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Co-Productive Engagement, Service-Quality Perception, and Sustained Use of Fresh-Grocery Digital Platforms in Guangdong: A Boundary-Conditional Mediation Model with Technology-Related Apprehension

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Abstract: The rapid growth of China's online fresh-grocery market has not translated into consistent user retention. Although prior research recognises user engagement on digital platforms, it remains unclear which forms of engagement foster sustained platform use and through what psychological mechanisms. Drawing on the stimulus-organism-response framework, this study examines four dimensions of co-productive engagement—task cognition, information seeking, effort expenditure, and human-computer interaction—as separate antecedents of continuance intention. Perceived service quality is modelled as a mediator, and technology-related apprehension as a moderator. Survey data from 550 fresh-grocery users in Guangdong Province were analysed using partial least squares structural equation modelling (SmartPLS 4.1.1). All four engagement dimensions positively influence perceived service quality, which in turn increases continuance intention and partially mediates these relationships. Effort expenditure shows the strongest effect. Technology-related apprehension negatively affects perceived service quality and significantly weakens only the information-seeking pathway. Within the limits of a cross-sectional, non-probability sample, the findings extend the participatory perspective of the stimulus-organism-response framework, identify service quality as a key transmission mechanism, and indicate that technology-related apprehension influences engagement selectively rather than uniformly. The results suggest that platforms should simplify information processing for apprehensive users while encouraging forms of engagement that make user effort more rewarding.

Keywords: Fresh-grocery e-commerce; Co-productive engagement; Service-quality; Continuance intention; Technology-related apprehension; Partial-least-squares structural equation modelling (PLS-SEM)

Introduction

China's digital-retail apparatus is no longer a frontier sector. Within this established market, the rapid-fulfilment grocery segment - operated by integrated online-to-offline players such as Hema, JD Fresh, Dingdong Maicai, Meituan Maicai, Pupu, and Pinduoduo's Duoduo Maicai - combines cold-chain logistics with mobile interfaces to support recurrent household purchasing. Because these services are easy to compare and switch, the strategic focus increasingly extends beyond first-time adoption toward retaining experienced users (Gao et al., 2015; Kim & Yum, 2024; Monoarfa et al., 2024). Sectoral growth has decelerated, and the conversation among operators has shifted from acquiring new

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users to keeping the ones already on the platform (Liu & Chen, 2025; Xiao & Wang, 2025; Wu & Liu, 2025).

Retention is not a neutral problem in this context. Fresh groceries differ from packaged goods on several dimensions that bear directly on user behaviour: products perish, quality cannot be inspected pre-purchase, fulfilment is time-critical, and any single failed delivery cascades into household disruption (Cui, 2025; Ren et al., 2025; Jia, 2024). Reported in-channel loss rates of 20-25% for perishables suggest substantial backstage volatility that is, sooner or later, reflected in the user's evaluation of the platform (Liu et al., 2024; Tao, 2025; Sun, 2025). Against this backdrop, the user is asked to do considerable work themselves - inspecting product images and provenance, comparing time-slot windows, parsing promotion stacks, communicating with chat agents, providing post-delivery feedback - and that work is itself an input to whether the user perceives the service as competently delivered (Xie et al., 2008; Wu & Chen, 2017; Shen, 2025).

A genuine theoretical puzzle sits underneath the practitioner concern. Three discrete strands of literature speak to the retention question but rarely come into contact. The participation literature (rooted in service-dominant and co-creation thinking) treats user engagement as a generic input into value creation but seldom interrogates the internal architecture of that engagement (Wu & Chen, 2017; Sadighha et al., 2025; Wang & Wei, 2011). The service-quality literature, traceable to Parasuraman and colleagues, supplies an evaluative scaffold but typically positions perceived quality as either an antecedent or an outcome rather than as a transmitting mechanism (Espino-Rodriguez & Rodriguez-Diaz, 2021; He et al., 2023; Brochado et al., 2019; Meijerink & Schoenmakers, 2021). The continuance-intention literature, originating in the information-systems tradition, isolates retention drivers but tends to do so without specifying how participatory behaviours upstream feed into those drivers (Liu X.N. et al., 2025; Cheng et al., 2024; Chi et al., 2024; Yi & Zhu, 2025; Fu & Zhang, 2025). And almost none of these strands distinguish those users whose interaction with the platform is hampered by an underlying apprehension toward the technology itself (Tarafdar et al., 2019; Tarhini et al., 2021).

The present study addresses this puzzle by integrating, within a single estimable structural model, four interlocking propositions. First, user engagement on a fresh-grocery platform should be decomposed rather than aggregated; we treat it as a four-strand construct consisting of procedural awareness of platform mechanics (task cognition), proactive informational acquisition (information seeking), behavioural-resource investment (effort expenditure), and interface-mediated interaction (human-computer interaction). Second, the path from engagement to behavioural intention is not exclusively direct; it is partly routed through the user's overall judgement of service quality - a perceptual organism in stimulus-organism-response terms. Third, that perceptual organism translates into a behavioural response, namely the user's stated intention to keep using the platform. Fourth, an individual-difference variable - technology-related apprehension - should be permitted both a direct depressing effect on service-quality perception and a path-conditional moderating effect, because not every engagement strand is equally cognitively demanding.

Relative to the earlier report of the core model using the same dataset (Yue et al., 2026), the present manuscript makes four analytical and reporting contributions. Theoretically, it formalises co-productive engagement as an organising umbrella for four distinct first-order constructs rather than as a measured higher-order factor. Methodologically, it reports a fully specified mediation-moderation structural model, including direct, indirect, total, and proportion-mediated estimates, alongside fuller measurement and robustness diagnostics. Empirically, it documents the path-specific moderation of technology-related apprehension with a simple-slope analysis while qualifying the pattern to this sample. Practically, it offers design-oriented guidance, tempered by the modest effect sizes observed, that distinguishes general-purpose engagement design from apprehension-sensitive interface design.

The remainder of the paper proceeds as follows. Section 2 situates the empirical setting and surveys the four literatures we draw on. Section 3 develops the conceptual model and articulates thirteen hypotheses. Section 4 documents the research design, sampling, instrumentation, and analytical procedure. Section 5 presents descriptive, measurement-model, and structural-model results, including reliability, validity, multicollinearity, common-method bias, path-coefficient, mediation, and simple-slope evidence. Section 6 discusses interpretive, theoretical, and managerial implications, and the closing sections flag limitations and avenues for future enquiry.

Empirical Setting and Literature Foundations

The fresh-grocery channel in Guangdong

Guangdong Province offers an empirically apposite setting for this enquiry on several grounds (Li & Jiang, 2025; Liu Y.C. et al., 2025; Wang & Li, 2025). It is one of China's most digitally penetrated regions, with mobile-internet adoption well above the national average and a household-spending profile that has been measurably reshaped by application-mediated grocery purchasing. Major platforms operate at scale in the province - national-network apps such as Meituan Maicai, JD Daojia, and Hema coexist with regionally rooted services such as Pupu, Qian Dama, and local-supermarket apps such as Walmart/Sam's Club, Vanguard, and Yonghui Life. The provincial geography spans densely urban core cities of the Pearl River Delta (Guangzhou, Shenzhen, Foshan, Dongguan), peripheral Delta cities (Zhuhai, Zhongshan, Huizhou, Jiangmen, Zhaoqing), and second- and third-tier cities in eastern, western, and northern Guangdong (Shantou, Shanwei, Chaozhou, Jieyang, Zhanjiang, Maoming, Yangjiang, Yunfu, Shaoguan, Qingyuan, Meizhou, Heyuan), providing useful behavioural heterogeneity within a single administrative jurisdiction (although, given the non-probability design detailed in Section 4.2, statistical generalisation to the full population is not claimed) (Yang J., 2025; Liu Y.C. et al., 2025).

Two consumption-side trends warrant particular note. First, the post-pandemic normalisation of digital grocery use has produced a base of users who are not novices but who nonetheless face new app features (live-stream sourcing, AR product previews, conversational assistants, biometric checkout) at a steady rate, exposing the gap between competence with the platform's basic functions and ease with its newer ones (Singh et al., 2023). Second, the segment is dominated by repeat-purchase rhythms (weekly or twice-weekly) rather than one-off acquisitions, which raises the operational weight of any factor that influences whether the user returns next week (Yang F.M., 2025; Fei & Chen, 2025; Liu W.J. & Liu J.H., 2025).

Continuance intention as a post-adoption behavioural construct

The dependent construct in this study - continuance intention - belongs to the post-adoption family of behavioural-intention measures originally formalised in the information-systems literature and subsequently extended into platform-based digital commerce (Liu X.N. et al., 2025; Davis & Chandrasekar, 2025; Yu F.H., 2025; Zhou J.H., 2025). Continuance differs in important ways from adoption. Adoption asks whether a user will initiate a relationship with a system; continuance asks whether the user, having already initiated and reflected on the experience, will sustain it. The literature consistently identifies satisfaction, perceived performance, trust, expectation-performance fit, and habit formation as the proximate drivers of continuance (Cheng et al., 2024; Sharma et al., 2024).

In digital-grocery contexts, continuance has special bite. Switching costs are low (alternative apps are one tap away), basket sizes are recurrent rather than monolithic, and even small dips in confidence can dissolve a habit (Monoarfa et al., 2024; Yang F.M., 2025; Jiao et al., 2025). Continuance has been studied across many adjacent settings - smart-education platforms (Fu & Zhang, 2025), mobile-government applications (Yi & Zhu, 2025), internet-medical platforms (Liu X.N. et al., 2025; Yu H.X., 2025), AR retail applications (Song et al., 2025), AI-assistant chatbots (Xu et al., 2025), social-networking apps (Lin, 2025; Yang Z.Y., 2025), AIGC mobile apps (Zhou J.H., 2025), and even VR exhibitions (Wang M. et al., 2023; Zhang Q. et al., 2025) - each enriching the inventory of antecedents but each also leaving open the question of how user-side participatory behaviours feed in.

Related evidence from Douyin shows that content practices can erode platform stickiness through declining user trust, while algorithmic regulation can buffer this retention loss (Gan et al., 2025).

Co-productive engagement: Why aggregation loses information

The construct we label "co-productive engagement" sits in the long tradition that conceptualises customers as participants in value creation rather than passive recipients of provider-delivered service (Xie et al., 2008; Wu & Chen, 2017; Verhagen et al., 2014). The conceptual move that organises this paper is the disaggregation of that construct into four observable strands that map cleanly onto distinct cognitive and behavioural resources. We adopt this decomposition because aggregated treatments cannot tell us, for instance, whether the apprehensive user is suffering at the informational-acquisition step or at the interaction step - a distinction with sharp design consequences.

A clarification of construct status is warranted. We use co-productive engagement as an organising, umbrella concept rather than as a measured higher-order (second-order) latent variable. Empirically, the four strands, task cognition, information seeking, effort expenditure, and human-computer interaction, are modelled as four distinct first-order reflective constructs, each entered as a separate antecedent of service-quality perception. We do not estimate a reflective-reflective or formative-reflective higher-order construct, and we make no claim that the four strands are interchangeable indicators of a single latent engagement factor. Accordingly, references throughout to the “architecture” or “decomposition” of engagement denote this conceptual organisation, and the results should be read as evidence about four related but separable engagement dimensions rather than about a superordinate construct.

The first strand, task cognition, refers to a user's understanding of platform rules, navigation logic, promotion rules, and the procedural sequence required to convert browsing into delivery. Conceptually it draws on job-characteristics work that links role clarity to performance and motivation; in digital retail it has been recast as a user-side awareness of how recommender systems, filtering options, and check-out flows actually operate. It is foundational in the sense that the other three strands depend on it.

The second strand, information seeking, captures the user's proactive collection and verification of product- and service-relevant information from in-app and external sources - reading provenance labels, comparing freshness ratings, scrutinising user reviews, reading promotion fine print. For perishable goods this strand is unusually consequential because pre-purchase physical inspection is impossible (Qi et al., 2024; Shen, 2025; Wang & Li, 2025).

The third strand, effort expenditure, captures the time, attention, and behavioural-resource investment a user is willing to make - daily check-ins, custom requests in order notes, schedule adjustments to receive deliveries, participation in review programmes, tolerance of minor product imperfections (Wu & Chen, 2017). It is the most observable of the four strands and frequently the most consequential for service-quality perception, because effort tends to crystallise into a sense of investment and ownership.

The fourth strand, human-computer interaction, captures the interaction quality with the platform's digital interface - the smoothness of filters, the helpfulness of intelligent search, the responsiveness of in-app customer service, the seamlessness of the browse-cart-checkout chain (Chattaraman et al., 2012; Huang & Benyoucef, 2013; Tarafdar et al., 2019). Where the first three strands describe what the user does, this fourth strand describes how the platform reciprocates.

The decomposition is conceptually clean and, apart from the authors' earlier report using the same dataset (Yue et al., 2026), remains uncommon in the fresh-grocery literature, where prior empirical work has either combined the dimensions or studied them in smaller subsets (Yang F.M., 2025; Monoarfa et al., 2024; Ren et al., 2025; Wang & Li, 2025).

Service-quality perception as cognitive bridge

The service-quality construct used here is grounded in the SERVQUAL tradition (Parasuraman et al., 1988) but adapted in two ways. First, the five classical dimensions - tangibles, reliability, responsiveness, assurance, empathy - are recast for a perishable-delivery context, where tangibles include packaging integrity and the delivery uniform; reliability turns on freshness and on-time fulfilment; responsiveness means the speed of after-sales remediation; assurance means the credibility of provenance disclosure and the security of payment; and empathy includes regionally tailored offerings (e.g., recommending Cantonese-cuisine ingredients) and flexible delivery windows (Kim & Yum, 2024; Monoarfa et al., 2024).

Second - and this is the conceptual move that distinguishes our use of the construct from much prior work - we treat service-quality perception as a transmitting mechanism rather than a static evaluation. In the language of stimulus-organism-response models, it is the organism that receives the participatory stimulus and translates it into a behavioural response (Mehrabian & Russell, 1974; Cheng et al., 2024; Gao et al., 2015). Service quality, in this formulation, is what stands between what the user does on the platform and whether the user comes back next week.

Technology-related apprehension as a boundary condition

Technology-related apprehension - an enduring sense of discomfort, friction, or anxious anticipation when interacting with digital systems - has been studied principally in the technology-adoption tradition (Tarafdar et al., 2019; Tarhini et al., 2021; Singh et al., 2023; Sharma et al., 2024). Most treatments hypothesise a generalised inhibitory effect: apprehensive users do less, evaluate less favourably, and continue less reliably. We retain that baseline expectation for the direct effect on service-quality perception but argue that the moderating effect should be path-conditional. Apprehension should weigh on routes that demand active information processing and cognitive filtering (i.e., information seeking) but should weigh less on routes that are essentially behaviour (effort expenditure) or that depend on the platform's design quality (human-computer interaction) or that pre-suppose existing rule-comprehension (task cognition).

This nuanced expectation is consistent with recent empirical work that finds heterogeneity rather than uniformity in technology-related affective burdens. It also aligns with the technostress-trifecta proposal that techno-distress is task-specific rather than person-specific (Tarafdar et al., 2019).

Complementary evidence from AI-personalised digital platforms shows that consumer engagement translates into loyalty more strongly when algorithmic trust is high, reinforcing the need to model technology-specific boundary conditions (Xiao et al., 2025).

Conceptual Model and Hypotheses

The conceptual model contains thirteen hypothesised relations. Four direct effects (H1a–H1d) link the engagement dimensions to service-quality perception. One direct effect (H2) links service-quality perception to continuance intention. Four moderating effects (H3a–H3d) propose that technology-related apprehension dampens the four engagement-to-perception routes. Four additional direct effects (H4a–H4d) link the engagement dimensions to continuance intention, allowing a formal test of partial mediation. The model, including the direct engagement-to-continuance paths shown as dashed arrows, is depicted in **Figure 1**.

From engagement strands to service-quality perception

The standard expectation-confirmation logic implies that perceived service quality - an aggregated cognitive judgement about platform performance - forms the most stable basis for the user's intention to keep using the platform (Kim & Yum, 2024). Where service quality is judged high, repeat use becomes the path of least resistance; where it is judged low, switching is comparatively easy because the rival apps are one tap away.

H1a. Task cognition is positively related to service-quality perception. Information seeking allows the user to overcome the unusually high pre-purchase uncertainty of perishable goods. The user who reads a provenance label, compares supplier ratings, and checks delivery-window logistics enters into the purchase with calibrated expectations that the platform can more easily satisfy. Information seeking thereby raises perceived reliability and assurance.

H1b. Information seeking is positively related to service-quality perception. Effort expenditure raises perceived quality through two routes: instrumental (more effort surfaces more relevant information and unlocks better matched delivery slots) and psychological (effort fosters a sense of co-production and ownership that biases evaluation upward). Because behavioural investment is directly observable and

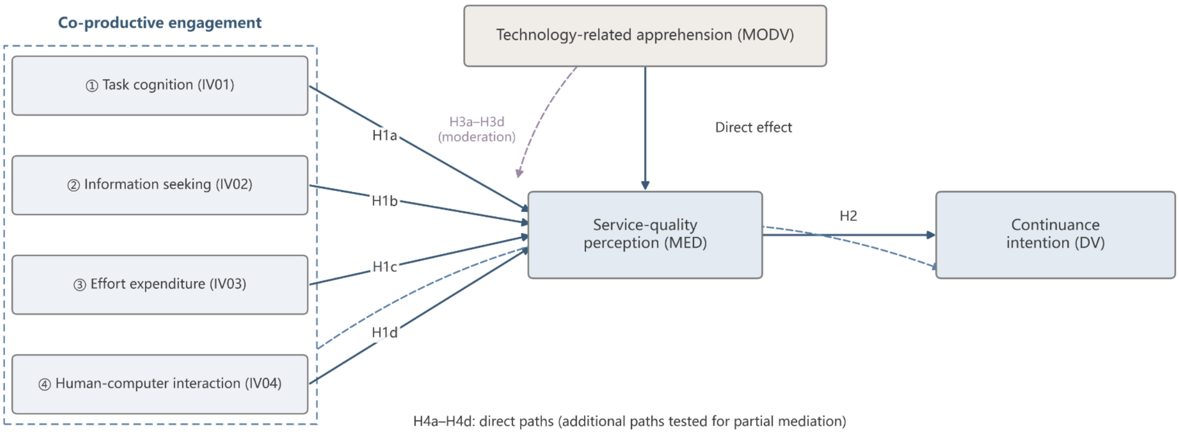

Figure 1 | Conceptual research framework

Solid arrows denote the hypothesised paths (H1a–H1d, H2); the dashed arrows denote the moderation of the four engagement→service-quality paths by technology-related apprehension (H3a–H3d) and the additional direct engagement→continuance paths (H4a–H4d).

personally costly, its quality-enhancing effect should be the strongest of the four.

H1c. Effort expenditure is positively related to service-quality perception. Human-computer interaction translates platform capability into perceptible smoothness. A clean filtering pane, a precise intelligent search, an attentive chatbot, and a seamless purchase chain are all read as evidence of quality. Conversely a clunky interface is read as low quality regardless of backstage performance.

H1d. Human-computer interaction is positively related to service-quality perception.

From service-quality perception to continuance intention

The standard expectation-confirmation logic implies that perceived service quality - an aggregated cognitive judgement about platform performance - forms the most stable basis for the user's intention to keep using the platform (Yu Y. et al., 2024; Nguyen et al., 2024; Kim & Yum, 2024; Dandis et al., 2026; Utami et al., 2025). Where service quality is judged high, repeat use becomes the path of least resistance; where it is judged low, switching is comparatively easy because the rival apps are one tap away.

H2. Service-quality perception is positively related to continuance intention.

Although the framework routes engagement through perceived service quality, the engagement dimensions may also influence continuance intention directly, for example, through habit formation or accumulated familiarity that bypasses explicit quality evaluation. To represent this possibility in the model, and to enable a formal test of partial versus full mediation, we additionally estimate direct engagement-to-continuance paths and state the following hypotheses:

H4a. Task cognition is positively related to continuance intention.

H4b. Information seeking is positively related to continuance intention.

H4c. Effort expenditure is positively related to continuance intention.

H4d. Human-computer interaction is positively related to continuance intention.

We further expect each engagement dimension to exert a positive indirect effect on continuance intention through service-quality perception; the joint presence of a significant direct effect and a significant indirect effect would indicate complementary partial mediation.

Technology-related apprehension as path-conditional moderator

For each engagement strand, we propose a moderating effect of technology-related apprehension. Our prior, however, is asymmetric: the moderating effect should be largest for the route that depends most heavily on cognitive-informational processing.

H3a. Technology-related apprehension dampens the task-cognition to service-quality-perception relation.

H3b. Technology-related apprehension dampens the information-seeking to service-quality-perception relation.

H3c. Technology-related apprehension dampens the effort-expenditure to service-quality-perception relation.

H3d. Technology-related apprehension dampens the human-computer-interaction to service-quality-perception relation.

Table 1 | Construct definitions, item-set composition, and adaptation sources for the seven latent variables

Construct (Code)	Operational definition in the fresh-grocery context	Items	Principal adaptation sources
Task cognition (IV01)	A user's procedural understanding of platform rules, navigation flow, promotion logic, and the steps needed to translate browsing into a delivered order	5	Hackman & Oldham (1976); Xie et al. (2008); Wu & Chen (2017)
Information seeking (IV02)	A user's proactive acquisition and verification of product- and service-related information from in-app and external sources	5	Punj & Staelin (1983); Xie et al. (2008)
Effort expenditure (IV03)	The time, attention, and behavioural-resource investment a user is willing to make to obtain platform benefits and complete purchase tasks	5	Xie et al. (2008); Wu & Chen (2017)
Human-computer interaction (IV04)	The user's interaction quality with the platform interface, including filtering, search, recommendations, in-app customer service, and process fluency	5	Larivière et al. (2017); Chattaraman et al. (2012); Huang & Benyoucef (2013); Tarafdar et al. (2019)
Service-quality perception (MED)	The user's overall cognitive evaluation of platform performance across packaging, freshness, after-sales responsiveness, security, and tailored offerings	5	Parasuraman et al. (1988); Kim & Yum (2024); Monoarfa et al. (2024); Huang & Benyoucef (2013)
Continuance intention (DV)	The user's intention to keep purchasing fresh groceries from the platform, prefer it over alternatives, recommend it, and treat it as a primary channel	5	Bhattacherjee (2001); Gao et al. (2015); Kim & Yum (2024); Monoarfa et al. (2024)
Technology-related apprehension (MODV)	A user's discomfort, nervousness, or unease in interacting with platform technology, new features, and data-privacy considerations	5	Meuter et al. (2003); Tarhini et al. (2021); Tarafdar et al. (2019)

Note. Items = number of measurement items per construct. Sources are the principal instruments from which items were adapted and contextualised to the fresh-grocery setting. Full item wording is provided in Appendix A.

We expect H3b to receive the strongest support because information seeking is the strand most cognitively demanding of platform-system fluency. The other three hypotheses are stated with directional priors but with weaker expected magnitudes.

Research Design

Philosophical orientation and approach

The investigation adopts a positivist orientation, on the grounds that the constructs of interest are measurable, the relationships among them are amenable to statistical estimation, and the theoretical framework (S-O-R, with SERVQUAL as the perceptual mediator) generates falsifiable predictions. This stance is consonant with recent methodological guidance for quantitative research in digital-commerce contexts. Consistent with established PLS-SEM guidance (Hair et al., 2022), partial-least-squares structural equation modelling (PLS-SEM) was elected over covariance-based SEM for four reasons: **1)** the model is structurally complex, with multiple latent constructs, a mediator, and four interaction terms; **2)** PLS-SEM is prediction-oriented, aligning with the study's emphasis on explaining variance in continuance intention; **3)** PLS-SEM is robust to non-normal data, common in survey work on perceptions; and **4)** it accommodates exploratory model extensions of the kind we propose here.

Equations (1) and (2) specify the estimated structural model. In Equation (1), service-quality perception (MED) is regressed on the four engagement dimensions (IV_k, k = 1–4: task cognition, information seeking, effort expenditure, human-computer interaction), technology-related apprehension (MODV), and the four latent interaction terms (MODV × IV_k); β_k are the engagement path coefficients, β_m the direct apprehension effect, γ_k the moderation coefficients, and ε_1 the disturbance. In Equation (2), continuance intention (DV) is regressed on service-quality perception (β) and, through the direct paths, on the four engagement dimensions (δ_k), with disturbance ε_2.

$$\mathrm{MED} = \sum_{k=1}^{4} \beta_k \mathrm{IV}_k + \beta_m \mathrm{MODV} + \sum_{k=1}^{4} \gamma_k \left(\mathrm{MODV} \times \mathrm{IV}_k\right) + \varepsilon_1 \quad (1)$$

$$\mathrm{DV} = \beta\, \mathrm{MED} + \sum_{k=1}^{4} \delta_k \mathrm{IV}_k + \varepsilon_2 \quad (2)$$

Population, sampling, and sample size

The target population was operationalised as active fresh-grocery e-commerce users in Guangdong Province, defined by four jointly applied screening criteria: **a)** experience with platforms that deliver perishable groceries (vegetables, fruit, meat, seafood, dairy); **b)** at least one fresh-grocery purchase in the preceding six months; **c)** a baseline purchase frequency of at least once per month; and **d)** evidence of at least one form of engagement behaviour (information seeking, effort expenditure, human-computer interaction, or feedback provision).

The effective target population, after these criteria are applied, was estimated at 25-35 million users (against a provincial fresh-grocery user base of 40-50 million and a national base exceeding 450 million). Sample-size determination proceeded through three triangulating logics. The "10-times rule" implied a floor of 200-300 cases given the complexity of the structural model; the Krejcie-Morgan table implied a floor of roughly 384 for large populations; and statis-

Table 2 | Pre-test results by item: content-validity ratio, factor loading, item-total correlation, and comprehensibility (n = 40)

Construct	Item	CVR	Loading	Item-total	Understand
Task cognition (WC)	WC1	0.87	0.741	0.576	4.6
	WC2	0.85	0.855	0.582	4.5
	WC3	0.86	0.924	0.718	4.4
	WC4	0.88	0.910	0.719	4.7
	WC5	0.84	0.669	0.738	4.6
Information seeking (IS)	IS1	0.86	0.857	0.610	4.6
	IS2	0.85	0.609	0.376	4.5
	IS3 (R)	0.82	0.880	0.809	4.3
	IS4	0.87	0.670	0.497	4.6
	IS5	0.84	0.780	0.514	4.5
Effort expenditure (EF)	EF1	0.85	0.619	0.489	4.5
	EF2	0.83	0.486	0.561	4.4
	EF3	0.82	0.662	0.560	4.3
	EF4	0.81	0.740	0.439	4.2
	EF5	0.84	0.811	0.520	4.5
Human-computer interaction (HCI)	HCI1	0.86	0.924	0.699	4.7
	HCI2	0.85	0.673	0.721	4.6
	HCI3 (R)	0.82	0.834	0.735	4.3
	HCI4	0.84	0.787	0.328	4.5
	HCI5	0.88	0.526	0.397	4.7
Service-quality perception (SQ)	SQ1	0.87	0.568	0.322	4.7
	SQ2	0.88	0.750	0.680	4.8
	SQ3	0.86	0.582	0.420	4.6
	SQ4	0.85	0.523	0.460	4.6
	SQ5	0.84	0.671	0.517	4.5
Continuance intention (CI)	CI1	0.89	0.625	0.466	4.8
	CI2	0.87	0.601	0.567	4.7
	CI3	0.88	0.898	0.701	4.8
	CI4	0.86	0.758	0.561	4.6
	CI5	0.85	0.722	0.507	4.6
Technology-related apprehension (TA)	TA1	0.86	-0.810	0.508	4.6
	TA2	0.85	-0.791	0.543	4.5
	TA3	0.88	-0.886	0.426	4.7
	TA4 (R)	0.82	-0.862	0.334	4.3
	TA5	0.87	-0.905	0.548	4.6

Notes. (R) denotes reverse-coded items; negative loadings on TA items reflect the reverse-coded construct direction. Acceptance thresholds: CVR > 0.80, |loading| > 0.50, item-total > 0.30, understandability > 4.0. n = 40.

tical-power considerations for detecting interaction effects implied a further increment. After allowing for typical 10-20% post-cleaning loss, the targeted sample size was set at 600. After data cleaning, 550 valid cases were retained.

A combined purposive-convenience sampling approach was used. Purposive sampling ensured that respondents met the four screening criteria; convenience sampling allowed efficient online recruitment via social-media platforms and digital communities frequented by fresh-grocery users. Several procedures, IP and device tracking, minimum response-time thresholds, and consistency checks against reverse-coded items, were applied during fieldwork to protect data integrity. Because recruitment combined purposive screening with convenience-based online channels, the resulting sample is non-probabilistic; we therefore treat it as analytically useful for testing structural relationships rather than as statistically representative of the entire fresh-grocery user population in Guangdong, and we qualify all generalisation claims accordingly.

Instrument and measurement

All latent variables were measured with multi-item scales adapted from validated prior instruments and contextualised to the fresh-grocery setting. Items were rated on a five-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). The five-point format was chosen for its established discriminability and respondent-friendliness in consumer-perception research. Table 1 summarises the construct definitions, the sub-dimensions tapped by each item set, and the principal sources from which each item set was adapted.

Pre-test and pilot test

Two pre-fieldwork stages refined the instrument. A pre-test assessed semantic clarity, construct alignment, and con-

Table 3 | Pilot-test reliability statistics by construct (n = 40)

Construct	Cronbach's alpha	Items meeting (all criteria)	Action taken
Task cognition (WC)	0.807	5/5	All items retained
Information seeking (IS)	0.801	5/5	All items retained
Effort expenditure (EF)	0.776	4/5	EF2 retained after triangulation
Human-computer interaction (HCI)	0.853	5/5	All items retained
Service-quality perception (SQ)	0.792	5/5	All items retained
Continuance intention (CI)	0.838	5/5	All items retained
Technology-related apprehension (TA)	0.929	5/5	All items retained

Note. α = Cronbach's alpha. EF2 was retained after triangulation against its item-total correlation and content validity. n = 40.

Table 4 | Missing-data audit by measurement item-set (n = 550 respondents, 35 items in total)

Item-set	Items	Cases	Missing	Missing rate (%)
Task cognition (IV01-Q1 to Q5)	5	550	0	0.0
Information seeking (IV02-Q1 to Q5)	5	550	0	0.0
Effort expenditure (IV03-Q1 to Q5)	5	550	0	0.0
Human-computer interaction (IV04-Q1 to Q5)	5	550	0	0.0
Service-quality perception (MED-Q1 to Q5)	5	550	0	0.0
Continuance intention (DV-Q1 to Q5)	5	550	0	0.0
Technology-related apprehension (MODV-Q1 to Q5)	5	550	0	0.0

Note. Missing rate = missing cases / 550. No imputation was required. Source: authors' data audit.

textual fit against four benchmarks: content validity ratio (CVR > 0.80), factor loadings (|lambda| > 0.50), item-total correlations (> 0.30), and comprehensibility scores (mean > 4.0 on a five-point understandability scale). Expert reviews and respondent debriefs led to several revisions: ambiguous wording was simplified, double-barrelled items were split, redundant items were removed, and context-specific terms (e.g., "delivery time-slot," "freshness inspection") were introduced. A pilot test with 40 respondents then assessed reliability (Cronbach's alpha > 0.70; CR > 0.70), convergent validity (loadings > 0.50; AVE > 0.50), discriminant clarity, and operational feasibility. **Table 2** and **Table 3** report the pre-test and pilot-test results respectively.

Data-collection procedure and ethical safeguards

Questionnaires were distributed online over a continuous multi-week fieldwork window. Screening questions enforced the four eligibility criteria at the front of the survey. Continuous monitoring detected uneven regional representation (rebalanced through targeted channel adjustments), repeated devices, anomalously short completion times, and uniform-response (straight-lining) patterns. Of the 600 responses collected, 50 (8.3%) were removed, for duplicate IP/device fingerprints, completion times below one-third of the median time, straight-lining across reverse-coded items, or failed embedded consistency checks, leaving 550 valid cases. The retained sample spanned core Pearl River Delta cities (60.0%), non-core Delta cities (25.1%), and eastern, western, and northern Guangdong (14.9%); its gender split was 52.0% female and 48.0% male.

The present manuscript draws on the same Guangdong survey (N = 550) and structural model previously reported by Yue et al. (2026); it is presented here as an expanded methodological and interpretive account, not as an independent sample or replication. Relative to that report, this manuscript clarifies the umbrella status of co-productive engagement, provides fuller direct, indirect, total-effect and robustness reporting, adds the simple-slope analysis, and supplies the complete instrument in Appendix A.

The study followed the World Medical Association's Declaration of Helsinki (2013) and complied with both China's Personal Information Protection Law (2021) and the EU General Data Protection Regulation. A digital informed-consent mechanism appeared on the first page of the survey, identifying the study's purpose, the nature of the data collected, the anonymity and voluntariness of participation, and the right to withdraw without penalty. No personally identifying information was captured. Data were transmitted via SSL-encrypted channels and stored on access-controlled, password-protected systems; data retention was capped at three years post-publication. Third-party recruitment platforms were ISO 27001-certified. An optional, segregated email field allowed respondents to request a results summary without compromising anonymity.

Results

Sample profile

After cleaning, the analytical sample comprised 550 respondents. Demographic and behavioural profiles are visualised in **Figure 2** through **Figure 8**: gender, age, education, city-tier, most-frequently-used platform, purchase frequency, and average monthly spend each followed reasonable empirical distributions for the target population.

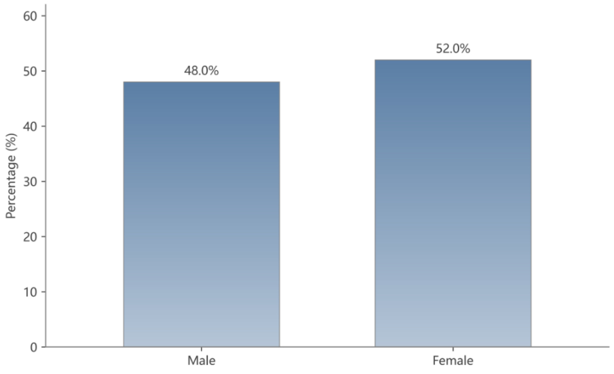

Figure 2 | Gender distribution of respondents (n = 550)

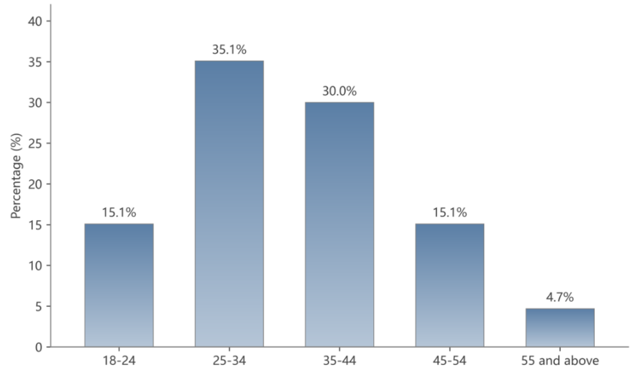

Figure 3 | Age distribution of respondents (n = 550)

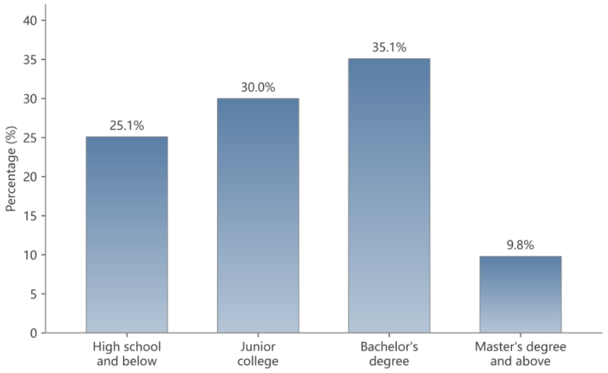

Figure 4 | Educational-attainment distribution of respondents (n = 550)

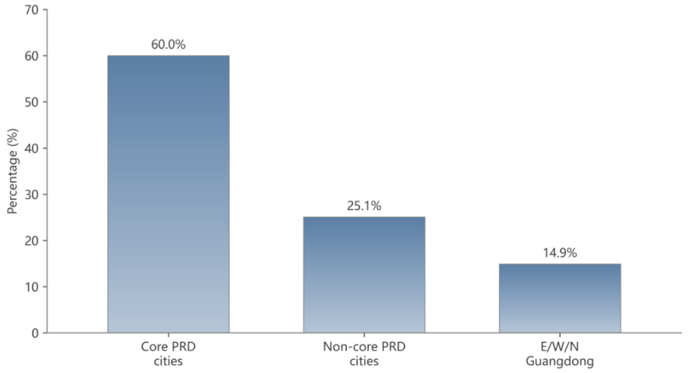

Figure 5 | Long-term residential city classification of respondents (n = 550)

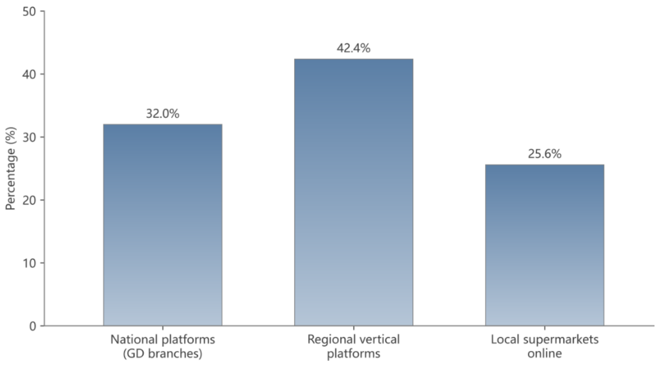

Figure 6 | Distribution of the most frequently used fresh-grocery e-commerce platform (n = 550)

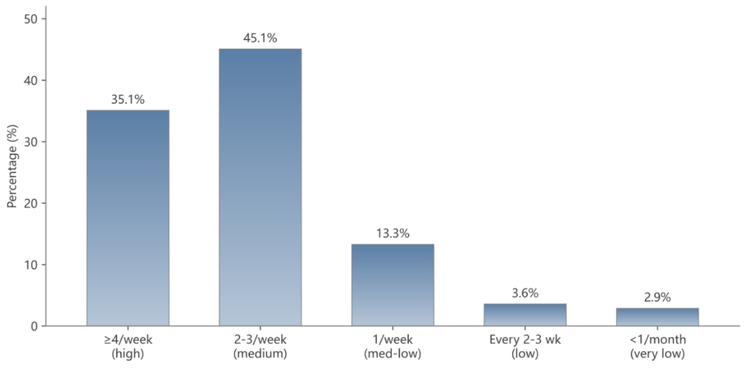

Figure 7 | Purchase frequency on the most frequently used fresh-grocery platform (n = 550)

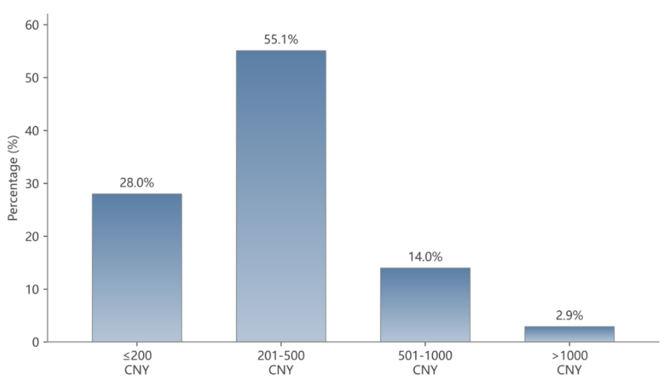

Figure 8 | Average monthly spending on fresh-grocery e-commerce (n = 550)

Table 5 | Descriptive statistics and normality diagnostics by item (n = 550). All items rated 1–5 Likert

Item	Min	Max	Mean	Median	SD	Skewness	Kurtosis
IV01-Q1	1.00	5.00	3.71	4	1.14	-0.74	0.07
IV01-Q2	1.00	5.00	3.71	4	1.10	-0.76	0.04
IV01-Q3	1.00	5.00	3.69	4	1.10	-0.76	0.08
IV01-Q4	1.00	5.00	3.69	4	1.13	-0.75	-0.05
IV01-Q5	1.00	5.00	3.74	4	1.17	-0.73	-0.26
IV02-Q1	1.00	5.00	3.70	4	1.10	-0.81	0.19
IV02-Q2	1.00	5.00	3.71	4	1.21	-0.77	-0.28
IV02-Q3	1.00	5.00	3.69	4	1.17	-0.89	0.09
IV02-Q4	1.00	5.00	3.62	4	1.16	-0.79	-0.05
IV02-Q5	1.00	5.00	3.74	4	1.18	-0.85	-0.02
IV03-Q1	1.00	5.00	3.67	4	1.24	-0.83	-0.20
IV03-Q2	1.00	5.00	3.63	4	1.20	-0.65	-0.43
IV03-Q3	1.00	5.00	3.67	4	1.26	-0.81	-0.29
IV03-Q4	1.00	5.00	3.63	4	1.14	-0.71	-0.08
IV03-Q5	1.00	5.00	3.69	4	1.16	-0.82	0.01
IV04-Q1	1.00	5.00	3.60	4	1.14	-0.69	-0.17
IV04-Q2	1.00	5.00	3.65	4	1.22	-0.77	-0.31
IV04-Q3	1.00	5.00	3.63	4	1.23	-0.69	-0.45
IV04-Q4	1.00	5.00	3.70	4	1.16	-0.85	-0.01
IV04-Q5	1.00	5.00	3.65	4	1.15	-0.69	-0.20
MED-Q1	1.00	5.00	3.67	4	1.17	-0.76	-0.16
MED-Q2	1.00	5.00	3.75	4	1.23	-0.85	-0.19
MED-Q3	1.00	5.00	3.64	4	1.16	-0.76	-0.05
MED-Q4	1.00	5.00	3.65	4	1.17	-0.81	-0.07
MED-Q5	1.00	5.00	3.73	4	1.17	-0.82	-0.12
DV-Q1	1.00	5.00	3.75	4	1.15	-0.74	-0.20
DV-Q2	1.00	5.00	3.76	4	1.13	-0.72	-0.26
DV-Q3	1.00	5.00	3.96	4	1.13	-1.01	0.24
DV-Q4	1.00	5.00	3.70	4	1.21	-0.76	-0.33
DV-Q5	1.00	5.00	3.89	4	1.12	-0.93	0.16
MODV-Q1	1.00	5.00	2.16	2	1.00	1.23	1.42
MODV-Q2	1.00	5.00	2.13	2	0.97	1.24	1.62
MODV-Q3	1.00	5.00	2.17	2	0.98	1.16	1.31
MODV-Q4	1.00	5.00	2.15	2	0.94	1.33	1.93
MODV-Q5	1.00	5.00	2.15	2	1.02	1.23	1.25

Note. The corrected continuance-intention (DV) rows replace values that, in the previously submitted version, had been transcribed from the information-seeking (IV02) item-set. The mean/skewness asymmetry between IV/MED/DV items (left-skewed, positive evaluations) and MODV items (right-skewed, low apprehension on average) is theoretically expected. n = 550.

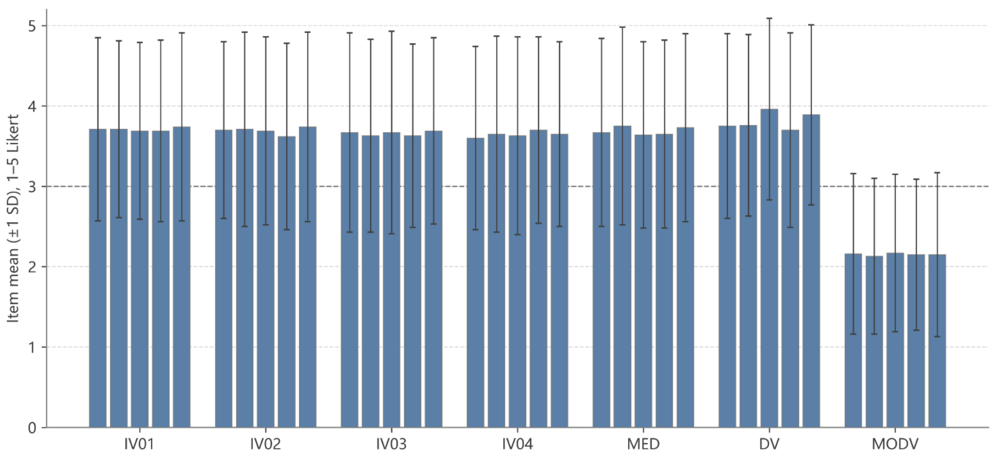

Figure 9 | Item-level means (±1 SD) across the 35 indicators, grouped by construct; the dashed line marks the 3.0 scale mid-point

Data preparation

Missing-value analysis indicated 0% missingness across all measurement items; consequently no imputation was required ([Table 4](#)). Outlier detection combined Z-score screening (|Z| > 3) with boxplot inspection; no extreme cases were identified that warranted exclusion. Reverse-coded items (notably within the technology-related apprehension and selected information-seeking and human-computer interaction items) were recoded to ensure uniform directionality. Distributional inspection produced item-level skewness values mostly in the range -1.08 to -0.65 for the four IV, mediator, and DV item sets and reverse-direction values around +1.16 to +1.34 for the MODV items, with kurtosis values close to zero ([Table 5](#)). Although Kolmogorov-Smirnov tests rejected the null of strict normality, the deviations are modest, and the use of PLS-SEM does not require strict normality.

[Figure 9](#) profiles the item-level means with ±1 SD. The four engagement dimensions, the mediator, and the dependent construct cluster above the scale mid-point (means ≈ 3.6–3.9), whereas the technology-related-apprehension items sit well below it (means ≈ 2.1), consistent with a sample of experienced, low-apprehension users.

[Figure 10](#) provides a normality check: histograms of the seven construct composites with a normal reference curve. The four engagement dimensions, the mediator, and the dependent construct are mildly left-skewed, whereas technology-related apprehension is right-skewed; all departures are modest, consistent with the skewness and kurtosis reported in [Table 5](#) and with the use of PLS-SEM, which does not require multivariate normality.

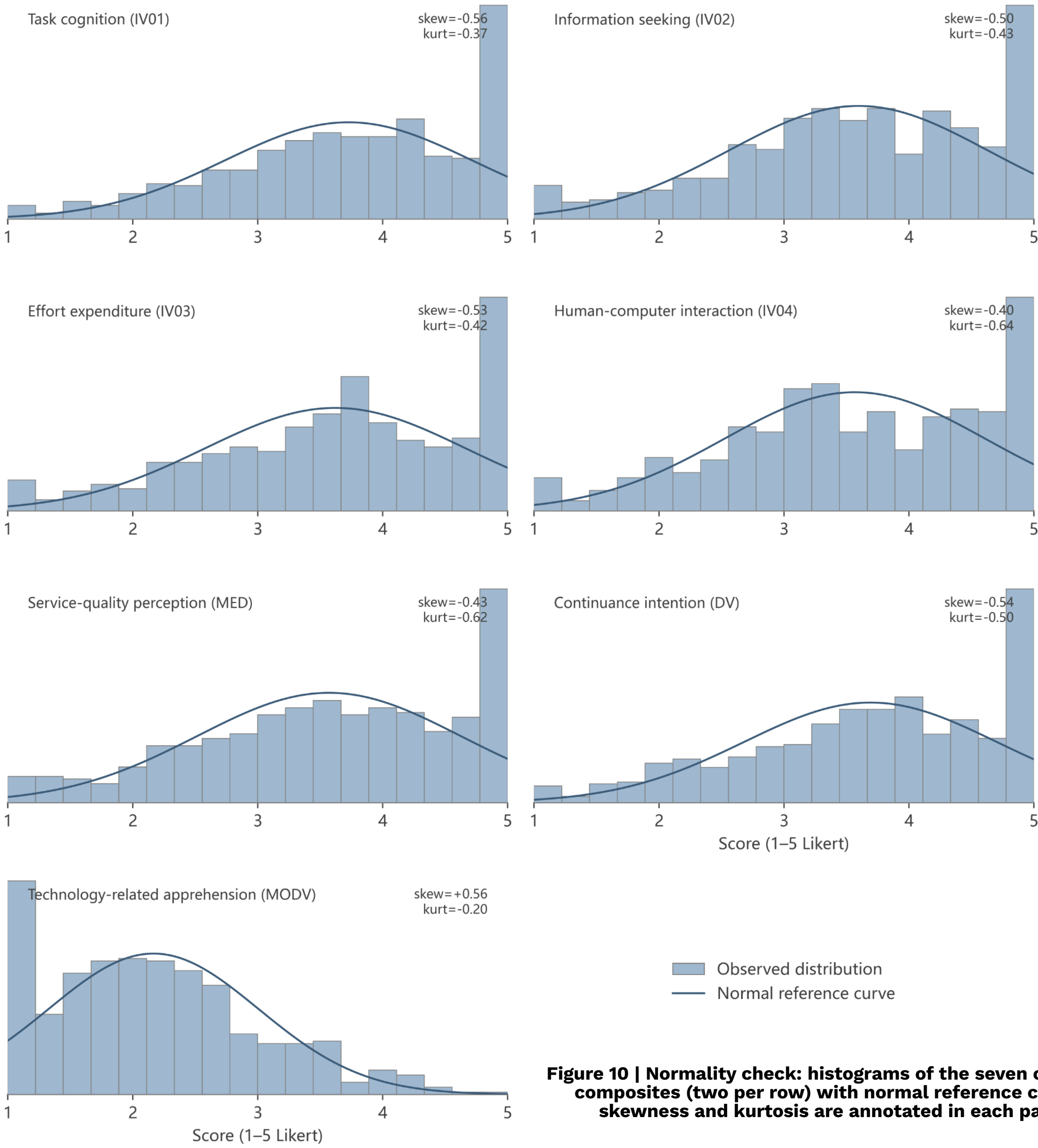

Figure 10 | Normality check: histograms of the seven construct composites (two per row) with normal reference curves; skewness and kurtosis are annotated in each panel

Common-method bias and multicollinearity

To assess the possibility that common-method variance had artificially inflated the inter-construct correlations, an unrotated principal-axis extraction was used to implement Harman's single-factor test. Seven factors emerged with eigenvalues above 1.0, and the first factor accounted for 27.36% of the total variance - well below the conventional 40% (and the more conservative 50%) cutoff (Table 6). The seven-factor cumulative variance reached 66.13%. We therefore concluded that common-method bias is unlikely to drive the substantive results.

Variance inflation factors (VIF) for all 35 indicators ranged from 1.376 (IV01-Q3) to 2.650 (MODV-Q5), all well below the conservative 3.3 ceiling and the more permissive 5.0 ceiling (Table 7), confirming that multicollinearity does not threaten parameter stability.

Because Harman's single-factor test offers only limited evidence, we applied the full-collinearity assessment proposed by Kock (2015), in which each latent construct is regressed on all the other constructs and the resulting variance inflation factors are inspected. All full-collinearity VIFs were below the 3.3 threshold (maximum 2.65), which provides no indication of pathological collinearity or substantial

Table 6 | Harman's single-factor test: extracted components and explained variance

Component	Eigenvalue	% of variance	Cumulative %
1	9.575	27.36	27.36
2	3.688	10.54	37.89
3	2.317	6.62	44.52
4	2.067	5.90	50.42
5	1.919	5.48	55.90
6	1.813	5.18	61.08
7	1.767	5.05	66.13
8	0.987	2.82	68.95
9-35	< 0.611 each	< 1.75 each	100.00

Note. Unrotated principal-axis extraction; the first factor explains 27.36% (< 40% threshold). n = 550.

Table 7 | Indicator-level variance inflation factors across the seven latent constructs

Indicator	VIF	Indicator	VIF	Indicator	VIF
DV-Q1	2.008	IV03-Q1	1.764	MED-Q1	1.908
DV-Q2	2.045	IV03-Q2	1.969	MED-Q2	2.090
DV-Q3	1.908	IV03-Q3	2.051	MED-Q3	2.065
DV-Q4	1.891	IV03-Q4	1.932	MED-Q4	2.035
DV-Q5	2.015	IV03-Q5	2.108	MED-Q5	1.867
IV01-Q1	1.963	IV04-Q1	2.429	MODV-Q1	2.493
IV01-Q2	1.993	IV04-Q2	2.040	MODV-Q2	2.393
IV01-Q3	1.376	IV04-Q3	2.135	MODV-Q3	2.258
IV01-Q4	2.005	IV04-Q4	1.989	MODV-Q4	2.334
IV01-Q5	2.103	IV04-Q5	2.010	MODV-Q5	2.650
IV02-Q1	1.901	\	\	\	\
IV02-Q2	1.889	\	\	\	\
IV02-Q3	1.862	\	\	\	\
IV02-Q4	2.004	\	\	\	\
IV02-Q5	1.728	\	\	\	\

Note. Outer-model (indicator) VIFs; all values are below the conservative 3.3 ceiling. n = 550.

Table 8 | SPSS-derived Cronbach's alpha and item-deletion diagnostics

Construct	Overall alpha	Alpha-if-deleted range across items
Task cognition (IV01)	0.779	0.728 - 0.781
Information seeking (IV02)	0.860	0.812 - 0.851
Effort expenditure (IV03)	0.870	0.831 - 0.861
Human-computer interaction (IV04)	0.885	0.852 - 0.879
Service-quality perception (MED)	0.873	0.839 - 0.868
Continuance intention (DV)	0.873	0.841 - 0.869
Technology-related apprehension (MODV)	0.904	0.875 - 0.897

Note. Alpha-if-deleted ranges replace the previously submitted values, which were uniform across constructs in error; in every construct, deleting any single item does not raise alpha above the overall coefficient, so all items are retained. n = 550.

Table 9 | Bootstrap composite reliability (ρc) from SmartPLS 4.1.1 (5,000 resamples)

Construct	Bootstrap alpha	rho_c	T (rho_c)	p (rho_c)
Continuance intention (DV)	0.873	0.908	180.90	0.000
Task cognition (IV01)	0.876	0.892	155.53	0.000
Information seeking (IV02)	0.861	0.899	166.26	0.000
Effort expenditure (IV03)	0.872	0.906	162.08	0.000
Human-computer interaction (IV04)	0.885	0.916	231.88	0.000
Service-quality perception (MED)	0.877	0.908	195.48	0.000
Technology-related apprehension (MODV)	0.907	0.929	212.55	0.000

Note. ρc = composite reliability; T and p from 5,000 bootstrap resamples. n = 550.

common-method bias under this diagnostic. Because all constructs were nonetheless measured from the same respondents on a single occasion, we retain common-method variance as a residual limitation rather than treating it as fully excluded.

Measurement-model evaluation

Construct reliability was excellent across all seven constructs (Table 8 and Table 9). SPSS-derived Cronbach's alpha coefficients ranged from 0.779 (task cognition) to 0.904 (technology-related apprehension), all above the 0.70 acceptance threshold. SmartPLS bootstrap estimates generated highly significant T-values (all $p < 0.001$) and ranged from 0.861 to 0.907. Composite reliability (rho_c) for each latent construct ranged from 0.892 to 0.929, all well above the 0.70 baseline.

Figure 11 plots the outer (indicator) loadings for all seven constructs. Every indicator exceeds the 0.708 benchmark except IV01-Q3 (0.617), which is discussed below; Figure 12 summarises Cronbach's alpha and composite reliability against the 0.70 threshold.

Discriminant validity was evaluated using the heterotrait-monotrait (HTMT) ratio with bootstrap-derived 95% confidence intervals (Table 10). The largest HTMT was

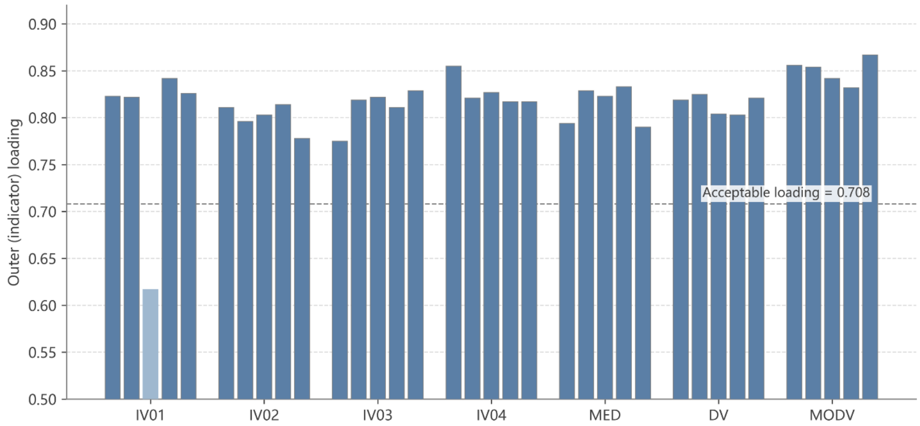

Figure 11 | Outer (indicator) loadings for the seven constructs. The dashed line marks the 0.708 acceptance benchmark; IV01-Q3 (0.617, hatched) is the only sub-benchmark indicator and is retained on content and item-total grounds.

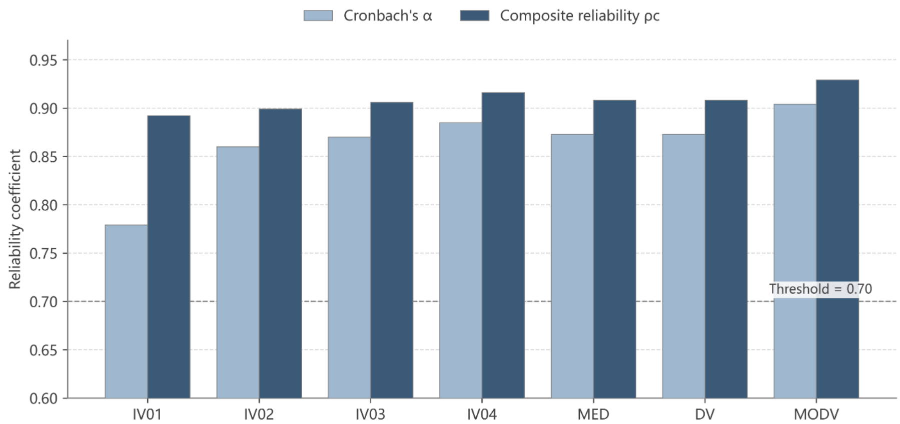

Figure 12 | Cronbach's alpha and composite reliability (ρc) by construct, against the 0.70 acceptance threshold

0.505 (IV03 to DV), comfortably below the 0.85 threshold; upper confidence-interval bounds never approached 1.0 (the highest was 0.596). HTMTs involving the moderator were uniformly low (0.075-0.324), confirming its conceptual independence from the other constructs.

Figure 13 displays the same HTMT ratios as a heat map.

Sampling-adequacy testing supported the measurement structure further. The Kaiser-Meyer-Olkin statistic was 0.921 (well above the 0.90 "excellent" threshold) and Bartlett's test of sphericity was highly significant (chi-square = 9939.146, df = 595, $p < 0.001$), summarised in Table 11. Exploratory factor analysis with varimax rotation extracted seven factors with eigenvalues above 1.0, accounting for 66.13% of variance jointly (Table 12); each measurement item loaded strongly on its intended factor (Table 13 condenses the post-rotation loading profile).

Figure 14 presents the scree plot; the eigenvalues elbow after the seventh component, and seven factors satisfy the Kaiser (eigenvalue > 1) criterion.

Because the continuance-intention scale combines continued-use, preference, recommendation, and primary-channel items, we verified that these behavioural-intention facets form a single coherent construct. The five items load

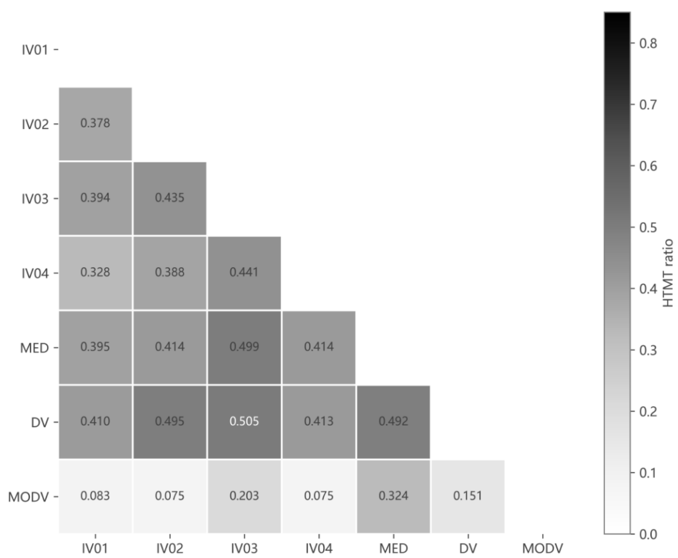

Figure 13 | Heterotrait-monotrait (HTMT) ratios among the seven constructs (lower triangle); all values are below the 0.85 threshold.

Table 10 | Heterotrait-monotrait (HTMT) ratios with 95% bootstrap confidence intervals (5,000 resamples)

Construct pair	HTMT	2.5% CI	97.5% CI
IV01 - DV	0.410	0.307	0.511
IV02 - DV	0.495	0.394	0.587
IV02 - IV01	0.378	0.276	0.479
IV03 - DV	0.505	0.408	0.596
IV03 - IV01	0.394	0.295	0.494
IV03 - IV02	0.435	0.331	0.535
IV04 - DV	0.413	0.315	0.513
IV04 - IV01	0.328	0.229	0.429
IV04 - IV02	0.388	0.285	0.486
IV04 - IV03	0.441	0.341	0.537
MED - DV	0.492	0.388	0.592
MED - IV01	0.395	0.293	0.490
MED - IV02	0.414	0.313	0.510
MED - IV03	0.499	0.402	0.594
MED - IV04	0.414	0.314	0.511
MODV - DV	0.151	0.060	0.258
MODV - IV01	0.083	0.042	0.182
MODV - IV02	0.075	0.048	0.175
MODV - IV03	0.203	0.095	0.313
MODV - IV04	0.075	0.059	0.159
MODV - MED	0.324	0.224	0.425

Note. All HTMT ratios are below the 0.85 threshold and no upper CI bound approaches 1.0, supporting discriminant validity (Henseler et al., 2015). n = 550.

Table 12 | