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Title

Framing the Attitude-Behavior Gap as Structural Disconnection: A Dual-Level Diagnostic of Customer Experience Quality

Abstract

Retail and consumer-service managers often face an attitude–behavior gap: high satisfaction does not translate into higher share of wallet (SoW). This study frames this gap as structural disconnection and examines the links among customer experience quality (EXQ), relative satisfaction (RSAT), and SoW in Japan. Survey data from repeat customers of face-to-face services (n = 532) were analyzed using structural equation modeling (SEM) and psychological network analysis (PNA). SEM supports EXQ as a higher-order construct and shows a clear positive association between EXQ and RSAT, but the RSAT → SoW path is small and explains little variance in SoW (R^2 = .008). In the network, SoW is isolated from a dense EXQ–RSAT core, suggesting that wallet allocation is structurally disconnected from experience evaluations within the measured system. We propose a dual-level diagnostic workflow that uses SEM to assess global associations and PNA to map microstructure and the (dis)connection of behavioral outcomes, providing context-specific evidence from Japan.

Keywords

Customer experience; Customer experience quality (EXQ); Share of wallet; Psychological network analysis; Structural disconnection

1. Introduction

Retail and consumer-service managers face a persistent challenge: why do high satisfaction scores often fail to translate into greater share of wallet (SoW)? This long-standing attitude–behavior gap calls into question the return on customer experience (CX) investments (Jones and Sasser, 1995; Kumar et al., 2013). While CX is increasingly viewed as a source of advantage, provider-centric scales have struggled to capture the cumulative, end-to-end nature of customer journeys. Recent work therefore advances customer experience quality (EXQ) as a holistic, journey-spanning construct (De Keyser et al., 2020; Klaus and Maklan, 2012, 2013; Lemon and Verhoef, 2016).

Despite this progress, the conditions under which CX translates into spending allocation remain unclear. Relative satisfaction (RSAT) and SoW are argued to be more behavior-proximal than absolute satisfaction, yet findings on the EXQ–RSAT–SoW chain are mixed (Keiningham et al., 2011; Aksoy et al., 2015). Latent-variable models, such as structural equation modeling (SEM), illuminate macro-level associations but may mask interactions among specific experience elements. Complementing this macro-level lens, psychological network analysis (PNA) maps item-level conditional relations, offering a diagnostic view of how evaluations connect—or fail to connect—to behavior (McColl-Kennedy et al., 2015, 2022; Epskamp and Fried, 2018; Borsboom et al., 2021).

Context likely shapes how evaluative judgments translate into spending. Prior evidence on the satisfaction–loyalty link is largely drawn from Western, low-context markets, whereas Japan's high-context setting may place greater weight on relational ease and feeling understood when customers evaluate their experiences and form comparative judgments (Minami and Dawson, 2008). Accordingly, this study provides context-specific evidence from Japan and discusses how the observed pattern aligns with, or diverges from, prior findings reported in predominantly Western settings.

This study integrates SEM and PNA with Japanese repeat-customer data to ask: (1) Does EXQ predict RSAT, and does RSAT predict SoW? (2) When modeled at the item level, is SoW structurally integrated into the EXQ–RSAT system, or does it appear weakly connected or disconnected, consistent with structural disconnection? (3) Which specific experience elements are structurally central and which bridge across the brand, service-provider, and post-purchase experience domains? Structural disconnection is defined as weak or absent connectivity between SoW and an EXQ–RSAT evaluative core within an item-level network. This concept concerns inter-item dependencies and is distinct from actor-level constructs (e.g., structural holes/brokerage).

This study contributes in three ways. First, it frames the attitude–behavior gap as structural disconnection—weak or absent connectivity of SoW relative to an EXQ–RSAT evaluative core in an item-level network. Second, it introduces a dual-level diagnostic workflow integrating SEM (macro-level associations) and PNA (micro-level interdependencies). Third, it outlines a practice-oriented playbook with structural metrics (e.g., SoW connectivity).

2. Literature Review

2.1 Customer Experience Quality (EXQ) and its Outcomes

The provider-centric service quality paradigm (e.g., SERVQUAL; Parasuraman et al., 1988) has been widely critiqued for failing to capture the holistic and subjective nature of CX across the customer journey (e.g., Cronin and Taylor, 1992; Klaus and Maklan, 2013; Lemon and Verhoef, 2016). More broadly, customer experience research has expanded rapidly but remains conceptually fragmented; integrative frameworks have been proposed to reconcile traditions that view CX as responses to firm-controlled stimuli versus as part of broader consumption processes (Becker and Jaakkola, 2020). In response, scholars developed EXQ, a multidimensional construct assessing experiences before, during, and after service interactions (Klaus and Maklan, 2012, 2013). This study adopts the established second-order EXQ model, in which pre-purchase brand experience (BRE), service-provider experience (SPE), and post-purchase experience (PPE) load on a single higher-order evaluation of CX (Klaus, 2014; Kuppelwieser and Klaus, 2021b). This framework has been validated as a robust operationalization of CX across diverse service and cultural contexts (e.g., Imhof and Klaus, 2020; Kuppelwieser and Klaus, 2021a). Accordingly, this study examines whether the internal configuration of EXQ—beyond its overall level—offers diagnostic insight into how CX evaluations translate into spending allocation (SoW).

A central challenge in CX research is the persistent attitude–behavior gap: high satisfaction often fails to translate into spending-based behavioral outcomes such as share of wallet (SoW) (Jones and Sasser, 1995; Kumar et al., 2013). This gap complicates the business case for CX investments. While scholars suggest relative satisfaction (RSAT) is a better predictor of SoW than absolute satisfaction (Aksoy et al., 2015; Keiningham et al., 2011), evidence linking EXQ to SoW remains mixed and sometimes contradictory (Imhof and Klaus, 2020), highlighting the need to clarify boundary conditions for this relationship.

2.2 A Dual-Level Perspective and Contextual Factors

One reason for these mixed findings may be an overreliance on latent-variable models (e.g., SEM), which can mask micro-level interdependencies among specific experience elements. To address this, SEM is complemented with psychological network analysis (PNA). Whereas social network analysis focuses on actor-level ties (e.g., structural holes/brokerage), PNA models partial correlations among items within a construct, thereby revealing the internal structure of a psychological construct such as CX (Borsboom et al., 2021). This dual-level approach supports a more granular, diagnostic view of how experience evaluations are organized. Although PNA has become increasingly prominent in psychology and related fields, its application to service marketing phenomena—particularly CX constructs and spending-allocation outcomes such as SoW—remains relatively sparse (e.g., Song and Kim, 2020). Consequently, service research has tended to rely predominantly on latent-variable SEM. As a result, little is known about whether spending-allocation outcomes such as SoW are structurally integrated into CX evaluative systems at the item level or instead remain weakly connected or disconnected.

The generalizability of CX models is another critical issue. Most research originates from Western, individualistic markets (Hwang and Seo, 2016), yet cultural values can shape which experience facets become salient and how comparative evaluations are formed. In collectivist, high-context settings such as Japan, relational harmony and feeling understood may be prioritized, potentially increasing the importance of specific EXQ dimensions (Minami and Dawson, 2008; Shobeiri et al., 2018). Testing the EXQ framework in such a context can therefore refine boundary conditions and advance cross-cultural theorizing. In this study, SEM is used to test the macro-level EXQ–RSAT–SoW pathways, and PNA is used to diagnose whether SoW is structurally integrated into—or weakly connected/disconnected from—the

EXQ–RSAT evaluative core, as well as to identify structurally central and bridging experience elements.

To position the present dual-level diagnostic, Table 1 summarizes representative prior evidence on the CX/satisfaction–SoW link—including methodologies, samples, and reported outcome patterns—and highlights the dominant reliance on macro-level models.

Table 1
Representative prior evidence on the CX/satisfaction–SoW link and positioning of the present dual-level diagnostic.

Study	**Context**	**Sample**	**Method / key measures**	**SoW-type outcome (summary)**	**Item-level network (PNA)?**
Cooil et al. (2007)	Retail banking (Canada)	4,319 households; 12,249 observations; 5-year panel	Longitudinal panel modeling (customer satisfaction; SoW)	Changes in satisfaction are positively associated with changes in SoW; income and relationship length negatively moderate the relationship	No
Buoye (2016)	Grocery retail (USA, Brazil, Chile, France, Germany)	1,172 customers; 3,793 satisfaction ratings	Relative metrics (Wallet Allocation Rule / ranked satisfaction) vs. absolute satisfaction	Relative satisfaction metrics outperform absolute satisfaction in explaining SoW; effects vary by customer characteristics/country	No
Imhof & Klaus (2020)	Automotive (UK)	201 recent car purchasers (multi-brand users)	Comparison of satisfaction, EXQ, and WAR; behavior measured as share-of-category (SoW-type)	EXQ and WAR provide stronger explanatory power than satisfaction for share-of-category outcomes (model-dependent patterns)	No
Williams et al. (2020)	Multi-brand services (survey)	1,070 respondents; 6,009 brand ratings	CX typology (memorable vs. frictionless) with mediation	Both memorable and frictionless CX are positively related to SoW; satisfaction	No

			modeling (satisfaction)	partially mediates these relationships	
This study	Consumer services (Japan)	Repeat customers (n = 532)	SEM + PNA (regularized partial correlation network); EXQ (BRE/SPE/PPE), RSAT, SoW	RSAT → SoW is statistically detectable but substantively small; PNA indicates SoW is isolated (no edges) from the EXQ–RSAT evaluative core	Yes

Note: SoW-type outcomes vary across studies (e.g., share of wallet, share of category, share of deposits). The PNA column indicates whether an item-level network model is estimated to examine the micro-structure of CX/evaluative constructs.

3. Conceptual Model and Hypotheses

Building on the literature review, this study develops and tests a conceptual model that examines the structural associations among EXQ, RSAT, and SoW. CX is defined as the customer's holistic cognitive, affective, behavioral, sensory, and social response to the entire customer journey with a firm (Lemon and Verhoef, 2016). The EXQ framework operationalizes this holistic nature through a hierarchical structure in which first-order experiences at each stage—brand experience (BRE), service provider experience (SPE), and post-purchase experience (PPE)—are integrated into a higher-order evaluation of overall EXQ (Klaus, 2014; Imhof and Klaus, 2020). Accordingly, overall EXQ is hypothesized to be positively associated with RSAT, which is in turn hypothesized to be positively associated with SoW. To provide a dual-level diagnostic, SEM tests these hypothesized macro-level associations, while PNA explores item-level interdependencies and assesses whether SoW is structurally integrated into the EXQ–RSAT evaluative core, or instead weakly connected or disconnected from it. Figure 1 presents the conceptual framework that guides these analyses.

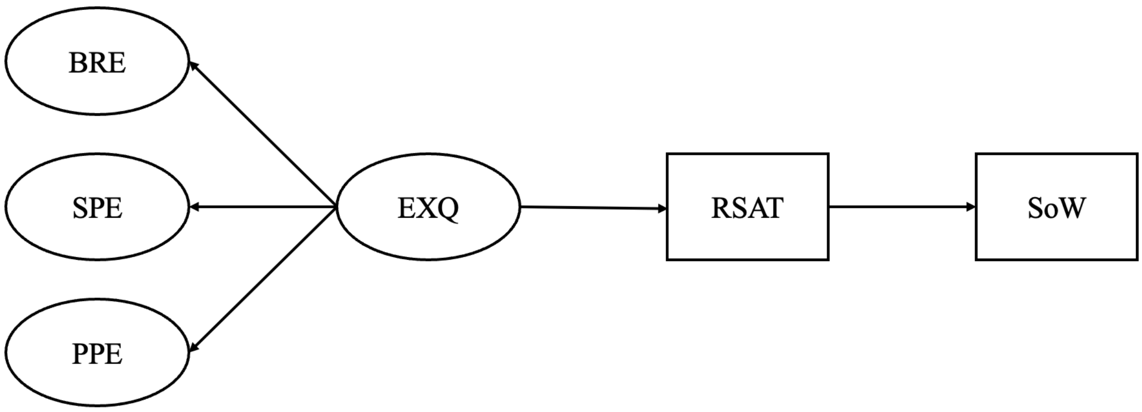


Fig. 1. Conceptual framework (controls omitted for clarity).

3.1 Customer Experience Quality and Relative Satisfaction

EXQ reflects customers' integrated evaluation of experiences across pre-purchase, service interaction, and post-purchase stages (Klaus, 2014). A high-quality experience is an antecedent of satisfaction because it fulfills or exceeds customer expectations across both functional and emotional dimensions (Lemon and Verhoef, 2016). Empirically, Klaus and Maklan (2012) showed that EXQ positively predicts customer satisfaction, and Imhof and Klaus (2020) reported a significant EXQ–satisfaction association using the Wallet Allocation Rule framework. Because EXQ captures the customer's holistic evaluation of the journey rather than isolated touchpoints, it provides a comprehensive benchmark against which competing alternatives are judged. Customers who perceive higher experience quality are therefore expected to evaluate their focal provider more favorably relative to competitors, resulting in higher relative satisfaction. Hence:

H1: EXQ is positively associated with RSAT.

3.2 Relative Satisfaction and Spending Allocation (SoW)

RSAT is a comparative evaluation across competing service providers and has been shown to predict SoW more effectively than absolute satisfaction (Keiningham et al., 2011; Aksoy et al., 2015). The theoretical basis for this link rests on the competitive nature of wallet allocation: customers distribute spending across a finite set of providers, and the rank ordering of satisfaction is expected to shape allocation (Keiningham et al., 2011). Empirically, Keiningham et al. (2011) demonstrated that a rank-based model of relative satisfaction explained a substantial proportion of SoW variance across multiple service categories. Customers who rate a focal provider as superior to alternatives are therefore expected to allocate a greater share of their category spending to that provider. Thus:

H2: RSAT is positively associated with SoW.

3.3 Mediating Role of Relative Satisfaction

The association between EXQ and SoW may be indirect rather than direct. Imhof and Klaus (2020) found that EXQ predicted satisfaction, while the direct EXQ–SoW link was inconsistent across samples, suggesting that an intervening comparative judgment may be required to translate experience perceptions into spending allocation. This is consistent with attitude–behavior accounts (Oliver, 1999), which propose that behavioral outcomes follow from attitudinal evaluations rather than directly from service evaluations. Accordingly, it is hypothesized that higher EXQ shapes customers' comparative judgment (i.e., relative satisfaction), and that this evaluative summary is associated with subsequent spending allocation. Therefore:

H3: RSAT mediates the relationship between EXQ and SoW.

3.4 Research Questions: Psychological Network Analysis

While SEM captures macro-level associations among EXQ, RSAT, and SoW, it does not directly reveal how specific experience elements interrelate or whether a spending-allocation outcome is structurally integrated into the evaluative system at the item level. To address this, PNA is used to (a) diagnose the structural connectivity of SoW within the EXQ–RSAT system and (b) identify structurally central and bridging experience elements. Specifically:

RQ1: In an item-level network that includes EXQ items, RSAT, and SoW, is SoW structurally integrated into the EXQ–RSAT core, or does it appear weakly connected or disconnected, consistent with structural disconnection?

RQ2: Which EXQ items exhibit the highest strength centrality within the overall network?

RQ3: Which items act as critical bridges connecting the brand (BRE), service provider (SPE), and post-purchase (PPE) experience domains?

4. Method

4.1 Research Design and Data Collection

A two-stage survey design was used. First, a pilot refined the Japanese translation of the measurement items and ensured the cultural appropriateness of the EXQ scale. Back-translation was conducted by a professional translator, with supplementary AI-assisted checks for consistency. An online pilot (n = 1,000; August 29, 2024) assessed clarity and item functioning, and minor wording changes were made. The main survey was fielded from September 5 to 6, 2024, using registered panel members from a major professional online panel provider in Japan. The target population was defined as adult consumers in Japan who regularly use face-to-face services.

To support the validity of the analysis, respondents were required to have sufficient cumulative experience with the focal service. Accordingly, a purposive screening criterion was used: respondents had to have used the same face-to-face service at least three times within the past three years. This criterion was intended to ensure an adequate experiential base to evaluate all facets of EXQ, including brand-related (BRE), service-provider (SPE), and post-purchase

(PPE) experiences.

An initial screening survey was distributed to 5,000 panel members to identify individuals meeting this experience-based criterion. The study employed a nonprobability sampling approach and did not apply demographic quotas (e.g., age, gender), because the theoretical focus was on the structure of accumulated experience rather than demographic representation. Respondents who met the screening criterion were invited to the main survey, yielding 1,000 responses. Following the data-quality checks detailed in Section 4.3, a final analytic sample of 532 cases (n = 532) was retained. Prior to data collection, the conceptual model, hypotheses, measures, and inclusion criterion (repeat use of the focal service) were specified, and the dual-level analysis plan (SEM for macro-level associations and PNA for item-level diagnostics) was defined. Because the study aimed to estimate both SEM and an item-level network, the data-collection target was set to yield at least approximately 500 high-quality cases after screening. The final SEM sample (n = 532) exceeds common recommendations for stable estimation in SEMs of comparable complexity (e.g., Wolf et al., 2013). For PNA, complete cases (n = 458) were used for correlation-matrix estimation, and network accuracy and centrality stability were evaluated using bootstrap diagnostics (Epskamp et al., 2018).

The survey was administered by a professional research firm. Prior to responding, panel members were presented with study information and provided informed consent via the provider’s standard procedure. The researcher received only anonymized data and had no access to personally identifying information. No institutional ethics review was sought for this anonymous online survey.

4.2 Sample Characteristics

The mean age of respondents was 53.3 years (SD = 13.6), and 40.2% were female. A full demographic breakdown is reported in Table A.1. Respondents nominated one focal face-to-face consumer service that met the repeat-usage screening criterion. The focal service categories were: Food & Beverage (restaurants/cafés) (n = 238), Beauty/Personal care (n = 151), Travel & Accommodation (n = 51), Healthcare & Welfare (n = 67), Finance (n = 19), and Education (n = 6). Because the primary objective was to diagnose structural disconnection in pooled repeat-customer evaluations rather than to draw category-level inferences, subgroup SEM or subgroup network comparisons by service category were not conducted.

4.3 Data Quality and Common Method Bias Control

To ensure high-quality data from the online panel, quality safeguards were implemented in a two-stage screening process. In the first stage, 347 cases were excluded based on noncompliance with the Directed Questions Scale (DQS; Maniaci and Rogge, 2014), implemented as three directed-response items (one each embedded in the BRE, SPE, and PPE blocks), reducing the sample from 1,000 to 653. In the second stage, a further 121 cases were removed due to substantial missing data (i.e., more than 25% “don’t know” responses) or straight-lining, yielding a final analytic sample of n = 532. Although this exclusion rate is substantial, it reflects a conservative approach intended to improve response validity for both SEM and PNA; however, it may also introduce selection effects, which are considered when interpreting the findings.

Procedural remedies for common method bias included randomizing items and guaranteeing anonymity. Additionally, Harman’s single-factor test was used as a diagnostic check: the first factor accounted for 41% of the variance, below a commonly used 50% threshold (Podsakoff et al., 2003). This result does not rule out common method bias, but it provides no strong indication that a single factor dominates the covariance structure.

4.4 Measures

All scales were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), unless otherwise noted.

Customer Experience Quality (EXQ): Adapted from Kuppelwieser and Klaus (2021b), the initial instrument included 25 items across three dimensions: brand experience (BRE), service provider experience (SPE), and post-purchase experience (PPE). A “don’t know” option was provided to avoid forcing uninformed judgments. All items, labels, and their item-level descriptive statistics (M, SD) are reported in Table B.1.

Relative Satisfaction (RSAT): Measured with a single comparative satisfaction item where respondents rated the focal service relative to competitors (Olsen, 2002; Aksoy *et al*., 2015; Sivadas and Jindal, 2017) on a 5-point Likert scale.

Share of Wallet (SoW): Spending allocation was operationalized using the Wallet Allocation Rule (WAR; Keiningham et al., 2011). Respondents reported (a) the focal provider’s rank relative to competitors (1 = first choice) and (b) the total number of providers used in the category (N). Predicted SoW was computed as SoW = 2(N - Rank + 1) / {N(N + 1)}. This calculation yields a continuous score bounded between 0 and 1. For example, if a consumer uses three providers N = 3 and ranks the focal provider first (Rank = 1), the resulting SoW score is 0.50; if ranked second, the score is 0.33. In the sample, SoW scores ranged from 0.02 to 0.67 (M = 0.33, SD = 0.15; see Table B.1).

4.5 Analytical Strategy

A dual-method approach was adopted to capture the hypothesized macro-level associations and the micro-level structural dynamics of CX. SEM was first used to test the hypotheses within a latent-variable framework. PNA was then used to examine bottom-up, item-level interdependencies that constitute the EXQ construct. In PNA, observed variables (survey items) are treated as nodes and their partial correlations as edges. Unlike SEM, which explains observed covariation via latent constructs, PNA focuses on direct inter-item dependencies, enabling the visualization and analysis of emergent structure. Integrating the two methods provides a more comprehensive account than either approach alone. Analyses proceeded in three phases in R (version 4.5.1).

Phase 1 focused on establishing the measurement model. To assess normality, Shapiro–Wilk tests were performed for each observed variable. All p-values were below .05, indicating departures from normality. Consequently, confirmatory factor analyses (CFA) were conducted using the lavaan package (version 0.6-19) in R with a robust maximum likelihood estimator (MLR). “Don’t know” responses were treated as missing and handled using full-information maximum likelihood (FIML), which is compatible with MLR.

Phase 2 focused on hypothesis testing. The selected measurement model was then used to test the hypothesized relationships (H1–H3) using structural equation modeling (SEM) in lavaan, again employing the MLR estimator.

Phase 3 involved exploratory psychological network analysis. PNA was employed to examine the internal microstructure of the EXQ construct. Because the data were ordinal and did not meet the assumption of multivariate normality, a standard Gaussian Graphical Model (GGM) could not be directly applied. Therefore, a two-step procedure recommended for such data was adopted (Epskamp and Fried, 2018).

First, a mixed correlation matrix (polychoric/polyserial) was computed using the cor_auto function to accommodate ordinal EXQ/RSAT items and the continuous SoW variable. Because cor_auto does not handle missing values, listwise deletion was applied, resulting in 458 complete cases for the PNA. Accordingly, SEM used the full analytic sample with FIML for missingness (n = 532), whereas PNA relied on complete cases due to correlation-matrix estimation constraints (n = 458). Second, the resulting correlation matrix was used to estimate a regularized partial-correlation network (EBICglasso). The lambda search range was extended (lambda.min.ratio = 0.0001) to avoid boundary selection, ensuring that the EBIC-selected lambda fell within the interior of the search grid. To assess robustness, nonparametric bootstrapping was used to evaluate edge-weight accuracy, and case-dropping bootstrapping was used to evaluate the stability of centrality indices (Epskamp et al., 2018). Finally, bridge centrality was calculated using the networktools package (version 1.6.0) to identify items connecting the EXQ dimensions.

5. Results

5.1 Measurement Model

To assess the measurement properties of the EXQ construct, CFA compared three competing measurement models: (1) the original 25-item model (Kuppelwieser and Klaus, 2021a; 2021b), (2) a 19-item model from prior research (Kuppelwieser and Klaus, 2021a), and (3) a 13-item model from prior research (Imhof and Klaus, 2020).

Model-fit comparisons indicated that the 13-item model (Model 3) provided acceptable fit, and information criteria favored it, with the lowest AIC among the three models (Table 2). Table 3 reports standardized factor loadings, inter-factor correlations, and scale properties (M, SD, Cronbach's α, CR, AVE, and HTMT). Although Model 3 exceeded conventional thresholds for internal consistency (Cronbach's α > .70; Hair et al., 2010) and composite reliability (CR > .70; Bagozzi and Yi, 1988), its average variance extracted (AVE) values—except for BRE—were below the recommended .50 cutoff (Fornell and Larcker, 1981). Fornell and Larcker (1981) note that convergent validity may still be adequate when AVE falls below .50 provided that composite reliability exceeds .60, a condition met by all three dimensions in the present study. In addition, the square roots of AVE did not consistently exceed inter-factor correlations. Regarding heterotrait–monotrait (HTMT) ratios, values associated with BRE were below the conservative .85 threshold (Henseler et al., 2015), whereas the SPE–PPE ratio exceeded the .90 threshold (Henseler et al., 2015). These high inter-factor correlations and the elevated SPE–PPE HTMT ratio are consistent with the second-order EXQ specification, in which the three dimensions share a common higher-order source.

Table 2
Model Fit Comparisons.

Model	**χ^2**	**df**	**CFI**	**TLI**	**RMSEA [90% CI]**	**SRMR**	**AIC**
Model 1: 25-item	748.510	272	.888	.877	.058 [.054, .062]	.052	24273.26
Model 2: 19-item	474.281	149	.893	.877	.064 [.059, .070]	.054	18478.44
Model 3: 13-item	171.874	62	.938	.922	.058 [.049, .067]	.046	13088.89

Note: Three measurement models validated in prior research were compared: Model 1 (25 items; Kuppelwieser and Klaus, 2021b), Model 2 (19 items; Kuppelwieser and Klaus, 2021a), and Model 3 (13 items; Imhof and Klaus, 2020). No data-driven item removal was performed; each model specification was adopted as published.

Table 3
Confirmatory Factor Analysis (CFA) Results for Model 3.

Factor	Item	Standardized factor loading	
Brand Experience (BRE)	BRE2	0.639	
	BRE6	0.776	
	BRE7	0.714	
Service Provider Experience (SPE)	SPE1	0.637	
	SPE2	0.437	
	SPE4	0.744	
	SPE6	0.749	
	SPE7	0.748	
	SPE9	0.667	
	SPE11	0.535	
Post-Purchase Experience (PPE)	PPE2	0.701	
	PPE3	0.664	
	PPE5	0.706	
Inter-factor correlations	**BRE**	**SPE**	**PPE**
	1.000		
	0.795	1.000	
	0.837	0.925	1.000
M	3.746	3.637	3.566
SD	0.599	0.569	0.627
Cronbach’s α	0.748	0.831	0.732
CR	0.753	0.839	0.733
AVE	0.506	0.439	0.475
HTMT ratio	**BRE**	**SPE**	**PPE**
	1.000		
	0.844	1.000	
	0.838	0.953	1.000

5.2 Structural Equation Modeling (SEM)

To test the main hypotheses (H1–H3), the structural equation model was estimated using maximum likelihood with robust standard errors (MLR) to account for non-normality. Missing data were handled via full information maximum likelihood (FIML). The model demonstrated acceptable fit to the data: $\chi^2(86) = 224.54$, CFI = .932, TLI = .916, SRMR = .047, and RMSEA = .055 (90% CI [.047, .063]).

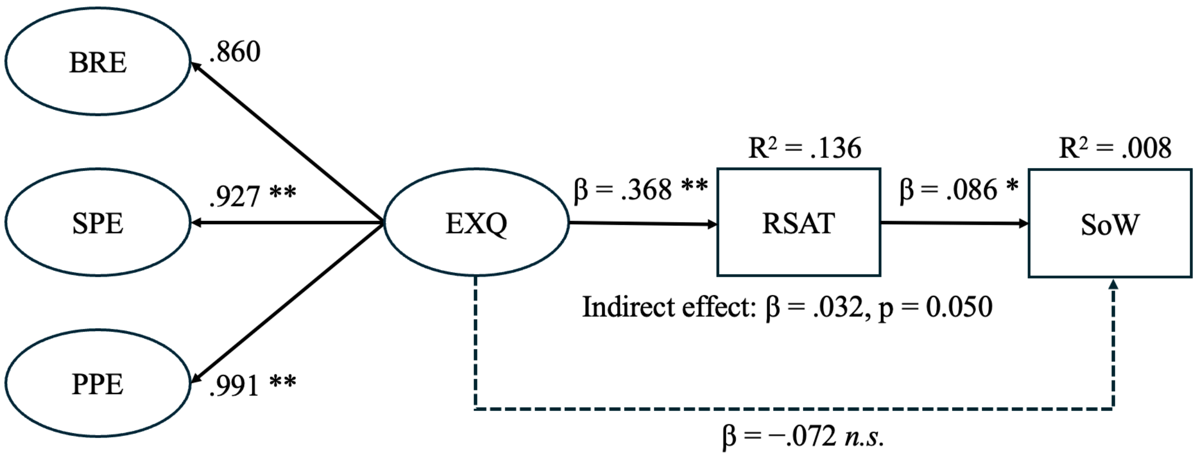


Fig. 2. Simplified structural equation model results.

Note: * p < .05; *** p < .001. Standardized coefficients shown. Items to first-order indicators omitted for clarity. Dashed lines indicate non-significant paths. BRE loadings fixed 1.0 for identification.

In the measurement model, all first-order factor loadings were significant ($p < .001$). Standardized loadings ranged from .639 to .776 for BRE, from .437 to .749 for SPE, and from .664 to .706 for PPE. At the second-order level, EXQ loaded strongly onto all three dimensions: BRE ($\beta = .860$), SPE ($\beta = .927$), and PPE ($\beta = .991$), with EXQ explaining 74.0%, 85.8%, and 98.1% of the variance in BRE, SPE, and PPE, respectively.

Regarding the structural paths, EXQ was positively associated with RSAT ($\beta = .368$, $p < .001$). RSAT was, in turn, positively associated with SoW ($\beta = .086$, $p = .042$), whereas the direct EXQ → SoW path was not significant ($\beta = -.072$, $p = .182$). The indirect association of EXQ with SoW via RSAT was marginally significant at the .05 level ($\beta = .032$, $p = .050$), but the model's explanatory power for SoW remained negligible. The total EXQ → SoW effect was not significant ($\beta = -.041$, $p = .437$). Overall, the model explained 13.6% of the variance in RSAT and 0.8% of the variance in SoW.

A supplementary model including demographic control variables (age, gender, marital status, income, and presence of children) was estimated. Among the controls, only the presence of children was significantly associated with SoW ($\beta = .113$, $p = .047$); no other control variable showed a significant association with either RSAT or SoW. The main path estimates remained substantively unchanged (e.g., EXQ → RSAT: $\beta = .381$ vs. .368; RSAT → SoW: $\beta = .086$ vs. .086). Moreover, the AIC increased from 13718.55 to 13729.95, indicating that the more parsimonious model without controls provided a better fit. Accordingly, the model without control variables is reported as the primary specification.

Table 4
Structural Equation Model Results.

Path / Factor Loading	**β**	**S.E.**	**z-value**	**p-value**	**Hypothesis**
Second-order factor: EXQ					
EXQ → BRE	.860	—	—	—	
EXQ → SPE	.927	.137	8.852	< .001	
EXQ → PPE	.991	.141	9.373	< .001	
Structural model					
EXQ → RSAT	.368	.102	6.295	< .001	Supported
RSAT → SoW	.086	.009	2.036	.042	Supported
EXQ → SoW	-.072	.020	-1.335	.182	Not supported
Indirect and total effect					
EXQ → RSAT → SoW	.032	.006	1.964	.050	Supported (borderline)
Total effect	-.041	.020	-0.778	.437	
R^2: RSAT = .136; SoW = .008; BRE = .740; SPE = .858; PPE = .981					

Note: N = 532. Standardized coefficients (β) are reported. S.E., z, and p-values correspond to the unstandardized estimates from the MLR solution. The BRE loading was fixed to 1.0 for identification; its standardized loading is reported without SE or p value. Model fit: $\chi^2(86) = 224.54$, CFI = .932, TLI = .916, SRMR = .047, RMSEA = .055, 90% CI [.047, .063].

5.3 Psychological Network Analysis (PNA)

To capture micro-level interactions among EXQ elements, a psychological network of 15 observed variables (13 EXQ items, RSAT, SoW) was estimated using the EBICglasso algorithm applied to mixed correlations. After listwise deletion of cases with missing values, 458 complete cases were used for the PNA. The estimated network contained 38 non-zero edges (density = 0.362; mean absolute edge weight = 0.066). The network is shown in Figure

3. Edges with larger weights are depicted with darker and thicker lines. Blue lines indicate positive values, and red lines indicate negative values. The majority of edges were positive; a small number of negative edges were observed (e.g., between SPE6 and BRE7).

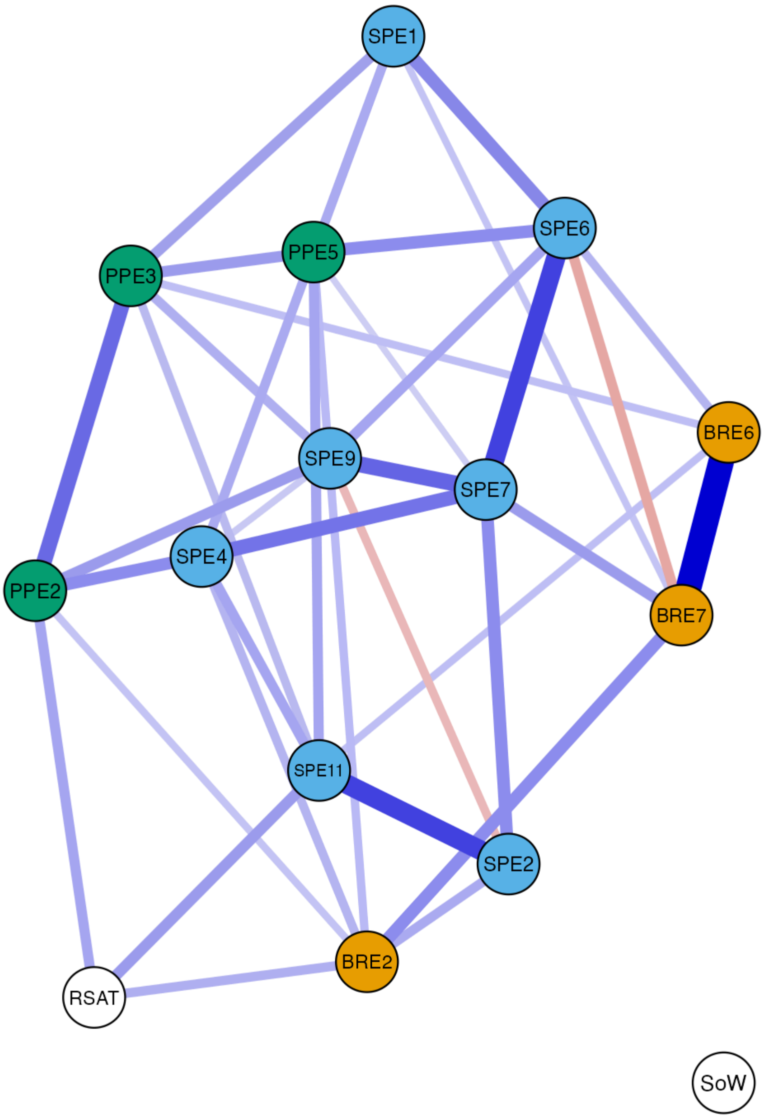


Fig. 3. The Network of EXQ and Outcome Variables.

To assess the reliability of centrality estimates, case-dropping bootstrap procedures were used. Only strength centrality met the minimum recommended stability threshold (CS = 0.284 > 0.25; Epskamp et al., 2018) and was therefore interpreted with caution. In contrast, closeness (CS = 0.00) and betweenness (CS = 0.05) did not reach this threshold; accordingly, subsequent interpretation focuses on strength centrality.

For the bridge centrality analysis, interpretation focuses on bridge strength, which is based on direct edge weights and aligns with strength centrality. In the case-dropping bootstrap, only strength-based indices showed acceptable stability; shortest-path indices (closeness and betweenness) did not meet the recommended stability threshold and are therefore not interpreted. Edge-weight accuracy was assessed via nonparametric bootstrapping (2,500 resamples), and bootstrap confidence intervals are reported in Fig. C.1.

Regarding the structural positioning of SoW (RQ1), Figure 3 shows that SoW was completely isolated from the network, with strength centrality of 0.00 and bridge strength of 0.00. In contrast, RSAT had strength centrality of 0.50, ranking seventh among the 15 nodes. Figure 4 displays strength centrality for all nodes, sorted by magnitude. The highest strength centrality was observed for SPE7 (1.48), followed by SPE6 (1.25) and BRE7 (1.14) (RQ2). The highest bridge strength values were observed for PPE2 (0.77), PPE5 (0.71), and BRE2 (0.68) (RQ3). As a sensitivity check, an unregularized partial-correlation network with significance thresholding was also estimated. The key finding—SoW's isolation/structural disconnection—was qualitatively consistent, supporting the robustness of this result.

Table 5
Node strength centrality (bootstrap accuracy) and Bridge centrality (strength).

Node	**Strength centrality**	**CI lower (2.5%)**	**CI upper (97.5%)**	**Bridge centrality**	**Bridge rank**
SPE7	1.48	1.06	2.34	0.38	10
SPE6	1.25	0.92	2.10	0.51	6
BRE7	1.14	0.77	2.06	0.45	9
SPE4	1.13	0.74	1.99	0.46	8
SPE11	1.11	0.66	1.86	0.59	4
PPE2	1.04	0.66	1.87	0.77	1
PPE3	1.03	0.70	1.90	0.58	5
SPE9	1.02	0.71	1.82	0.33	12

BRE2	0.89	0.53	1.66	0.68	3
PPE5	0.89	0.62	1.58	0.71	2
SPE2	0.85	0.56	1.74	0.15	14
BRE6	0.84	0.74	1.76	0.37	11
SPE1	0.66	0.38	1.38	0.28	13
RSAT	0.50	0.29	1.59	0.50	7
SoW	0.00	0.00	0.69	0.00	15

Note: CI = 95% bootstrap percentile confidence interval (2.5th and 97.5th percentiles; 2,500 resamples).

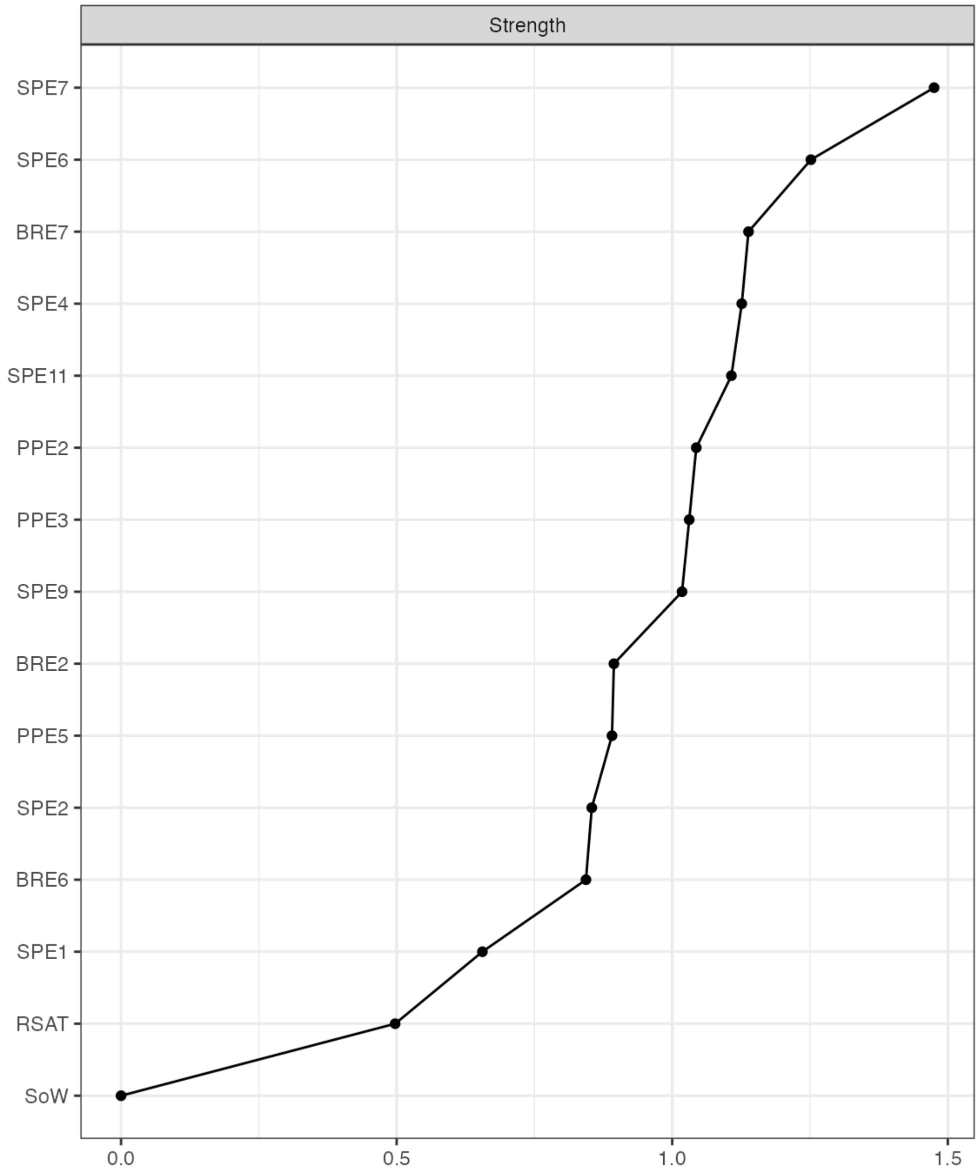


Fig. 4. Node Strength Centrality of the Estimated Network.

6. Discussion

This study examined how customer experience quality (EXQ) relates to relative satisfaction (RSAT) and share of wallet (SoW) in Japan using a dual-level diagnostic approach (SEM and psychological network analysis). SEM provided clear evidence that EXQ operates as a higher-order construct and is positively associated with RSAT (H1). The RSAT → SoW path was statistically detectable but substantively small ($\beta = .086$, $p = .042$), and the model explained only 0.8% of SoW variance ($R^2 = .008$). In other words, while comparative evaluations are related to wallet allocation in principle, the translation from experience evaluations to category spending is weak in magnitude in this setting.

Psychological network analysis (PNA) adds structural context to this pattern. In the regularized partial-correlation network, SoW was isolated (no edges; strength = 0.00), whereas RSAT was embedded within a dense EXQ core. The strongest nodes were concentrated in the service-provider and brand domains—SPE7 (pleasant interactions), SPE6 (personnel empathy), and BRE7 (superior to competitors)—while the strongest bridges connecting domains were PPE2 (accurately understands needs), PPE5 (handles problems well), and BRE2 (trusted expertise). Importantly, centrality in this framework is diagnostic rather than causal: it indicates which experience elements are structurally interdependent within the measured system, not which elements "cause" SoW.

Taken together, the attitude–behavior gap is not only a matter of weak coefficients; it can also be described as a configuration in which SoW is structurally disconnected from the EXQ–RSAT evaluative system. This structural view complements long-standing concerns about satisfaction metrics as behavioral predictors (Jones and Sasser, 1995; Kumar et al., 2013) and provides a compact way to diagnose where the translation from experience to spending appears to thin out.

6.1 Theoretical Contributions

6.1.1 From weak links to a structural disconnection as a diagnostic concept

A first contribution is conceptual: this study frames the attitude–behavior gap as structural disconnection, defined as weak or absent conditional dependencies between a behavioral outcome (SoW) and an experience–evaluation core in an item-level network. This is not a claim of causality or directionality. Rather, it is a diagnostic description of how the measured variables cohere. In the present data, the diagnostic is extreme: SoW was isolated in the PNA network, even though SEM detected a small positive RSAT → SoW path.

These findings are not contradictory. SEM estimates an average association between RSAT and SoW while controlling for EXQ at the latent level, whereas PNA evaluates conditional dependencies among observed items while controlling for all other nodes simultaneously and applying regularization. A small SEM path can coexist with an absent network edge if the association is weak, unstable, or not anchored to specific experience elements once inter-item dependencies are taken into account. This dual pattern therefore sharpens the interpretation: the RSAT → SoW association exists statistically, yet it does not manifest as a robust, item-level pathway linking concrete experience elements to wallet allocation.

6.1.2 Why wallet allocation may remain weakly connected to experience evaluations

A second contribution concerns boundary conditions. Wallet allocation is shaped by more than evaluative judgments. Even when customers recognize one provider as relatively superior, actual spending shares may remain constrained by factors not captured by EXQ and RSAT items—such as convenience and accessibility, time and scheduling constraints, repertoire purchasing, price/availability, or switching frictions. These drivers were not measured directly, so this explanation remains interpretive; however, the combination of (i) very low explained variance in SoW in SEM and (ii) SoW isolation in PNA is consistent with the possibility that wallet allocation is governed by additional mechanisms beyond the experience–satisfaction system.

Examining these relationships in Japan is theoretically meaningful for identifying boundary conditions. Prior work suggests that high-context, relational norms can shape which experience facets become salient in evaluations (Minami and Dawson, 2008; Shobeiri et al., 2018; Hwang and Seo, 2016). The network results indicate a dense EXQ core with prominent service-provider and brand nodes, consistent with the idea that relational and process-related elements can become structurally central in experience judgments. At the same time, the weak or absent linkage to SoW suggests that the evaluative core may not be sufficient to explain behavioral allocation under the competitive and situational constraints of consumer services. Imhof and Klaus (2020), for instance, reported that CX-related metrics can show stronger associations with wallet-allocation outcomes in a Western sample, suggesting that the degree of structural disconnection may vary across market contexts. Future cross-market work can test whether the structural integration of SoW differs in markets where spending allocation is more strongly driven by individual preference expression and lower situational constraint.

6.1.3 A dual-level workflow to study CX as both hierarchy and microstructure

A third contribution is methodological. The results support a dual-level view of EXQ: hierarchical at the latent level (a second-order factor structure) and interactional at the item level (a network of conditional dependencies). This is not a choice between competing paradigms; the two approaches answer different questions. SEM validates the macro structure and quantifies average associations along a hypothesized chain. PNA complements this topdown view by mapping the microstructure of experience elements, identifying which nodes are structurally central (SPE7, SPE6, BRE7) and which nodes bridge experience domains (PPE2, PPE5, BRE2). The network view suggests that experience elements are not passive indicators of latent dimensions but are directly interconnected through conditional dependencies, implying that CX may function as an emergent system whose internal configuration carries diagnostic value beyond aggregate scores. This combined workflow provides a replicable diagnostic template for CX research and measurement practice (Epskamp and Fried, 2018; Borsboom et al., 2021).

6.2 Managerial implications: using structural diagnostics without over-claiming causality

For managers, the key implication is not that a particular item "drives" SoW, but that experience evaluations can form a tight internal system while remaining weakly connected to wallet allocation. Accordingly, we propose a pragmatic diagnostic playbook.

Step 1: Assess the macro chain. Use a parsimonious SEM (or equivalent) to evaluate whether experience evaluations translate into comparative judgments and whether those judgments have a meaningful association with SoW. In the present data, EXQ was strongly associated with RSAT, whereas the RSAT → SoW association was small and explained little variance.

