especially as smart lunch policies continue to evolve.

Overall, the IPA findings reveal a pronounced performance gap within the Tangibles dimension, particularly in facility and equipment modernization. Addressing this gap should constitute a primary strategic focus for enhancing future smart campus catering and facility management services. By prioritizing investments in up-to-date hardware and software, stable system operation, and clear information delivery, school authorities can strengthen the operational backbone needed to implement healthy eating initiatives and sustainable procurement policies—such as the use of certified, locally sourced ingredients—within the smart lunch framework. At the same time, these results highlight the scope and boundaries of the present study: the IPA diagnosis is based on self-reported perceptions of service quality and does not directly incorporate objective indicators of nutritional intake or local food sourcing. Future research could therefore link the IPA-identified priority attributes with administrative data on menu composition, compliance with nutritional standards, food waste, and the proportion of local and certified products, to provide a more comprehensive assessment of how smart campus catering contributes to health promotion and sustainability goals.

5. Discussion

5.1. Theoretical Implications

Theoretically, this study extends the SERVQUAL and Importance–Performance Analysis (IPA) frameworks to the emerging context of smart campus dining services, conceptualizing them as a socio-technical subsystem within smart and sustainable campus ecosystems. By integrating perceived service quality gaps with importance–performance mappings, the study demonstrates how classic service quality models can be adapted to evaluate digital–physical hybrid services that combine AI-driven decision support, IoT-based monitoring, and face-to-face interactions in school settings. The findings further refine the role of the five SERVQUAL dimensions in public-sector food services: tangibles and assurance emerge as key predictors of overall perceived quality, while empathy is closely intertwined with the other dimensions, suggesting that trust, professionalism, and caring attitudes are co-produced with infrastructural and process quality in education-related services [11,12,15,16].

The medium-sized differences between service providers and faculty–staff–students on Reliability and Empathy underscore the theoretical centrality of “fulfilment of commitments” and “emotional understanding” in the SERVQUAL structure and align with cross-cultural evidence that these dimensions are particularly sensitive to role-based perceptual gaps. Within the provider subsystem, administrative planners reported substantially higher scores than school-level implementers across all SERVQUAL dimensions, with the largest gaps in Tangibles, Assurance, and Empathy, and large effect sizes, supporting arguments that institutional standardization and more stable resource bases tend to elevate perceived service quality [11].

From a strategic resource-allocation perspective, the IPA results provide visual evidence in line with Martilla and James, showing that many indicators within Reliability,

Responsiveness, Assurance, and Empathy fall into the “Keep Up the Good Work” quadrant, whereas the Tangibles item “having up-to-date hardware and software facilities” lies in the “Concentrate Here” quadrant, identifying infrastructural modernization as a critical bottleneck [12]. Items related to aesthetic appearance and the fit between facilities and services cluster in the “Low Priority” quadrant, indicating that respondents prioritize functional reliability and safety over purely cosmetic attributes, consistent with the view that IPA can highlight misalignments between managerial investment and user-perceived value [26]. Overall, the integrated SERVQUAL–IPA approach demonstrates strong theoretical relevance and offers a transferable analytical template for evaluating smart public catering governance and school nutrition policies, in line with empirical evidence on the benefits of combining gap-based measures with importance–performance mapping [14,29].

Within the provider subsystem, administrative planners reported substantially higher scores than school-level implementers across all SERVQUAL dimensions, with the largest gaps in Tangibles, Assurance, and Empathy, and large effect sizes, echoing Seth, Deshmukh, and Vrat’s argument that institutional standardization and stable resource allocation enhance perceived service quality. Higher-level agencies, with broader access to information and more stable infrastructures, are inclined to rate services closer to the intended design, whereas frontline staff—who directly experience staffing constraints, aging facilities, and contextual complexity—tend to evaluate Reliability, Assurance, and Empathy more conservatively, thereby revealing a salient implementation–perception gap [44,45].

From a theoretical standpoint, the model developed in this study explicitly links the expectation–disconfirmation logic of SERVQUAL with the strategic, value-based reasoning of Importance–Performance Analysis. On the one hand, the five service quality dimensions capture users’ expectation–performance gaps in tangible facilities, process reliability, responsiveness, assurance, and empathy. On the other hand, the IPA component translates these gaps into differentiated strategic priorities based on users’ perceived importance, thereby extending gap-based service quality models toward a more decision-oriented sustainability governance framework. In doing so, the proposed model advances existing theory by conceptualizing smart campus dining services as a sustainability-relevant socio-technical system in which perceived service quality functions as a mechanism linking digital infrastructure, organizational processes, and stakeholder well-being.

5.2. Practical Implications for Sustainable Campus Governance

In practice, these findings align with Jonkisz et al. and Alfatafta et al., who underscore the centrality of empathy and professional credibility in public and health-related services, suggesting that smart campus catering should evolve along two interrelated trajectories [44,46]. First, human resource and service culture initiatives centered on Reliability and Empathy—including standardized procedures, explicit service promise management, and cross-level feedback mechanisms—are required to narrow perceptual gaps across stakeholder groups. Second, scarce resources should be prioritized toward critical tangible assets (e.g., central kitchen equipment, cold-chain logistics, digital ordering and tracking platforms), enabling AI-based decision support and IoT monitoring to translate into perceivable quality gains. Insights from Minvielle et al. and Jain et al. on innovation in healthcare and food services can guide the design of differentiated, personalized interventions that align technological capabilities with user expectations [47,48].

