



AI-Enabled service quality in university foodservice: The mediating role of perceived value in customer satisfaction

Yingduo Wu^{*}
Wen-Hwa Ko[‡]
Ching-Sung Lee[‡]

^{*}Institute of Ph.D. Program in Nutrition and Food Science, Fu Jen Catholic University, No. 510 Zhongzheng Rd., Xinzhuang District, New Taipei City 24205, Taiwan.
Email: wuyingduo777@gmail.com

^{‡‡}Department of Restaurant, Hotel and Institutional Management, Fu Jen Catholic University, No. 510 Zhongzheng Rd., Xinzhuang District, New Taipei City 24205, Taiwan.

[‡]Email: 073770@mail.fju.edu.tw

[‡]Email: 038614@mail.fju.edu.tw

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(* Corresponding Author)

Abstract

AI-enabled foodservice increasingly combines operational benefits with data-related concerns, yet these attributes may shape customer evaluations differently. Focusing on efficiency and privacy as salient performance and data-protection attributes, this study examines their direct and value-mediated associations with customer satisfaction. University canteens provide a high-frequency, routine service setting in which users repeatedly encounter digitally mediated services. Survey data from 596 users at three Chinese universities were analyzed using covariance-based structural equation modeling and bootstrapping. Efficiency was strongly associated with satisfaction both directly and indirectly through perceived value, indicating a substantial dual pathway. Privacy was positively associated with perceived value but had no significant direct association with satisfaction, producing a much weaker, primarily value-mediated pathway. Perceived value was positively associated with satisfaction. These findings reveal attribute asymmetry in AI-enabled foodservice: efficiency operates through strong direct and value-mediated pathways, whereas privacy contributes more modestly and mainly through customers' value evaluations of routine service experiences.

1. Introduction

In this study, AI-enabled foodservice refers to a digitally mediated service environment in which algorithmic or data-driven capabilities support functions such as prediction, recommendation, recognition, adaptive information provision, or automated decision support. This definition distinguishes AI-enabled services from conventional digital systems that merely execute fixed-rule ordering or payment processes. Recent foodservice research reflects a corresponding shift from viewing technology primarily as an operational tool toward examining its implications for consumer experience and behavior (Singh & Vijay, 2026). Meta-analytic evidence further suggests that consumers' responses to AI in foodservice are shaped by factors such as perceived usefulness, service quality, trust, and perceived risk (Lohani Harjani & Batra, 2026). As these technologies become embedded in routine foodservice encounters, an important question is therefore not only whether consumers adopt AI-enabled services, but also how they evaluate the quality and value of these services after adoption.

Electronic service quality provides an established foundation for addressing this question. E-S-QUAL conceptualizes electronic service quality as multidimensional rather than as a single overall judgment, with efficiency and privacy among its core dimensions (Parasuraman, Zeithaml, & Malhotra, 2005). Efficiency captures the ease and speed with which customers complete service processes, whereas privacy concerns the protection of personal and transaction-related information. These attributes remain highly relevant as service interfaces become increasingly intelligent and data dependent. Yet their contributions to customer evaluations need not be equivalent. Efficiency produces immediately observable functional benefits by reducing the time and effort required to complete a transaction. Privacy, by contrast, operates through a less visible aspect of the service encounter: customers exchange personal and transactional information with digital systems but may

not directly observe the effectiveness of the safeguards protecting that information. Treating these attributes as interchangeable manifestations of an overall service-quality judgment may therefore obscure potentially different pathways through which they contribute to customer outcomes.

This distinction is particularly relevant in university canteens. Unlike many discretionary hospitality encounters, university dining services are embedded in users' everyday routines and are characterized by repeated use, relatively stable customer groups, concentrated peak-hour demand, and frequent interaction with digital service systems. Digitally mediated ordering, payment, and information functions, together with AI-supported recommendation and other intelligent service capabilities, can consequently become recurring components of the dining experience. Under such conditions, efficiency may become especially salient because small reductions in transaction time and effort accumulate across repeated interactions and become particularly consequential during peak meal periods. At the same time, repeated digital transactions generate continuing exchanges of personal and transactional data, making privacy relevant even when its benefits are less immediately observable. University canteens therefore provide a useful setting in which to examine whether distinct AI-enabled service attributes enter customer evaluations through different mechanisms.

Understanding these mechanisms requires moving beyond a direct service quality–satisfaction relationship. Perceived value offers an important theoretical bridge. Rather than representing service performance itself, perceived value reflects customers' overall assessment of what they receive relative to what they give up in obtaining a service (Zeithaml, 1988). This benefit–sacrifice perspective suggests that service attributes acquire significance partly through the value customers derive from them. Efficient AI-enabled services can enhance value by reducing temporal, cognitive, and transactional sacrifices. Privacy may enhance value differently, by reducing the informational risks or sacrifices associated with sharing data during digital service encounters. Perceived value can therefore be understood as an evaluative mechanism through which specific service attributes are translated into broader customer judgments. Consistent with this reasoning, service research has long distinguished service quality, perceived value, and satisfaction while demonstrating systematic relationships among them (Cronin, Brady, & Hult, 2000).

Despite increasing scholarly interest in AI-enabled hospitality and foodservice, important questions remain regarding how customers evaluate AI-enabled services after adoption. Research on intelligent service technologies has frequently emphasized technology adoption, acceptance, automation, and operational applications. Although these perspectives explain whether and why customers engage with new technologies, they provide less insight into customer evaluations once such technologies become embedded in recurring service encounters. This distinction matters because technology acceptance and service evaluation represent different stages of the customer experience. Once AI-enabled services become routine, customer evaluations may depend increasingly on the quality and value delivered through the service rather than on technological novelty alone.

This post-adoption perspective also calls for greater attention to specific service attributes. Existing service-quality research often relies on aggregate evaluations or assumes broadly similar downstream consequences across quality dimensions. However, the multidimensional foundation of E-S-QUAL suggests that customers distinguish among different attributes of electronic services (Parasuraman et al., 2005). In AI-enabled environments, efficiency and privacy are particularly relevant because they capture two distinct aspects of the service experience: the operational benefits of streamlined service and the protection of customer information in increasingly data-dependent interactions. Whether these attributes contribute to customer evaluations through similar mechanisms remains unclear.

Perceived value provides a useful mechanism for addressing this question. Although perceived value is well established as a central customer evaluation in service and hospitality research, less attention has been given to whether distinct AI-enabled service attributes translate into satisfaction through different pathways. The issue is therefore not simply whether better service quality is associated with greater satisfaction, but whether efficiency and privacy influence satisfaction directly, indirectly through perceived value, or through both pathways. Examining these relationships provides a more attribute-specific account of post-adoption customer evaluation and allows potential asymmetry between efficiency and privacy to be identified rather than obscured within an aggregate assessment of AI-enabled service quality.

Accordingly, this study examines how efficiency and privacy influence customer satisfaction through perceived value in AI-enabled university canteens. Drawing on the E-S-QUAL framework and the benefit–sacrifice conceptualization of perceived value, efficiency and privacy are treated as distinct service-quality attributes rather than combined into a higher-order quality construct. The study evaluates their relationships with perceived value and customer satisfaction and examines perceived value as a mediating mechanism linking each attribute to satisfaction.

This study contributes to emerging research on AI and technological innovation in foodservice by shifting attention from technology adoption to post-adoption service evaluation. It advances an attribute-level perspective by showing that distinct dimensions of AI-enabled service quality need not contribute to customer evaluations in the same way. In particular, the findings reveal an asymmetric pattern between efficiency and privacy: efficiency exhibits a strong direct and value-mediated association with satisfaction, whereas privacy shows a much weaker relationship that operates primarily through perceived value. This distinction suggests

that the importance of a service-quality attribute should not be equated with its direct effect on satisfaction. By identifying perceived value as a mechanism through which these differentiated effects emerge, the study provides a more nuanced account of post-adoption customer evaluation in AI-enabled foodservice. Evidence from university foodservice further extends this perspective to a high-frequency institutional setting characterized by repeated interactions with AI-enabled service systems.

2. Literature Review and Hypothesis Development

2.1. E-Service Quality in AI-Enabled Foodservice: Efficiency and Privacy as Distinct Service Attributes

Within foodservice, technological innovation increasingly shapes both operational processes and customer-facing service encounters. Singh and Vijay (2026) identify digital ordering, self-service systems, automation, and AI-based applications as part of a broader technology-driven transformation of foodservice, with implications extending from operational efficiency to customer experience. Similarly, Lohani Harjani and Batra (2026) meta-analytic review demonstrates that consumers' responses to AI in foodservice depend on multiple technological and perceptual factors. Together, these developments suggest that evaluating AI-enabled foodservice requires attention not only to technology adoption but also to the quality of the service experience generated through these systems.

Electronic service quality refers to customers' evaluations of the extent to which digital interfaces facilitate effective and satisfactory service delivery (Zeithaml, Parasuraman, & Malhotra, 2002). The growing integration of artificial intelligence (AI) into customer-facing service processes complicates this evaluation. Importantly, AI-enabled describes the broader service environment rather than implying that every customer-facing function is itself an AI application. AI capabilities may be embedded within a broader digital interface to support prediction, recommendation, recognition, adaptive interaction, or decision support, while routine ordering and payment functions may remain conventional digital processes.

The E-S-QUAL framework provides an established basis for such an analysis. Parasuraman et al. (2005) conceptualized core electronic service quality through four dimensions—efficiency, fulfillment, system availability, and privacy—thereby treating e-service quality as multidimensional rather than as a single undifferentiated judgment. This distinction is theoretically consequential. If customers evaluate multiple aspects of an electronic service, individual quality attributes need not carry equal weight or contribute to subsequent evaluations through identical processes. Empirical applications of E-S-QUAL further suggest that its dimensions need not contribute equally to subsequent customer evaluations. For example, Ghosh (2018) found differential relationships between individual E-S-QUAL dimensions and perceived value, reinforcing the need to examine service quality at the attribute level rather than assuming uniform downstream effects. The present study focuses on two core E-S-QUAL dimensions that capture contrasting aspects of AI-enabled service encounters: efficiency and privacy. Efficiency concerns the ease and speed with which users accomplish service tasks, whereas privacy concerns the safeguarding of personal and transaction-related information (Parasuraman et al., 2005). Both are relevant to AI-enabled university canteens, but for different reasons. University dining involves repeated transactions within relatively compressed meal periods, making the time and effort required to interact with digital systems particularly salient. At the same time, repeated ordering and payment generate continuing exchanges of user and transaction data, making information protection an integral, albeit often less observable, aspect of service provision.

This distinction does not imply that efficiency and privacy constitute exhaustive representations of AI-enabled e-service quality. Nor does the study treat them as interchangeable indicators of a higher-order quality construct. Rather, they are examined as selected service attributes whose relationships with subsequent customer evaluations can be identified separately. Such an attribute-level approach shifts the theoretical question from whether “better e-service quality” produces better customer outcomes to a more precise question: how do different characteristics of an AI-enabled service enter customers' evaluations of value and satisfaction?

2.2. Efficiency and Privacy as Sources of Customer Evaluation

Efficiency captures the ease and speed with which customers access information and complete service processes through electronic interfaces (Parasuraman et al., 2005). In an AI-enabled university canteen, this includes locating meal information, navigating ordering functions, completing transactions, and obtaining the required service with minimal effort. These benefits are especially relevant when dining demand is concentrated within limited periods and the same users repeatedly perform similar transactions.

The evaluative significance of efficiency can be understood through the benefit–sacrifice conception of perceived value. Zeithaml (1988) conceptualizes value as an overall assessment of what is received relative to what is given. What customers “give” is not restricted to monetary price; time, effort, inconvenience, and other nonmonetary sacrifices can also enter the evaluation. Efficiency can therefore create value by reducing the resources required to obtain a service. This reasoning is consistent with service research showing that service quality contributes to perceived value by improving the utility customers obtain relative to their sacrifices (Cronin et al., 2000). Empirical research in electronic service settings similarly indicates that service-quality and information-quality attributes contribute to the creation of perceived value (Pearson, Tadisina, & Griffin,

2012) supporting the view that customers incorporate specific characteristics of digital service delivery into broader value judgments. In university canteens, where transaction costs recur across frequent service encounters, reductions in time and effort should make AI-enabled service appear more worthwhile.

H₁: Efficiency is positively associated with perceived value.

Efficiency may also have a more immediate relationship with satisfaction. Whereas perceived value represents an assessment of the trade-off involved in obtaining the service, satisfaction constitutes a broader evaluation of the service experience. Smooth and timely transactions can contribute directly to this evaluation because speed and ease are themselves experienced features of service performance. Prior service research has established links among service quality, value, and satisfaction while maintaining their conceptual distinctiveness (Cronin et al., 2000). Accordingly, efficiency may contribute to satisfaction beyond whatever contribution is transmitted through value.

H₂: Efficiency is positively associated with customer satisfaction.

Privacy concerns customers' perceptions that personal and transaction-related information is appropriately safeguarded during electronic service interactions (Parasuraman et al., 2005). Its importance has increased as digital services rely on customer data to support transactions and increasingly personalized functions. Ordering, payment, recommendation, and consumption records can expose users to privacy concerns, while perceived information protection may reduce privacy-related risk and strengthen trust.

Privacy, however, presents a different evaluative problem from efficiency. Efficiency is typically experienced through the performance of a transaction; effective privacy is often difficult to observe directly because successful protection is partly reflected in the absence of an adverse event. Digital-service research consequently provides a less uniform account of the downstream consequences of privacy than of immediately experienced functional attributes. Some studies associate privacy and security with stronger trust and favorable service evaluations, whereas other e-service studies report weak or nonsignificant relationships between privacy and perceived value. This mixed evidence suggests that privacy should not simply be assumed to operate identically to efficiency.

A value-based perspective provides a rationale for expecting a positive relationship between privacy and perceived value. Perceived value reflects customers' assessment of the benefits received relative to the sacrifices associated with a service. In digital services, such sacrifices may include the disclosure of personal information and associated privacy concerns (Lee & Cranage, 2011) while the collection and use of personal data can increase perceived privacy risk when users feel reduced control over their information (Mutimukwe, Kolkowska, & Grönlund, 2020). Stronger privacy protection may therefore reduce this informational component of perceived sacrifice and improve the overall benefits-sacrifices trade-off. Consistent with this reasoning, prior e-service research has found a positive relationship between security and privacy and perceived value (Pham, Limbu, Le, & Nguyen, 2023). Privacy is therefore expected to be positively associated with the perceived value of AI-enabled foodservice.

H₃: Privacy is positively associated with perceived value.

Privacy may also contribute directly to satisfaction. Customers generally expect digital service providers to manage information responsibly, and confidence in secure information handling can support favorable evaluations of a service provider. At the same time, because effective privacy practices may remain relatively unobtrusive during routine transactions, the magnitude of this direct relationship is theoretically less self-evident than that associated with efficiency. Testing the relationship separately therefore allows the analysis to determine whether a protective service attribute contributes directly to overall satisfaction rather than assuming uniform effects across e-service quality dimensions. Evidence regarding privacy-related attributes is less uniform. Meta-analytic evidence suggests that the relationship between security/privacy and satisfaction varies across electronic service settings (Lionello, Slongo, & Matos, 2020) indicating that protective service attributes may not translate into overall customer evaluations as consistently as more immediately experienced service characteristics.

H₄: Privacy is positively associated with customer satisfaction.

2.3. Perceived Value and Customer Satisfaction

Perceived value provides the conceptual bridge between specific service attributes and customers' broader evaluations. Zeithaml (1988) defines perceived value as an overall assessment of a product or service based on perceptions of what is received and what is given. Sweeney and Soutar (2001) further demonstrate that value is not reducible to low price; consumers may incorporate functional, emotional, social, and other benefits into their assessment of whether an offering is worthwhile. The common implication is that value is an evaluative judgment rather than a property inherent in the service itself.

This distinction is particularly useful for AI-enabled services. Faster transactions or stronger information protection constitute service attributes, but customers must still determine whether the benefits produced by these attributes justify the resources exchanged during service use. Prior research supports this attribute-to-value relationship in digital service contexts. For example, Jiang, Jun, and Yang (2016) found that multiple e-

service quality dimensions, including ease of use and security, were positively associated with customer-perceived value in B2C e-commerce. Perceived value therefore captures the conversion from attribute-level service performance to an overall benefit–sacrifice assessment.

Perceived value is also conceptually distinct from customer satisfaction. Whereas value concerns the relative benefits and sacrifices associated with consumption, satisfaction reflects an overall evaluation formed in response to the service experience. Cronin et al. (2000) empirically distinguished service quality, service value, and satisfaction while showing that value contributes to customer evaluations and behavioral intentions. Similar relationships have been documented in foodservice and hospitality contexts, where perceived or experiential value has been shown to contribute to customer satisfaction (Ghosh, Jhamb, & Dhiman, 2023; Li, Mahasuweerachai, & Suttikun, 2026).

Applied to university canteens, this reasoning suggests that customers who regard AI-enabled services as delivering worthwhile benefits relative to the time, effort, monetary resources, and other sacrifices involved in their use should form more favorable overall evaluations of those services. Perceived value should therefore provide a proximal basis for customer satisfaction.

H₅: Perceived value is positively associated with customer satisfaction.

2.4. The Mediating Role of Perceived Value

The preceding arguments imply more than a sequence of positive associations. They position perceived value as an evaluative mechanism linking concrete service attributes with a broader post-consumption judgment. Service-quality attributes describe characteristics of the service customers encounter; perceived value captures whether the benefits generated by those characteristics justify the sacrifices associated with obtaining them; satisfaction subsequently reflects customers' overall evaluation of the service experience. This distinction provides the theoretical basis for mediation.

For efficiency, the proposed mechanism originates primarily in reductions in transaction sacrifice. Easier and faster service lowers the time, effort, and inconvenience required to accomplish dining tasks. These reductions increase the perceived return obtained from the service, which should subsequently strengthen satisfaction. At the same time, because ease and speed are directly experienced aspects of service performance, efficiency may retain a relationship with satisfaction after perceived value is taken into account. Perceived value is therefore expected to transmit part of the relationship between efficiency and satisfaction rather than being assumed to exhaust all possible mechanisms.

H_{6a}: Perceived value mediates the positive relationship between efficiency and customer satisfaction.

For privacy, the proposed mechanism concerns informational sacrifice. Users of AI-enabled services repeatedly provide transaction-related and potentially personal information, but the benefits of safeguarding that information are often less directly visible than improvements in transaction speed. Privacy can nevertheless improve the terms of the service exchange by reducing perceived informational exposure and uncertainty. When users incorporate this protection into their assessment of whether the service is worthwhile, stronger perceived value should subsequently contribute to greater satisfaction.

Importantly, this argument does not require privacy and efficiency to affect satisfaction in the same manner. Rather, it predicts a common value-based route while allowing their direct relationships with satisfaction to differ. This distinction is consistent with an attribute-level view of e-service quality: different attributes can contribute to the same downstream evaluation through pathways of different strength.

H_{6b}: Perceived value mediates the positive relationship between privacy and customer satisfaction.

Taken together, the proposed framework conceptualizes customer evaluation as a progression from service attributes to value assessment and, ultimately, satisfaction, while allowing attribute-specific direct effects. It therefore integrates the multidimensional logic of E-S-QUAL with the benefit–sacrifice perspective on perceived value rather than treating service quality as an aggregate predictor of satisfaction. In doing so, the framework provides a parsimonious basis for examining whether operational and protective characteristics of AI-enabled services are translated into customer evaluations in equivalent or different ways.

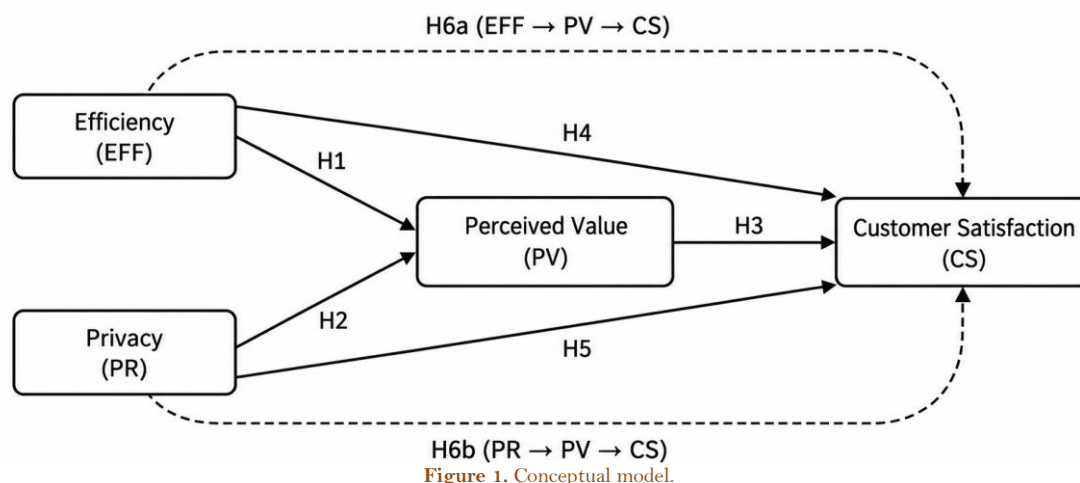


Figure 1. Conceptual model.

3. Methodology

3.1. Research Design

This study employed a quantitative, cross-sectional survey design to examine customer evaluations of AI-enabled university canteen services. The target population comprised users with prior experience of AI-enabled university canteen services, as meaningful evaluations of the focal service attributes required respondents to have interacted with such systems. The term AI-enabled refers to the service environment in which AI-supported capabilities were embedded; it does not imply that every transaction or every customer-facing function used by each respondent was itself generated by AI.

Drawing on the theoretical framework developed in the preceding section, the research model focuses on two selected dimensions of routine electronic service quality—efficiency and privacy—and examines their relationships with perceived value and customer satisfaction. Efficiency and privacy are modeled as distinct exogenous constructs rather than as indicators of an aggregate higher-order electronic service-quality construct. Perceived value is specified as an endogenous mediator, while customer satisfaction represents the final endogenous construct. The model therefore examines both the direct relationships of efficiency and privacy with customer satisfaction and their indirect relationships through perceived value.

3.2. Measurement Development

The questionnaire was developed using established measurement scales from the electronic service quality and consumer behavior literature. The original survey incorporated a broader set of service-quality and customer-evaluation measures. Items were adapted to the context of AI-enabled university canteen services while retaining the conceptual meanings of their source constructs.

Efficiency (EFF) and privacy (PR) were derived from the core E-S-QUAL framework developed by Parasuraman et al. (2005). E-S-QUAL conceptualizes routine electronic service quality through efficiency, fulfillment, system availability, and privacy, while distinguishing these dimensions from recovery-specific service attributes captured by E-RecS-QUAL. In the final measurement specification, efficiency was measured using eight items assessing the ease and speed with which users could locate information, navigate the service interface, and complete service processes. Privacy was measured using three items assessing the protection of personal, payment, and transaction-related information.

Perceived value (PV) was theoretically grounded in the benefit–sacrifice perspective of Zeithaml (1988) with measurement items adapted and contextualized from the PERVAL framework of Sweeney and Soutar (2001). The original PERVAL scale conceptualizes consumer value as a multidimensional construct encompassing quality/performance, emotional, price/value-for-money, and social value. Rather than reproducing the complete 19-item PERVAL scale, the present study initially used four context-specific items to capture respondents' overall evaluations of the benefits, sacrifices, and worth associated with AI-enabled university canteen services. Following measurement-model refinement, three indicators were retained in the final specification.

Customer satisfaction (CS) was operationalized with reference to the customer-satisfaction framework of Fornell, Johnson, Anderson, Cha, and Bryant (1996) supplemented by the performance-based service perspective of Cronin and Taylor (1992). Four context-specific items were initially used to capture respondents' evaluations of their decision to use and overall experience with AI-enabled university canteen services. Following measurement-model refinement, three indicators were retained in the final specification.

All focal constructs were assessed using five-point Likert-type scales ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), with higher scores indicating more favorable evaluations. The retained measurement items and their respective sources are reported in Table 1.

Table 1. Measurement constructs and theoretical sources.

Construct	Initial items	Final items	Source
Efficiency (EFF)	8	8	Parasuraman et al. (2005)
Privacy (PR)	3	3	Parasuraman et al. (2005)
Perceived Value (PV)	4	3	Sweeney and Soutar (2001)
Customer Satisfaction (CS)	4	3	Fornell et al. (1996) and Cronin and Taylor (1992)

Note: PV and CS were initially measured using four indicators each. One indicator from each construct was removed during measurement-model refinement, resulting in three retained indicators for each construct in the final measurement model.

3.3. Questionnaire Design and Translation

The questionnaire consisted of two sections. The first collected demographic and usage-related information, including respondents' gender, age, education level, frequency of university canteen use, and experience with AI-enabled canteen services. These variables were used to characterize the sample and provide contextual information regarding respondents' dining and technology-use experience.

The second section contained multi-item measures assessing the focal constructs as well as additional service-evaluation constructs included in the broader survey. Because the source measurement scales were originally developed in English whereas the survey was administered in Chinese, a translation and back-translation procedure was employed to enhance linguistic and conceptual equivalence between the source measures and the Chinese questionnaire (Brislin, 1980). The translated items were subsequently reviewed for semantic clarity and contextual appropriateness. Minor wording modifications were made where necessary to reflect AI-enabled university canteen services while preserving the conceptual content of the original measures.

3.4. Sampling and Data Collection

Data were collected from users with prior experience of AI-enabled university canteen services at three universities in China: Jilin University, China Agricultural University, and Zhejiang University. The three universities were purposively selected because they are major research-intensive institutions with comparatively strong institutional and technological resources and provided established university foodservice environments in which AI-enabled and digitally mediated service technologies had been implemented. This made them appropriate research sites for examining customer evaluations based on actual prior experience rather than hypothetical exposure to AI-enabled foodservice. The selection also provided variation in institutional settings across Northeast China, northern China, and the eastern coastal region. Thus, the multi-site design was intended primarily to ensure access to relevant AI-enabled service contexts while reducing dependence on the conditions of a single university or region. It was not intended to provide a statistically representative sample of all Chinese universities.

Because meaningful evaluations of efficiency, privacy, perceived value, and customer satisfaction require prior interaction with the focal service environment, purposive sampling was employed to recruit respondents with relevant experience of AI-enabled university canteen services. Data were collected from October 17, 2025, to March 31, 2026, via WJX.cn, a widely used online survey platform in China. Respondents were instructed to answer the questionnaire based on their own experiences and actual perceptions of AI-enabled university canteen services.

Participation was voluntary and anonymous. The questionnaire did not request personally identifiable information, and respondents were informed that the data would be used solely for academic research purposes. A total of 596 completed responses were obtained and included in the analysis. The demographic characteristics of the sample are presented in Table 2.

Table 2. Sample characteristics.

Characteristic	Category	n	%
Gender	Male	292	49.0
	Female	304	51.0
Education	Junior high school or below	2	0.3
	High school/vocational school	9	1.5
	Junior college	106	17.8
	Undergraduate	335	56.2
	Postgraduate or above	144	24.2
Age	≤19	65	10.9
	20–25	435	73.0
	26–29	78	13.1
	30–34	8	1.3
	35–39	1	0.2

	40–49	5	0.8
	50–59	2	0.3
	≥60	2	0.3
Weekly canteen use	Once	45	7.6
	2–3 times	113	19.0
	4–5 times	137	23.0
	6–10 times	152	25.5
	≥11 times	149	25.0
Total		596	100.0

3.5. Ethical Considerations

This study employed an anonymous, non-invasive questionnaire and did not collect personally identifiable or sensitive information. Research ethics were incorporated into the study design by ensuring voluntary participation, anonymity and confidentiality of responses, the right to discontinue participation at any time, and the exclusion of sensitive personal data. Before beginning the questionnaire, all participants were informed of the purpose of the study, the voluntary nature of participation, and the intended academic use of the collected data. Electronic informed consent was obtained from all participants prior to participation.

3.6. Measurement Specification

The questionnaire was developed as part of a broader investigation of users' evaluations of AI-enabled university canteen services and therefore contained measures beyond those examined in the present study. Measurement refinement was conducted prior to structural-model estimation and was guided jointly by conceptual correspondence, item performance, reliability, convergent validity, and discriminant validity rather than by the statistical significance of the hypothesized structural paths, consistent with recommendations that scale purification should integrate statistical diagnostics with substantive judgment regarding item content (Wieland, Kock, & Josiassen, 2018). Perceived value and customer satisfaction were initially represented by four indicators each. Assessment of the initial measurement specification indicated comparatively limited empirical distinctiveness between these two constructs, prompting further item-level examination. The refinement process jointly considered discriminant-validity diagnostics and the conceptual specificity of individual indicators rather than relying solely on a single statistical cutoff. PV1 and CS4 exhibited comparatively limited construct specificity. Their removal improved the empirical distinction between perceived value and customer satisfaction while preserving the conceptual coverage and internal consistency of the retained indicators. The refined specifications therefore retained three indicators for each construct.

The final measurement specification comprised efficiency (eight indicators), privacy (three indicators), perceived value (three indicators), and customer satisfaction (three indicators). These constructs were modeled as distinct first-order latent variables and were evaluated using confirmatory factor analysis before estimation of the structural model.

3.7. Data Analysis

Data were analyzed in R (version 4.6.1) using the *lavaan* package for covariance-based structural equation modeling (CB-SEM) (Rosseel, 2012). Following the two-step approach to structural equation modeling recommended by Anderson and Gerbing (1988) the measurement model was first evaluated using confirmatory factor analysis before the hypothesized structural relationships were estimated.

The adequacy of the measurement model was assessed using standardized factor loadings, internal consistency reliability, composite reliability (CR), average variance extracted (AVE), and discriminant validity. CR and AVE were examined as indicators of construct reliability and convergent validity, respectively. Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT) (Cheung, Cooper-Thomas, Lau, & Wang, 2024; Henseler, Ringle, & Sarstedt, 2015). Because discriminant validity should not be determined solely by applying a mechanical cutoff to a single statistic, HTMT results were interpreted together with the conceptual distinctiveness of the constructs and the broader measurement-model evidence (Rönkkö & Cho, 2022). Overall model fit was assessed using the chi-square statistic (χ^2), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR).

Following evaluation of the measurement model, latent-variable SEM was used to estimate the hypothesized relationships among efficiency, privacy, perceived value, and customer satisfaction. Standardized path coefficients were used to assess the direction and magnitude of the hypothesized relationships, while coefficients of determination (R^2) were reported for the endogenous constructs. Finally, the mediating role of perceived value was examined by estimating the specific indirect effects of efficiency and privacy on customer satisfaction through perceived value. Indirect effects were evaluated using 5,000 bootstrap resamples and 95% percentile bootstrap confidence intervals. Evidence for an indirect effect was inferred when the corresponding bootstrap confidence interval did not include zero.

4. Results

4.1. Sample Characteristics

A total of 596 responses were included in the final analysis. As shown in Table 2, the sample was nearly balanced by gender, comprising 292 male respondents (49.0%) and 304 female respondents (51.0%). Most respondents were aged 20–25 years (73.0%), followed by those aged 26–29 years (13.1%) and those aged 19 years or younger (10.9%). Respondents aged 30 years or above represented only a small proportion of the sample.

Respondents with undergraduate-level education constituted the largest group (56.2%), followed by those with postgraduate education or above (24.2%) and those with junior-college education (17.8%). Regarding university canteen use, 25.5% of respondents reported using the canteen 6–10 times per week, 25.0% reported 11 times or more, and 23.0% reported 4–5 times per week. Thus, a substantial proportion of respondents were frequent users of the university canteen service environment.

4.2. Measurement Model

Before testing the hypothesized structural relationships, confirmatory factor analysis (CFA) was conducted to assess the four-factor measurement model comprising efficiency, privacy, perceived value, and customer satisfaction. The initial measurement specification included four indicators each for perceived value and customer satisfaction. Discriminant-validity assessment indicated comparatively high empirical overlap between these constructs (HTMT = .924). Item-level examination was therefore undertaken as described in Section 3.6. Following the removal of PV1 and CS4, the PV–CS HTMT ratio decreased to .892 while both constructs retained satisfactory internal consistency and convergent validity. The following results therefore refer to the refined four-factor measurement model.

As reported in Table 3, all standardized factor loadings were statistically significant ($p < .001$) and ranged from .795 to .894. The loadings for efficiency ranged from .814 to .844, those for privacy from .837 to .894, those for perceived value from .795 to .830, and those for customer satisfaction from .826 to .851.

Internal consistency and convergent validity were also supported. Cronbach's alpha coefficients ranged from .849 to .946, composite reliability (CR) values ranged from .850 to .946, and average variance extracted (AVE) values ranged from .654 to .747. Specifically, the CR and AVE values were .946 and .688 for efficiency, .898 and .747 for privacy, .850 and .654 for perceived value, and .879 and .707 for customer satisfaction, respectively. These results indicated satisfactory reliability and convergent validity for the four constructs.

Table 3. Reliability and Convergent Validity.

Construct	Item	Loading	α	CR	AVE
EFF	EFF1	0.830	0.946	0.946	0.688
	EFF2	0.842			
	EFF3	0.821			
	EFF4	0.814			
	EFF5	0.816			
	EFF6	0.829			
	EFF7	0.844			
	EFF8	0.843			
PR	PR1	0.837	0.897	0.898	0.747
	PR2	0.894			
	PR3	0.862			
PV	PV2	0.795	0.849	0.850	0.654
	PV3	0.802			
	PV4	0.830			
CS	CS1	0.845	0.878	0.879	0.707
	CS2	0.851			
	CS3	0.826			

Evidence of discriminant validity was evaluated jointly from the four-factor CFA solution and the HTMT ratios. In the refined measurement model, HTMT values ranged from .590 to .892. The highest ratio was observed between perceived value and customer satisfaction (.892), indicating that these constructs remained relatively closely related. This result was therefore interpreted together with their conceptual distinction, factor structure, and the broader measurement-model evidence rather than on the basis of a single cutoff criterion.

Table 4. HTMT.

Construct	EFF	PR	PV	CS
EFF	—			
PR	0.706	—		
PV	0.861	0.670	—	
CS	0.857	0.590	0.892	—

Note: Values refer to the refined measurement model.

The overall CFA also demonstrated satisfactory fit to the observed data: $\chi^2(113) = 196.720$, $\chi^2/df = 1.741$, CFI = 0.990, TLI = 0.988, RMSEA = 0.035, and SRMR = 0.018. Taken together, the factor loadings, reliability estimates, convergent-validity evidence, discriminant-validity assessment, and overall model fit provided adequate support for proceeding to structural-model estimation.

Table 5. Fit Indices for the Final Measurement Model

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	SRMR
CFA measurement model	196.720	113	1.741	0.990	0.988	0.035	0.018

4.3. Structural Model and Hypothesis Testing

The structural relationships were subsequently estimated to test H1–H5. As reported in Table 6, efficiency was positively associated with perceived value ($\beta = .774$, $p < .001$), supporting H1. Privacy was also positively associated with perceived value, although the magnitude of this relationship was considerably smaller ($\beta = .120$, $p = .040$); therefore, H2 was supported.

Perceived value was positively associated with customer satisfaction ($\beta = .606$, $p < .001$), supporting H3. Efficiency also retained a significant positive direct association with customer satisfaction after perceived value was included in the structural model ($\beta = .409$, $p < .001$), providing support for H4.

In contrast, the direct association between privacy and customer satisfaction was negative and did not reach the conventional .05 significance level ($\beta = -.102$, $p = .062$). H5 was therefore not supported. Accordingly, although privacy was positively associated with perceived value, the results did not provide evidence of a direct positive association between privacy and satisfaction in the estimated model.

The model explained 74.5% of the variance in perceived value ($R^2 = .745$) and 82.9% of the variance in customer satisfaction ($R^2 = .829$).

Table 6. Structural Model and Hypotheses.

Hypothesis	Path	Standardized β	p	Result
H1	EFF $\rightarrow$ PV	0.774***	<0.001	Supported
H2	PR $\rightarrow$ PV	0.120*	0.040	Supported
H3	PV $\rightarrow$ CS	0.606***	<0.001	Supported
H4	EFF $\rightarrow$ CS	0.409***	<0.001	Supported
H5	PR $\rightarrow$ CS	−0.102	0.062	Not supported

Note. * $p < 0.05$, *** $p < 0.001$

4.4. Mediating Role of Perceived Value

H6a and H6b examined whether perceived value transmitted the associations of efficiency and privacy with customer satisfaction. Indirect effects were evaluated using 5,000 bootstrap resamples and 95% percentile bootstrap confidence intervals. Evidence for an indirect effect was inferred when the corresponding bootstrap confidence interval did not include zero.

As shown in Table 7, the indirect effect of efficiency on customer satisfaction through perceived value was positive ($B = .481$, Boot SE = .090; standardized indirect effect = .469). Its 95% bootstrap confidence interval, [.325, .678], did not include zero, providing support for H6a. At the same time, the direct efficiency–satisfaction path remained positive and statistically significant ($\beta = .409$, $p < .001$). Thus, the results indicate that efficiency was associated with satisfaction through both a direct pathway and an indirect pathway through perceived value.

The indirect effect of privacy on customer satisfaction through perceived value was substantially smaller ($B = .064$, Boot SE = .033; standardized indirect effect = .073). The 95% percentile bootstrap confidence interval, [−.003, .132], narrowly excluded zero. Thus, the bootstrap analysis provided evidence of a small indirect effect, although the lower bound of the confidence interval was close to zero. Accordingly, H6b received modest support and should be interpreted cautiously.

Importantly, the pattern for privacy differed from that observed for efficiency. Privacy showed a small positive association with perceived value ($\beta = .120$, $p = .040$), and perceived value was positively associated with satisfaction ($\beta = .606$, $p < .001$), whereas the direct privacy–satisfaction path was not statistically significant ($\beta = -.102$, $p = .062$). Following Zhao, Lynch, and Chen (2010) the efficiency pathway was

consistent with complementary mediation because both the direct and indirect effects were positive and statistically supported. The privacy pathway, by contrast, showed a pattern suggestive of indirect-only mediation: the direct privacy–satisfaction relationship was not statistically significant, whereas the 95% percentile bootstrap confidence interval for the indirect effect narrowly excluded zero. Given the small magnitude of the indirect effect and the proximity of the lower confidence bound to zero, this pattern should be interpreted cautiously.

Table 7. Bootstrap Mediation.

Hypothesis	Indirect effect	B	Boot SE	Std. indirect effect	95% percentile bootstrap CI
H6a	EFF → PV → CS	0.481	0.090	0.469	[0.325, 0.678]
H6b	PR → PV → CS	0.064	0.033	0.073	[0.003, 0.132]

Note: Bootstrap confidence intervals are 95% percentile confidence intervals based on 5,000 resamples.

5. Discussion

This study examined how two attributes of AI-enabled university foodservice—efficiency and privacy—are associated with perceived value and customer satisfaction. The findings reveal a clear asymmetry between the two attributes. Efficiency was strongly associated with perceived value and retained a direct association with satisfaction, whereas privacy showed a considerably weaker association with perceived value and no significant direct association with satisfaction. These findings contribute to emerging foodservice research on technology-enabled customer experience by demonstrating that individual AI-enabled service attributes do not necessarily generate equivalent consumer responses.

The strong role of efficiency is consistent with the benefit–sacrifice view of perceived value (Zeithaml, 1988). Efficient digital services reduce time, effort, and inconvenience, thereby improving the benefits users receive relative to their sacrifices. This mechanism is particularly relevant in university canteens, where users repeatedly complete relatively standardized transactions under time constraints. Prior research similarly links service quality with value and satisfaction (Cronin et al., 2000) while recent foodservice research emphasizes efficiency as an important feature of technology-mediated restaurant experiences (Cavusoglu, Collins, DeMicco, & Cobanoglu, 2025). The significant direct and indirect relationships observed here therefore suggest that efficiency contributes to satisfaction both as an immediately experienced service benefit and through its contribution to perceived value.

Privacy followed a different pattern. Its positive but relatively small association with perceived value, together with its nonsignificant direct relationship with satisfaction, does not imply that privacy is unimportant. Rather, privacy may be less immediately observable than efficiency during routine service encounters. Successful privacy protection is often experienced through the absence of problems, whereas efficiency is directly experienced whenever users search, order, or pay. Prior e-service research likewise suggests that individual service-quality dimensions may have different downstream consequences across contexts (Lionello et al., 2020). In the present setting, privacy therefore appears to contribute primarily through users' value evaluations rather than as an immediate source of satisfaction.

The mediating results reinforce the importance of perceived value as an evaluative mechanism. Service research has long positioned value between service-quality evaluations and satisfaction (Cronin et al., 2000). Recent evidence from AI-enabled restaurant settings similarly shows that service and smart-service quality contribute to experiential value, which subsequently relates strongly to satisfaction (Li et al., 2026). The mediation patterns also differed. Efficiency exhibited complementary mediation, with perceived value transmitting part of its association with satisfaction while a significant direct association remained. Privacy, by contrast, showed a small indirect association with satisfaction through perceived value, whereas its direct relationship with satisfaction was not statistically significant. Although this pattern is consistent with indirect-only mediation, the small magnitude of the indirect effect and the proximity of the lower confidence bound to zero warrant cautious interpretation.

5.1. Theoretical Contributions

Recent JFBR research has highlighted the expanding role of technological innovation and AI in shaping foodservice operations, adoption, and consumer experience (Lohani Harjani & Batra, 2026; Singh & Vijay, 2026). The present study extends this stream by shifting attention from technology adoption to post-adoption service evaluation. Whereas recent foodservice research has identified usefulness, trust, quality, and perceived risk as important antecedents of AI adoption (Lohani Harjani & Batra, 2026) this study examines how users evaluate AI-enabled services after interacting with them in routine service settings. In doing so, it positions AI-enabled foodservice not only as a technology-adoption context but also as an ongoing service environment in which customers form evaluations based on experienced service performance.

The findings further support an attribute-level perspective on e-service quality. E-S-QUAL conceptualizes electronic service quality as multidimensional (Parasuraman et al., 2005) and prior research suggests that individual service-quality attributes need not contribute uniformly to customer evaluations. The

substantially different patterns observed for efficiency and privacy reinforce the analytical value of treating these dimensions as distinct service attributes rather than subsuming them within an aggregate quality construct. Efficiency was strongly associated with both perceived value and satisfaction, whereas privacy showed a much weaker association with perceived value and no significant direct association with satisfaction. This asymmetry indicates that the importance of a service-quality attribute should not be equated with the strength of its direct relationship with satisfaction. Privacy may remain relevant to customers' evaluation of AI-enabled services even when its contribution to satisfaction operates primarily through perceived value.

Perceived value therefore provides an important evaluative mechanism for explaining how specific service attributes are translated into broader customer evaluations. Rather than functioning merely as another antecedent of satisfaction, perceived value helps explain how customers convert attribute-level service experiences into overall judgments of whether an AI-enabled service is worthwhile. The mediation results further show that this conversion is attribute dependent: efficiency was associated with satisfaction through both a substantial value-mediated pathway and a direct pathway, whereas the contribution of privacy was considerably weaker and primarily value mediated. Taken together, these findings extend service-quality research by showing that distinct attributes within the same AI-enabled service environment can reach customer satisfaction through asymmetric evaluative pathways.

5.2. Practical Implications

For universities and AI dining-service providers, the findings indicate that reducing service friction should be a priority. Ordering interfaces should enable users to locate information, navigate options, and complete transactions quickly, particularly during peak meal periods. Technology investment should therefore be evaluated not simply by the sophistication of AI functions but by whether those functions reduce users' time, effort, and inconvenience.

Privacy should nevertheless remain an essential service requirement. Because effective privacy protection may be relatively invisible, providers should combine substantive safeguards with clear communication regarding data collection, use, protection, and user control. Making otherwise unobtrusive privacy practices understandable may help users recognize their contribution to overall service value.

5.3. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design does not establish temporal or causal relationships; longitudinal or experimental research could provide stronger evidence. Second, the study was conducted in AI-enabled university canteens at three Chinese universities, limiting generalization to other populations and service environments. Future research could test the framework in commercial restaurants, food-delivery services, or other AI-mediated settings.

Third, the study examined users' evaluations of an AI-enabled service environment but did not independently verify which specific AI capability each respondent encountered during individual transactions. The findings should therefore be interpreted as evidence regarding service-quality attributes within an AI-enabled foodservice context rather than as evidence of the effects of a specific AI technology. Future research could use feature-level screening questions, system logs, or experimental designs to link customer evaluations to specific AI capabilities.

Fourth, the final measurement specification was refined and evaluated using the same sample. Independent-sample replication is therefore needed to assess the stability of the refined three-item measures, particularly because the empirical distinction between perceived value and customer satisfaction remained comparatively close. Finally, the study examined selected routine e-service-quality attributes rather than the complete E-S-QUAL framework. Future studies could examine additional routine attributes or investigate recovery-related dimensions among users who have actually experienced service failures.

6. Conclusion

This study demonstrates that efficiency and privacy are associated with customer evaluations of AI-enabled university foodservice through distinct pathways. Efficiency was strongly associated with satisfaction through both direct and value-mediated pathways, whereas privacy showed a substantially weaker relationship with satisfaction that operated primarily through perceived value.

These findings highlight the value of an attribute-level perspective on AI-enabled e-service quality rather than assuming that different service-quality dimensions contribute uniformly to customer evaluations. In routine, high-frequency service environments, customers' evaluations of AI-enabled services appear to depend not simply on the presence of technology, but on how particular service attributes translate into perceived value and satisfaction. By distinguishing these pathways, the study provides a more differentiated understanding of how AI-enabled service environments contribute to everyday customer experiences.

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