Step 2: Map the experience microstructure. Use PNA to identify which experience elements form the evaluative core and which elements bridge domains. In the present data, pleasant interactions (SPE7) and personnel empathy (SPE6) were the most central nodes, and accurately understands needs (PPE2), handles problems well (PPE5), and trusted expertise (BRE2) were the strongest cross-domain bridges (Table 5). These nodes are strong candidates for monitoring and experimentation rather than guaranteed levers for behavioral change. Because centrality is diagnostic, these elements should be treated as focal points for maintaining coherence in overall experience judgments rather than as confirmed causal drivers of behavioral outcomes.

Step 3: If SoW is structurally disconnected, broaden the measurement set and design tests. When SoW appears isolated—as in the estimated network—raising experience scores alone may not translate into materially higher wallet share. Managers should therefore measure and test additional wallet-allocation mechanisms (e.g., convenience constraints, switching frictions, habit/repertoire patterns, price-value tradeoffs) and evaluate whether interventions aimed at these mechanisms increase SoW connectivity over time. For example, a service firm might maintain improvements in interaction quality and process ease while simultaneously reducing repurchase friction (e.g., easier rebooking, streamlined payments) and then track whether SoW becomes more structurally integrated with RSAT and key experience nodes in follow-up measurements.

6.3 Limitations and Future Research

Several limitations temper inference and point to next steps. First, the design is cross-sectional and based on self-reports, which limits causal interpretation. The sample was drawn from an online consumer panel using purposive screening; accordingly, findings may not generalize to the broader population of service customers, and the substantial exclusion rate may introduce selection effects. Second, SoW was operationalized via the Wallet Allocation Rule using reported rank and choice set size; future research should validate structural disconnection using behavioral data (e.g., transaction histories) and richer measures of wallet-allocation constraints. Third, PNA results depend on the included node set and estimation choices; SoW isolation should be interpreted as disconnection within the measured EXQ–RSAT system, not as a universal claim about SoW determinants. Fourth, the PNA relied on complete cases (listwise deletion), and centrality stability supported interpretation primarily for strength; future work can improve robustness using planned missing-data designs and repeated measurements. Fifth, the HTMT ratio between SPE and PPE exceeded conventional thresholds and inter-factor correlations were high; although these values are consistent with the second-order EXQ specification and with prior findings, future research should examine whether the SPE–PPE distinction holds in other cultural or service contexts. Sixth, relative satisfaction was measured with a single comparative item; multi-item measures could improve reliability and strengthen both SEM and PNA estimates.

More broadly, future studies should (a) include external moderators and constraints (e.g., competitive intensity, switching barriers, convenience, habitual purchasing) as additional nodes, (b) test dynamic change using longitudinal or post-intervention network designs, and (c) develop a parsimonious Network Disconnection Index that quantifies the structural integration of behavioral outcomes within experience–evaluation systems.

7. Conclusion

Integrating structural equation modeling (SEM) and psychological network analysis (PNA), this study examined how customer experience quality (EXQ) relates to relative satisfaction (RSAT) and share of wallet (SoW) among repeat customers in consumer-service contexts in Japan. SEM supported EXQ as a higher-order construct and showed that EXQ is positively associated with RSAT. Although the RSAT → SoW association was statistically detectable ($\beta = .086$, $p = .042$), its substantive explanatory power was minimal (R^2 for SoW = .008). Thus, comparative evaluations and wallet allocation are related in principle, but the translation from experience evaluations to spending share is weak in magnitude in this setting.

PNA complements this macro-level picture by revealing the microstructure of experience evaluations. The estimated network showed a dense EXQ–RSAT evaluative core, whereas SoW was structurally disconnected (no edges; strength = 0). This pattern reframes the attitude–behavior gap not only as a small coefficient but also as a structural disconnection between an experience–evaluation system and a spending-allocation outcome. Importantly, network centrality is interpreted diagnostically rather than causally: it highlights which experience elements are structurally interdependent within the measured system, not guaranteed "drivers" of SoW.

For theory, these findings support a dual-level view of EXQ—hierarchical in latent structure yet interactional in item-level dependencies. This perspective moves beyond treating CX dimensions as passive reflective indicators and suggests that the internal configuration of experience elements carries diagnostic value beyond aggregate scores. The findings also clarify boundary conditions under which CX metrics may have limited behavioral translation. For practice, the study offers a replicable diagnostic workflow: use SEM to quantify the overall evaluative chain, and use PNA to map which experience elements constitute the evaluative core and how (or whether) behavioral outcomes connect to it. A practical application is to track, across repeated measurements, whether initiatives that improve core experience elements (e.g., interaction quality and process ease) and reduce wallet-allocation constraints (e.g., convenience limitations, switching frictions, habitual/repertoire purchasing) are accompanied by stronger structural integration of SoW with the evaluative system. Future research should test the generalizability of structural disconnection across markets and service settings, validate findings using longitudinal and behavioral data, and develop a robust Network Disconnection Index as a candidate metric for assessing behavioral translation.

Appendix A.

Table A.1 Demographic characteristics of respondents (N = 532).

Variable	**Category**	**n**	**%**
Gender	Female	214	40.2
	Male	318	59.8
Marital status	Married	346	65.0
	Single	186	35.0
Children in household	Yes	316	59.4
	No	216	40.6
Household income (JPY; millions)	< 3.0	98	18.4
	3.0–4.99	122	22.9
	5.0–6.99	92	17.3
	7.0–9.99	113	21.2
	≥ 10.0	107	20.1
Service sector	Food & Beverage (restaurants/cafés)	238	44.7
	Beauty / Personal care	151	28.4
	Healthcare & Welfare	67	12.6
	Travel & Accommodation	51	9.6
	Finance	19	3.6
	Education	6	1.1
		M	**SD**
Age		53.3	13.6

Note: Percentages are based on N = 532 and may not sum to 100 due to rounding. “Millions” denotes JPY 1,000,000.

Appendix B.

Table B.1 Item-level descriptive statistics (N = 532).

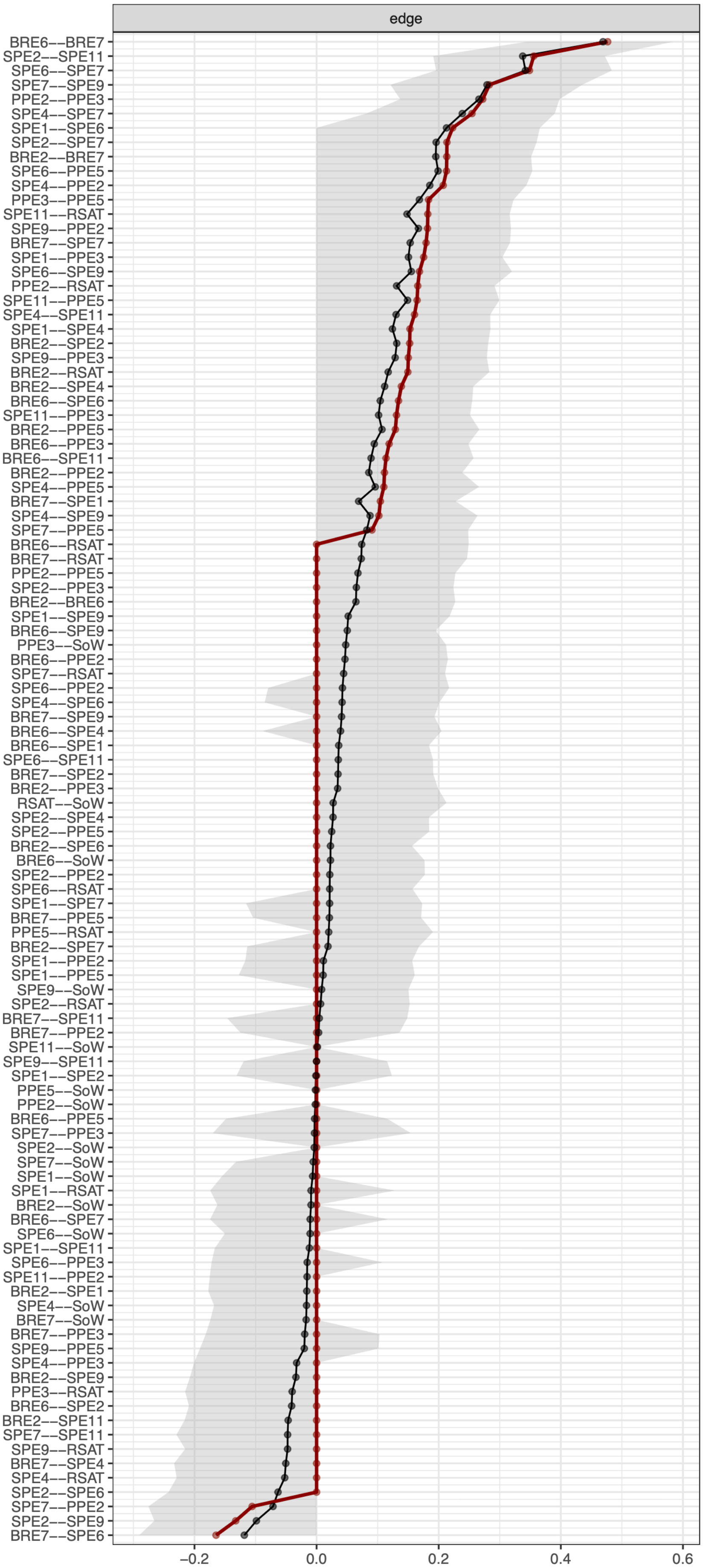
Construct	**Survey item wording**	**Item label**	**M**	**SD**	**Used in final CFA/SEM**
Brand Experience (BRE)	BRE1: [The provider] has a good reputation.	Good reputation	3.86	0.72	
	BRE2: I am confident in [the provider]’s expertise.	Trusted expertise	3.89	0.74	✓
	BRE3: [The provider] gives independent advice (on which product/service will best suit my needs).	Independent advice	3.64	0.75	
	BRE4: I choose [the provider] not because of the price alone.	Value beyond price	3.94	0.78	
	BRE5: The people who work at [the provider] represent the [provider] brand well.	On-brand employees	3.62	0.70	
	BRE6: [The provider]’s offerings have the best quality.	Top quality	3.63	0.74	✓

	BRE7: [The provider]'s offerings are superior.	Superior to competitors	3.74	0.70	✓
Service-Provider Experience (SPE)	SPE1: [The provider] advises(d) me throughout the process.	Advice throughout process	3.47	0.85	✓
	SPE2: Dealing with [the provider] is easy.	Ease of use	3.92	0.72	✓
	SPE3: [The provider] keeps me informed.	Ongoing information	3.68	0.80	
	SPE4: [The provider] demonstrates flexibility in dealing with me.	Flexible response	3.66	0.82	✓
	SPE5: At [the provider] I always deal with the same forms and/or same people.	Consistent procedures/staff	3.51	0.94	
	SPE6: [The provider]'s personnel relate to my wishes and concerns.	Personnel empathy	3.59	0.84	✓
	SPE7: The people I am dealing with (at [the provider]) have good people skills.	Pleasant interactions	3.79	0.76	✓
	SPE8: [The provider] delivers a good customer service.	Good customer service	3.85	0.71	
	SPE9: I have built a personal relationship with the people at [the provider].	Close relationship	3.34	0.89	✓
	SPE10: [The provider]'s facilities are better designed to fulfill my needs than their competitors.	Superior facilities (vs. competitors)	3.50	0.73	
	SPE11: [The provider]'s (online and/or offline) facilities are designed to be as efficient as possible (for me).	Efficient usability (on/offline)	3.70	0.75	✓
Post-Purchase Experience (PPE)	PPE1: I choose [the provider] because they know me.	Familiarity-based choice	3.47	0.83	
	PPE2: [The provider] knows exactly what I want.	Accurately understands needs	3.53	0.78	✓
	PPE3: [The provider] keeps me up-to-date about their products and latest developments.	Post-purchase information	3.50	0.81	✓
	PPE4: [The provider] will look after me for a long time.	Long-term care/commitment	3.63	0.82	

	PPE5: [The provider] deal(t) well with me when things go(went) wrong.	Handles problems well	3.67	0.72	✓
	PPE6: I am happy with [the service provider] as my provider.	Satisfaction with provider	3.92	0.72	
	PPE7: Being a client at/customer of [the provider] gives me social approval.	Socially acceptable to be a customer	4.00	0.73	
Outcomes	RSAT: Compared to its competitors, how satisfied are you with the provider?	Relative satisfaction	3.91	0.72	SEM only
	SoW: (a) Regarding [Provider Name], how many rival or competing companies can you think of? (b) Including those rivals and competitors, if you were to rank [Provider Name], what rank would it be?	Share of Wallet score	0.33	0.15	SEM only

Note: Response format = 5-point Likert (1 = strongly disagree, 5 = strongly agree); a "Don't know" option was available and treated as missing using FIML. Measurement origin = EXQ items adapted from Kuppelwieser & Klaus (2021b) with forward/back translation and reconciliation prior to data collection.

Appendix C.


edge
BRE6--BRE7
SPE2--SPE11
SPE6--SPE7
SPE7--SPE9
PPE2--PPE3
SPE4--SPE7
SPE1--SPE6
SPE2--SPE7
BRE2--BRE7
SPE6--PPE5
SPE4--PPE2
PPE3--PPE5
SPE11--RSAT
SPE9--PPE2
BRE7--SPE7
SPE1--PPE3
SPE6--SPE9
PPE2--RSAT
SPE11--PPE5
SPE4--SPE11
SPE1--SPE4
BRE2--SPE2
SPE9--PPE3
BRE2--RSAT
BRE2--SPE4
BRE6--SPE6
SPE11--PPE3
BRE2--PPE5
BRE6--PPE3
BRE6--SPE11
BRE2--PPE2
SPE4--PPE5
BRE7--SPE1
SPE4--SPE9
SPE7--PPE5
BRE6--RSAT
BRE7--RSAT
PPE2--PPE5
SPE2--PPE3
BRE2--BRE6
SPE1--SPE9
BRE6--SPE9
PPE3--SoW
BRE6--PPE2
SPE7--RSAT
SPE6--PPE2
SPE4--SPE6
BRE7--SPE9
BRE6--SPE4
BRE6--SPE1
SPE6--SPE11
BRE7--SPE2
BRE2--PPE3
RSAT--SoW
SPE2--SPE4
SPE2--PPE5
BRE2--SPE6
BRE6--SoW
SPE2--PPE2
SPE6--RSAT
SPE1--SPE7
BRE7--PPE5
PPE5--RSAT
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SPE1--PPE2
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SPE9--SoW
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BRE7--SPE11
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PPE5--SoW
PPE2--SoW
BRE6--PPE5
SPE7--PPE3
SPE2--SoW
SPE7--SoW
SPE1--SoW
SPE1--RSAT
BRE2--SoW
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SPE6--SoW
SPE1--SPE11
SPE6--PPE3
SPE11--PPE2
BRE2--SPE1
SPE4--SoW
BRE7--SoW
BRE7--PPE3
SPE9--PPE5
SPE4--PPE3
BRE2--SPE9
PPE3--RSAT
BRE6--SPE2
BRE2--SPE11
SPE7--SPE11
SPE9--RSAT
BRE7--SPE4
SPE4--RSAT
SPE2--SPE6
SPE7--PPE2
SPE2--SPE9
BRE7--SPE6
−0.2
0.0
0.2
0.4
0.6

Fig. C.3 Edge-weight accuracy of the estimated network.

Note: Edge weights represent regularized partial correlations derived from the correlation matrix estimated via cor_auto (i.e., scale-free/standardized associations). Black points indicate bootstrap mean edge weights and red points indicate the sample estimates; shaded areas represent 95% nonparametric bootstrap confidence intervals (2,500 resamples).

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