From a sustainability perspective, these findings underscore the need to align human resource development, infrastructure investment, and policy design to strengthen smart campus catering as a lever for healthy eating, educational equity, and sustainable school operations. In line with prior observation that the diagnostic value of Importance–Performance Analysis hinges on how importance is conceptualized and scaled—prompting

them to derive importance values from ranked preferences to better guide managerial prioritization—our results highlight the need to treat different stakeholder groups' importance perceptions as a strategic input for resource allocation within smart campus catering systems [49]. First, the prominence of tangibles and assurance suggests that investments in up-to-date digital platforms, reliable hardware, and visible food safety controls should be accompanied by sustained professional training for frontline staff to enhance their communication, problem-solving, and nutrition-related competencies. Such combined improvements can simultaneously raise users' trust in the system, improve perceived transparency, and support long-term participation in healthy, school-based meal programs.

Second, the IPA matrix indicates that specific smart-catering functions—such as real-time information provision, temperature control, and integration with student health records—require priority enhancement, especially in schools or regions with less developed infrastructure. Scarce resources should therefore be prioritized toward critical tangible assets, including central kitchen equipment, cold-chain logistics, and digital ordering and tracking platforms, so that AI-based decision support and IoT monitoring can translate into perceivable quality gains. Insights from innovation studies in healthcare and food services can guide the design of differentiated, personalized interventions that better align technological capabilities with user expectations.

These practical implications are directly relevant to policy design and resource allocation in education and public health. By using the integrated SERVQUAL–IPA approach, education authorities can identify which service attributes most strongly influence satisfaction and where marginal investments will yield the greatest sustainability gains in terms of food safety, nutritional adequacy, and user equity. Consistent with prior finding that SERVQUAL instruments must be contextually adapted through expert input to validly reflect users' priorities in specific service environments, these results underscore the importance of tailoring service-quality diagnostics to the socio-technical characteristics of smart campus dining systems so that policy and resource decisions are grounded in locally salient expectations and performance criteria [50]. The results support the development of phased implementation strategies that distinguish between high-priority and low-priority attributes, enabling more efficient use of limited budgets while advancing the goals of healthy eating promotion and environmentally responsible procurement, particularly through collaboration with local agricultural supply chains. In this way, smart campus dining services can be positioned not only as an operational system but also as an integral instrument for achieving school-level and regional sustainability objectives [15].

5.3. *Synthesis and Directions for Future Research*

By bringing together these theoretical and practical implications, this study demonstrates that integrating SERVQUAL and Importance–Performance Analysis provides a robust lens for understanding how smart campus dining services perform within a broader sustainable school ecosystem. The evidence shows that user perceptions of service quality are closely tied to both technological infrastructures and human interactions, implying that sustainability-oriented reforms must simultaneously address digital systems, organizational processes, and frontline service capabilities. This is consistent with prior finding that multi-dimensional service quality, as captured by a modified SERVQUAL model, is positively and significantly associated with customer satisfaction, as well as with Arli et al.'s evidence that SERVQUAL dimensions significantly shape consumers' satisfaction, loyalty, and intention to continue using online food delivery services, together reinforcing that systematic improvements in key service quality attributes can generate durable attitudinal and behavioral benefits in technology-mediated food service systems [51,52]. In doing so, the findings not only enrich the service quality literature in education and public health but

also provide an actionable framework for policymakers and practitioners seeking to align smart campus catering initiatives with long-term goals in health promotion, educational equity, and responsible resource management.

Future research can build on these contributions in several ways. First, longitudinal and mixed-method designs would allow scholars to examine how changes in infrastructure, training, and governance structures affect service quality perceptions and behavioral outcomes over time, reflecting the conclusion that the dimensional structure and relative performance of SERVQUAL-type instruments should be rigorously tested and compared across specific higher education contexts to ensure their validity and usefulness for continuous improvement [53]. Second, extending the analysis to additional stakeholder groups—such as parents, catering vendors, and community organizations—would deepen understanding of expectation gaps and implementation challenges across the wider ecosystem. Third, comparative studies across regions or countries with different governance models could illuminate how institutional arrangements, contextual uncertainty, and measurement approaches shape the evaluation of service quality in complex public and health-related settings, thereby supporting the broader view that refined variants of SERVQUAL (including fuzzy extensions) can capture nuanced user perceptions and inform more precise quality-improvement strategies in specialized service environments. In parallel, synthesizing insights from systematic reviews of food recommender systems highlights that data-driven personalization and context-aware algorithms are becoming central to the design and optimization of food-related services, and emerging work on health-aware food recommendation further shows that combining knowledge-graph representations with multi-task learning can simultaneously account for users' dietary preferences and health constraints, pointing to concrete pathways for integrating personalized, health-oriented recommendation logic into smart campus dining platforms [54–56].

This perspective resonates with the broader technology acceptance literature, which posits that users are more likely to adopt and continue using technology when they perceive it as both useful for achieving valued outcomes and easy to use within their everyday practices, and recent applications of SERVQUAL in occupational health and safety similarly indicate that systematically assessing expectation–perception gaps can provide decision-makers with actionable insights into where service processes need to be strengthened to enhance overall service performance [57,58]. Moreover, comparative work on alternative service quality instruments, such as Magal's scale and SERVPERF, suggests that different measurement approaches may vary in their ability to predict user satisfaction and perceived usefulness, underscoring the importance of carefully matching diagnostic tools to context-specific evaluation goals in future smart campus dining research [59].

6. Conclusions

Several limitations should be acknowledged when interpreting the findings, and they point to clear avenues for future research. First, the study relied on non-probability purposive sampling within a specific time window (2023–2024) and a limited set of regions and institutions, which may introduce selection bias and restrict the generalizability of the results to other jurisdictions or national contexts. Future studies could adopt stratified random or multistage sampling strategies and expand coverage across different governance models and geographic areas to enhance external validity. Second, all data were collected via self-reported questionnaires at a single point in time, making the results susceptible to social desirability bias, common method variance, and the inability to draw strong causal inferences. Subsequent research should therefore integrate objective operational indicators (e.g., food safety incident records, on-time delivery rates, system usage logs) and employ longitudinal or experimental designs to build a multi-source, multi-method validation framework.

From a measurement perspective, the average variance extracted (AVE) for the tangibles dimension was slightly below commonly recommended thresholds, suggesting that this construct may capture a broader or more heterogeneous set of attributes than the other SERVQUAL dimensions. Prior work has shown that the traditional five-dimensional SERVQUAL structure does not always align with underlying psychometric evaluations and that separating tangibles from non-tangibles can yield a more stable representation of heterogeneous service quality perceptions [60]. Future researchers are encouraged to refine or expand the item pool for tangibles, test alternative measurement models, and compare results across different types of smart campus environments to improve construct validity. In addition, although this study validated the five-dimensional SERVQUAL structure using CFA and applied IPA to differentiate importance and performance, the design remains cross-sectional and thus cannot capture temporal dynamics in how service quality perceptions evolve in response to changes in infrastructure, training, or governance structures. Longitudinal and mixed-method studies could help clarify these dynamics and examine mediating and moderating mechanisms such as organizational support, resource accessibility, and digital literacy.

Finally, the current analysis focused on key stakeholders within the school system (students, faculty and staff, and education administrators), without incorporating the perspectives of parents, catering vendors, or community organizations, which may understate expectation gaps across the broader ecosystem. Future research should therefore adopt multi-stakeholder designs and include qualitative components (e.g., interviews or focus groups) to deepen contextual understanding of diverse needs and implementation challenges. Moreover, the present study assessed only perceived service quality and did not directly incorporate objective indicators of nutritional outcomes, menu composition, or the proportion of locally sourced ingredients; subsequent work could link the SERVQUAL–IPA results to administrative data from AI-based menu planning and procurement records to more fully examine how service quality interacts with healthy eating promotion and sustainable food supply.

Methodologically, the present work sits within a growing body of research that integrates SERVQUAL with other analytical frameworks to generate more actionable service quality diagnostics. Studies combining SERVQUAL with Kano models, importance–performance analysis, failure mode and effects analysis, fuzzy multi-criteria methods, and causal-structure techniques have shown that coupling gap-based measures with prioritization and risk-analysis tools can identify critical attributes, highlight where performance lags most behind importance, and offer clearer guidance for resource allocation in complex, capacity-constrained environments [61–68]. Building on this broader literature, recent work on AI and emerging technologies in operations management argues that such tools should be studied through structured research agendas grounded in technology adoption theories (e.g., UTAUT), emphasizing the need for mixed-methods designs that link organizational, technological, and environmental factors to the realized performance benefits of AI-powered tools in complex service systems [69]. In a related stream, UTAUT-based studies of mobile learning show that performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning significantly shape behavioural intention, and that age and gender moderate several of these relationships, highlighting the importance of accounting for user heterogeneity when evaluating acceptance of technology-enhanced educational services [70].

Evidence from healthcare and higher education further underscores the broader relevance of gap-based service quality diagnostics for public service systems. Empirical investigations in hospital settings consistently report that perceived service quality falls short of expectations across multiple SERVQUAL dimensions and argue that providers

must continuously monitor these gaps and implement targeted, context-specific quality improvement initiatives to enhance overall service performance and user satisfaction. In higher education, SERVQUAL-based studies and bibliometric reviews indicate that service quality remains a central determinant of student satisfaction and loyalty, while also calling for more context-sensitive conceptual models and alternative measurement approaches to capture emerging dimensions of service quality in increasingly competitive and digitally mediated environments. Complementary work on competitive forces in higher education suggests that service quality should be understood in relation to broader stakeholder expectations and strategic positioning, and that institutions need to move “beyond SERVQUAL” by integrating perception-based diagnostics within wider governance and value-creation frameworks. These insights collectively reinforce the view that SERVQUAL–IPA applications in smart campus catering should be embedded in a broader competitiveness and governance context, rather than treated as stand-alone measurement exercises [71,72]. Addressing these limitations will help validate and extend the integrated SERVQUAL–IPA framework and further elucidate how service quality, smart technologies, and sustainability objectives interact in public service systems.

Taken together, the primary contribution of this study lies in providing an integrated SERVQUAL–IPA evaluation framework specifically tailored to smart campus dining services and demonstrating its empirical applicability in the context of Taiwan’s smart school lunch governance. Rather than directly measuring nutrient intake or local food sourcing, the framework offers a structured, user-centred diagnosis of perceived service quality that can guide resource allocation, infrastructure upgrading, and process redesign in support of broader policy goals. In line with prior applications of SERVQUAL in higher education, which show that systematically leveraging students’ service quality perceptions can both enhance their satisfaction and strengthen the overall image of academic programs, these findings suggest that similar perception-based diagnostics in smart campus catering can be used to refine service strategies and reinforce the legitimacy of school lunch reforms. Extending this evidence base, recent studies confirm that SERVQUAL-based assessments can have a significant positive effect on understanding student satisfaction and can inform strategic enhancement of facilities and services in increasingly competitive higher education landscapes. This direction is also compatible with revised IPA approaches that integrate fuzzy multi-criteria techniques, indicating that combining importance–performance mapping with fuzzy AHP-style weighting of service attributes can provide more discriminating and context-sensitive guidance for prioritizing service improvements in complex, capacity-constrained environments. Complementing this line of work, advances in image-based AI nutrition analysis platforms for compartment trays demonstrate how automated recognition and nutrient estimation of plated foods can support more fine-grained monitoring of dietary quality in institutional meal settings, pointing to concrete opportunities to link perceived service quality with objective nutrition-related metrics in future smart campus dining research [73–76].

At the same time, comparative analyses of alternative service quality instruments, such as Magal’s scale and SERVPERF, indicate that different measurement approaches vary in their ability to predict satisfaction and perceived usefulness, underscoring the importance of aligning the choice of diagnostic tools with context-specific evaluation goals in future applications of the SERVQUAL–IPA framework [59]. In parallel, large-sample evidence from Chinese healthcare shows that patients’ perceived service quality systematically falls short of their expectations across multiple SERVQUAL dimensions, and that narrowing these gaps requires continuous, context-specific quality improvement efforts by service providers [77]. Alongside these developments, recent work on automated school lunch menu planning using machine learning algorithms demonstrates that AI-based systems can efficiently generate nutritionally balanced, cost-effective, and diverse menus, thereby offering a concrete technical

foundation for integrating objective, system-generated meal quality data with perceived service quality evaluations in smart campus dining research [78]. In sum, despite these limitations, the integrated framework and empirical evidence presented here offer a concrete and operational reference point for evaluating and refining smart campus catering policies and provide a valuable starting point for future inquiries into the formation and long-term impacts of service quality in smart public service systems.

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Institutional Review Board Statement: Ethical review and approval were waived for this study by Institution Committee due to Legal Regulations (This study is a questionnaire-based evaluation of service quality and satisfaction in a smart campus dining context. It involves no experimental or interventional procedures, and all responses were collected anonymously without identifying information. According to the relevant ethical research regulations in Taiwan, the following types of research are exempt from Institutional Review Board (IRB) or Ethics Committee review: Non-interactive, non-invasive, and anonymous studies conducted in public settings, where no personally identifiable information can be derived from the collected data. Research using publicly available information, provided that such use aligns with the original purpose for which the information was made public. Studies conducted within a normal educational setting that involve educational assessments, teaching evaluations, or classroom performance appraisals. The present study falls within these exempt categories. It collects anonymous, non-identifiable feedback from participants and involves no intervention or manipulation. The research was conducted in accordance with the ethical principles of the Declaration of Helsinki (1975, revised in 2013).)

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Appendix A

Table A1. Survey Items.

Tangibles (Tan)	Strongly Disagree				Strongly Agree
Tan 1. The Smart Campus Dining Services use modern machines and computer systems to make things work well and easily for students.	1	2	3	4	5
Tan 2. The Smart Campus Dining area looks clean and pretty, and it attracts students to eat there.	1	2	3	4	5
Tan 3. The people who work in Smart Campus Dining Services wear clean, tidy uniforms and look professional.	1	2	3	4	5
Tan 4. The Smart Campus Dining Services have enough good equipment to match the food and services they offer.	1	2	3	4	5

Table A1. Cont.

Tangibles (Tan)	Strongly Disagree				Strongly Agree
Reliability (Rel)					
Rel 5. The Smart Campus Dining Services deliver what they promise.	1	2	3	4	5
Rel 6. When students or teachers have a problem, the Smart Campus Dining Services try their best to help.	1	2	3	4	5
Rel 7. The Smart Campus Dining Services provide help or service right away when needed.	1	2	3	4	5
Rel 8. The Smart Campus Dining Services finish their work or provide meals on time.	1	2	3	4	5
Rel 9. The Smart Campus Dining Services keep their machines and computers working properly.	1	2	3	4	5
Responsiveness (Res)					
Res 10. The Smart Campus Dining Services tell students and teachers when the service is ready or available.	1	2	3	4	5
Res 11. The Smart Campus Dining Services assist students and teachers right away when needed.	1	2	3	4	5
Res 12. The Smart Campus Dining Services are always willing to help students and teachers	1	2	3	4	5
Res 13. The Smart Campus Dining Services respond quickly to student and teacher needs.	1	2	3	4	5
Assurance (Ass)					
Ass 14. The Smart Campus Dining Services make students and teachers feel confident about their service.	1	2	3	4	5
Ass 15. The Smart Campus Dining Services make students and teachers feel safe when using or talking to them.	1	2	3	4	5
Ass 16. The dining staff are kind and polite to students and teachers.	1	2	3	4	5
Ass 17. The dining staff know enough to answer students' and teachers' questions.	1	2	3	4	5
Empathy (Emp)					
Emp 18. The Smart Campus Dining Services care about each student and teacher.	1	2	3	4	5
Emp 19. The Smart Campus Dining Services try to give personal service to students and teachers.	1	2	3	4	5
Emp 20. The Smart Campus Dining Services think about what is best for students and teachers.	1	2	3	4	5
Emp 21. The Smart Campus Dining Services understands students' and teachers' special needs.	1	2	3	4	5
Emp 22. The Smart Campus Dining Services offer convenient meal times for students and teachers.	1	2	3	4	5

References

1. Trang Tran, T.N.; Atas, M.; Felfernig, A.; Stettinger, M. An overview of recommender systems in the healthy food domain. *J. Intell. Inf. Syst.* **2018**, *50*, 501–526. [\[CrossRef\]](#)
2. Trattner, C.; Elswiler, D. Food Recommender Systems: Important Contributions, Challenges and Future Research Directions. *arXiv* **2017**, arXiv:1711.02760. [\[CrossRef\]](#)
3. Freyne, J.; Berkovsky, S. *Intelligent Food Planning: Personalized Recipe Recommendation*; ACM: New York, NY, USA, 2010; pp. 321–324. [\[CrossRef\]](#)
4. El-Dosuky, M.A.; Rashad, M.Z.; Hamza, T.T.; El-Bassiouny, A.H. Food Recommendation using Ontology and Heuristics. *arXiv* **2013**, arXiv:1312.1448. [\[CrossRef\]](#)
5. Ueta, T.; Iwakami, M.; Ito, T.; Xiong, H.; Lee, W.B. *A Recipe Recommendation System Based on Automatic Nutrition Information Extraction*; Springer Nature: Berlin/Heidelberg, Germany, 2011; Volume 7091, pp. 79–90.

6. Al-Nazer, A.; Helmy, T.; Al-Mulhem, M.; Shakshuki, E.; Yasar, A. User's Profile Ontology-based Semantic Framework for Personalized Food and Nutrition Recommendation. *Procedia Comput. Sci.* **2014**, *32*, 101–108. [\[CrossRef\]](#)
7. Saad, A.M.; Rahi, M.R.H.; Islam, M.M.; Rabbani, G. Diet Engine: A real-time food nutrition assistant system for personal-ized dietary guidance. *Food Chem. Adv.* **2025**, *7*, 100978. [\[CrossRef\]](#)
8. Elahi, M.; Ricci, F.; Rubens, N. Active learning strategies for rating elicitation in collaborative filtering: A system-wide perspective. *ACM Trans. Intell. Syst. Technol.* **2013**, *5*, 13. [\[CrossRef\]](#)
9. Shen, P.I.; Huang, D.S.; Wang, J.S.; Yang, Y.T.C. AI-Based Multi-Objective Optimization Algorithm for Intelligent School Lunch Menu Planning System. In *Proceedings of the 2024 12th International Symposium on Computing and Networking Workshops, CANDARW 2024, Okinawa, Japan, 26–29 November 2024*; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2024; pp. 406–408. [\[CrossRef\]](#)
10. Buttle, F. SERVQUAL: Review, critique, research agenda. *Eur. J. Mark.* **1996**, *30*, 8–32. [\[CrossRef\]](#)
11. Ladhari, R. A review of twenty years of SERVQUAL research. *Int. J. Qual. Serv. Sci.* **2009**, *1*, 172–198. [\[CrossRef\]](#)
12. Martilla, J.A.; James, J.C. Importance-Performance Analysis. *J. Mark.* **1977**, *41*, 77–79. [\[CrossRef\]](#)
13. Sampson, S.E.; Showalter, M.J. The Performance-Importance Response Function: Observations and Implications. *Serv. Ind. J.* **1999**, *19*, 1–25. [\[CrossRef\]](#)
14. Deng, W. Using a revised importance–performance analysis approach: The case of Taiwanese hot springs tourism. *Tour. Manag.* **2007**, *28*, 1274–1284. [\[CrossRef\]](#)
15. Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. A Conceptual Model of Service Quality and Its Implications for Future Research. *J. Mark.* **1985**, *49*, 41–50. [\[CrossRef\]](#)
16. Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. SERVQUAL—A Multiple-item scale for measuring consumer perceptions of service quality. *J. Retail.* **1988**, *64*, 12–40.
17. Parasuraman, A.; Berry, L.L.; Zeithaml, V.A. Refinement and reassessment of the SERVQUAL scale. *J. Retail.* **1991**, *67*, 420–450.
18. Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. Reassessment of Expectations as a Comparison Standard in Measuring Service Quality: Implications for Further Research. *J. Mark.* **1994**, *58*, 111–124. [\[CrossRef\]](#)
19. Brady, M.K.; Cronin, J.J. Some New Thoughts on Conceptualizing Perceived Service Quality: A Hierarchical Approach. *J. Mark.* **2001**, *65*, 34–49. [\[CrossRef\]](#)
20. Babakus, E.; Boller, G.W. An empirical assessment of the SERVQUAL scale. *J. Bus. Res.* **1992**, *24*, 253–268. [\[CrossRef\]](#)
21. Carman, J.M. Consumer perceptions of service quality—An assessment of the SERVQUAL dimensions. *J. Retail.* **1990**, *66*, 33–55.
22. Cronin, J.J.; Taylor, S.A. Measuring Service Quality: A Reexamination and Extension. *J. Mark.* **1992**, *56*, 55–68. [\[CrossRef\]](#)
23. Barabino, B.; Deiana, E.; Tilocca, P. Measuring service quality in urban bus transport: A modified SERVQUAL approach. *Int. J. Qual. Serv. Sci.* **2012**, *4*, 238–252. [\[CrossRef\]](#)
24. Awasthi, A.; Chauhan, S.S.; Omrani, H.; Panahi, A. A hybrid approach based on SERVQUAL and fuzzy TOPSIS for evaluating transportation service quality. *Comput. Ind. Eng.* **2011**, *61*, 637–646. [\[CrossRef\]](#)
25. Celik, E.; Aydin, N.; Gumus, A.T. A multiattribute customer satisfaction evaluation approach for rail transit network: A real case study for Istanbul, Turkey. *Transp. Policy* **2014**, *36*, 283–293. [\[CrossRef\]](#)
26. Sever, I. Importance-performance analysis: A valid management tool? *Tour. Manag.* **2015**, *48*, 43–53. [\[CrossRef\]](#)
27. Oh, D.-G.; Elango, B. Quantitative analysis of the publication trends in four decades of SERVQUAL research: A bibliometric approach. *Total Qual. Manag. Bus. Excell.* **2024**, *35*, 297–319. [\[CrossRef\]](#)
28. Azzopardi, E.; Nash, R. A critical evaluation of importance–performance analysis. *Tour. Manag.* **2013**, *35*, 222–233. [\[CrossRef\]](#)
29. Shieh, J.-I.; Wu, H.-H. Applying importance-performance analysis to compare the changes of a convenient store. *Qual. Quant.* **2009**, *43*, 391–400. [\[CrossRef\]](#)
30. Izadi, A.; Jahani, Y.; Rafiei, S.; Masoud, A.; Vali, L. Evaluating health service quality: Using importance performance analysis. *Int. J. Health Care Qual. Assur.* **2017**, *30*, 656–663. [\[CrossRef\]](#)
31. Galeeva, R.B. SERVQUAL application and adaptation for educational service quality assessments in Russian higher education. *Qual. Assur. Educ.* **2016**, *24*, 329–348. [\[CrossRef\]](#)
32. Wade, D.J.; Eagles, P.F.J. The Use of Importance-Performance Analysis and Market Segmentation for Tourism Management in Parks and Protected Areas: An Application to Tanzania's National Parks. *J. Ecotourism* **2003**, *2*, 196–212. [\[CrossRef\]](#)
33. Vaske, J.J.; Kiriakos, R.; Cottrell, S.P.; Khuong, M.N. Importance-Performance and Segmentation: An Application at a Biosphere Reserve in Vietnam. *J. Travel Tour. Mark.* **2009**, *26*, 30–41. [\[CrossRef\]](#)
34. Chu, R.K.S.; Choi, T. An importance-performance analysis of hotel selection factors in the Hong Kong hotel industry: A comparison of business and leisure travellers. *Tour. Manag.* **2000**, *21*, 363–377. [\[CrossRef\]](#)
35. Kim, S.-A.; Park, S.; Kwak, M.; Kang, C. Examining product quality and competitiveness via online reviews: An integrated approach of importance performance competitor analysis and Kano model. *J. Retail. Consum. Serv.* **2025**, *82*, 104135. [\[CrossRef\]](#)
36. Kim, J.; Lee, S.; Lee, J.; Kang, S. Performance evaluation for the outsourcing of military base management services in the Republic of Korea using SERVQUAL and IPA. *Qual. Quant.* **2021**, *55*, 1497–1512. [\[CrossRef\]](#)

37. Mullen, M.R. Diagnosing Measurement Equivalence in Cross-National Research. *J. Int. Bus. Stud.* **1995**, *26*, 573–596. [\[CrossRef\]](#)
38. Levy, P.S.; Lemeshow, S. *Sampling of Populations: Methods and Applications*, 4th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2008.
39. Creswell, J.W.; Plano Clark, V.L. *Designing and Conducting Mixed Methods Research*, 2nd ed.; Sage Publications: Thousand Oaks, CA, USA, 2011.
40. Van den Berg, M.E.L.; Castellote, J.M.; Mahillo-Fernandez, I.; de Pedro-Cuesta, J. Incidence of Spinal Cord Injury Worldwide: A Systematic Review. *Neuroepidemiology* **2010**, *34*, 184–192. [\[CrossRef\]](#)
41. Hu, L.-t.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model.* **1999**, *6*, 1–55. [\[CrossRef\]](#)
42. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [\[CrossRef\]](#)
43. Mohebifar, R.; Hasani, H.; Barikani, A.; Rafiei, S. Evaluating Service Quality from Patients' Perceptions: Application of Importance–performance Analysis Method. *Osong Public Health Res. Perspect.* **2016**, *7*, 233–238. [\[CrossRef\]](#)
44. Jonkisz, A.; Karniej, P.; Krasowska, D. SERVQUAL Method as an “Old New” Tool for Improving the Quality of Medical Services: A Literature Review. *Int. J. Environ. Res. Public Health* **2021**, *18*, 10758. [\[CrossRef\]](#)
45. Seth, N.; Deshmukh, S.G.; Vrat, P. Service quality models: A review. *Int. J. Qual. Reliab. Manag.* **2005**, *22*, 913–949. [\[CrossRef\]](#)
46. Alfatafta, M.; Alsubahi, N.; Alfatafta, H.; Alshawabka, A.; McGarry, A.; Ahmad, A.; Derkacs, E.; Varga, D.; Molics, B. Assessing service quality and its impact on patient experience and satisfaction in prosthetics and orthotics: A SERVQUAL-based cross-sectional study. *BMC Health Serv. Res.* **2025**, *25*, 985. [\[CrossRef\]](#)
47. Minvielle, E.; Fourcade, A.; Ricketts, T.; Waelli, M. Current developments in delivering customized care: A scoping review. *BMC Health Serv. Res.* **2021**, *21*, 575. [\[CrossRef\]](#)
48. Jain, S.; Sundström, M. Toward a conceptualization of personalized services in apparel e-commerce fulfillment. *Res. J. Text. Appar.* **2021**, *25*, 414–430. [\[CrossRef\]](#)
49. Abalo, J.; Varela, J.; Manzano, V. Importance values for Importance–Performance Analysis: A formula for spreading out values derived from preference rankings. *J. Bus. Res.* **2007**, *60*, 115–121. [\[CrossRef\]](#)
50. Adhikari, Y.; Wagley, M.P.; Dahal, N. Developing the Contextualized SERVQUAL Instrument for Measuring the Service Quality of Nepali Resorts: An Application of the Modified Delphi Technique. *SAGE Open* **2023**, *13*. [\[CrossRef\]](#)
51. Ali, M.; Raza, S.A. Service quality perception and customer satisfaction in Islamic banks of Pakistan: The modified SERVQUAL model. *Total Qual. Manag. Bus. Excell.* **2017**, *28*, 559–577. [\[CrossRef\]](#)
52. Arli, D.; van Esch, P.; Weaven, S. The Impact of SERVQUAL on Consumers' Satisfaction, Loyalty, and Intention to Use Online Food Delivery Services. *J. Promot. Manag.* **2024**, *30*, 1159–1188. [\[CrossRef\]](#)
53. Bayraktaroglu, G.; Atrek, B. Testing the superiority and dimensionality of SERVQUAL vs. SERVPERF in higher education. *Qual. Manag. J.* **2010**, *17*, 47–59. [\[CrossRef\]](#)
54. Behdioğlu, S.; Acar, E.; Burhan, H.A. Evaluating service quality by fuzzy SERVQUAL: A case study in a physiotherapy and rehabilitation hospital. *Total Qual. Manag. Bus. Excell.* **2019**, *30*, 301–319. [\[CrossRef\]](#)
55. Bondevik, J.N.; Bennin, K.E.; Babur, Ö.; Ersch, C. A systematic review on food recommender systems. *Expert Syst. Appl.* **2024**, *238*, 122166. [\[CrossRef\]](#)
56. Chen, Y.; Guo, Y.; Fan, Q.; Zhang, Q.; Dong, Y. Health-Aware Food Recommendation Based on Knowledge Graph and Multi-Task Learning. *Foods* **2023**, *12*, 2079. [\[CrossRef\]](#)
57. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, *13*, 319–340. [\[CrossRef\]](#)
58. Demir, P.; Gul, M.; Guneri, A.F. Evaluating occupational health and safety service quality by SERVQUAL: A field survey study. *Total Qual. Manag. Bus. Excell.* **2020**, *31*, 524–541. [\[CrossRef\]](#)
59. Landrum, H.; Prybutok, V.R.; Zhang, X. A comparison of Magal's service quality instrument with SERVPERF. *Inf. Manag.* **2007**, *44*, 104–113. [\[CrossRef\]](#)
60. Park, S.-J.; Yi, Y.; Lee, Y.-R. Heterogeneous dimensions of SERVQUAL. *Total Qual. Manag. Bus. Excell.* **2021**, *32*, 92–118. [\[CrossRef\]](#)
61. Basfirinci, C.; Mitra, A. A cross cultural investigation of airlines service quality through integration of Servqual and the Kano model. *J. Air Transp. Manag.* **2015**, *42*, 239–248. [\[CrossRef\]](#)
62. Lu, S.-J.; Kao, H.-O.; Chang, B.-L.; Gong, S.-I.; Liu, S.-M.; Ku, S.-C.; Jerng, J.-S. Identification of quality gaps in healthcare services using the SERVQUAL instrument and importance–performance analysis in medical intensive care: A prospective study at a medical center in Taiwan. *BMC Health Serv. Res.* **2020**, *20*, 908. [\[CrossRef\]](#)
63. Nguyen Phu, T.; Nguyen Thi Thu, H. Assessment of tourism service quality for traditional craft villages in Da Nang city, Vietnam. *Cogent Soc. Sci.* **2022**, *8*, 2108636. [\[CrossRef\]](#)
64. Nurwahyudi, N.; Rimawan, E. Analysis of customer satisfaction in freight forwarder industry using Servqual, IPA and FMEA methods. *Pomorstvo* **2021**, *35*, 109–117. [\[CrossRef\]](#)

65. Park, S.-J.; Yi, Y. Assessing recommendation on a combination analysis of SERVPERF (or SERVQUAL) and IPA. *Total Qual. Manag. Bus. Excell.* **2022**, *33*, 1777–1798. [\[CrossRef\]](#)
66. Pekmaya, M.; Pulat İmamoğlu, Ö.; Koca, H. Evaluation of healthcare service quality via Servqual scale: An application on a hospital. *Int. J. Healthc. Manag.* **2019**, *12*, 340–347. [\[CrossRef\]](#)
67. Shieh, J.-I.; Wu, H.-H.; Huang, K.-K. A DEMATEL method in identifying key success factors of hospital service quality. *Knowl. Based Syst.* **2010**, *23*, 277–282. [\[CrossRef\]](#)
68. Tumsekcali, E.; Ayyildiz, E.; Taskin, A. Interval valued intuitionistic fuzzy AHP-WASPAS based public transportation service quality evaluation by a new extension of SERVQUAL Model: P-SERVQUAL 4.0. *Expert Syst. Appl.* **2021**, *186*, 115757. [\[CrossRef\]](#)
69. Venkatesh, V.; Raman, R.; Cruz-Jesus, F. AI and emerging technology adoption: A research agenda for operations management. *Int. J. Prod. Res.* **2024**, *62*, 5367–5377. [\[CrossRef\]](#)
70. Wang, Y.-S.; Wu, M.-C.; Wang, H.-Y. Investigating the determinants and age and gender differences in the acceptance of mobile learning. *Br. J. Educ. Technol.* **2009**, *40*, 92–118. [\[CrossRef\]](#)
71. Wider, W.; Tan, F.P.; Tan, Y.P.; Lin, J.; Fauzi, M.A.; Wong, L.S.; Tanucan, J.C.M.; Hossain, S.F.A. Service quality (SERVQUAL) model in private higher education institutions: A bibliometric analysis of past, present, and future prospects. *Soc. Sci. Humanit. Open* **2024**, *9*, 100805. [\[CrossRef\]](#)
72. Yeo, R.K.; Li, J. Beyond SERVQUAL: The competitive forces of higher education in Singapore. *Total Qual. Manag. Bus. Excell.* **2014**, *25*, 95–123. [\[CrossRef\]](#)
73. Gregory, J.L. Applying SERVQUAL: Using service quality perceptions to improve student satisfaction and program image. *J. Appl. Res. High. Educ.* **2019**, *11*, 788–799. [\[CrossRef\]](#)
74. Hsu, W.-K.K.; Yu, H.-F.; Huang, S.-H.S. Evaluating the service requirements of dedicated container terminals: A revised IPA model with fuzzy AHP. *Marit. Policy Manag.* **2015**, *42*, 789–805. [\[CrossRef\]](#)
75. Huang, S.C.; Chiang, W.C.; Yang, Y.T.; Wang, J.S. An image-based AI nutrition analysis platform for food in compartment trays. In *Proceedings of the 2023 14th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI), Koriyama, Japan, 8–13 July 2023*; IEEE: New York, NY, USA, 2023.
76. Seitova, M.; Temirbekova, Z.; Kazykhankyzy, L.; Khalmatova, Z.; Çelik, H.E. Perceived service quality and student satisfaction: A case study at Khoja Akhmet Yassawi University, Kazakhstan. *Front. Educ.* **2024**, *9*, 1492432. [\[CrossRef\]](#)
77. Li-hua, F.; Gao, L.; Liu, X.; Shi-hong, Z.; Hui-tong, M.; Li, Z.; Shi, L.; Ling-ling, W.; Xiao-li, J.; Ha, M.; et al. Patients' perceptions of service quality in China: An investigation using the SERVQUAL model. *PLoS ONE* **2017**, *12*, e0190123. [\[CrossRef\]](#)
78. Lin, H.Y.; Wang, J.S.; Yang, Y.T.C. Automated school lunch menu planning with machine learning algorithms. In *Proceedings of the 2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI 2024), Takamatsu, Japan, 6–12 July 2024*; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2024; pp. 679–680.

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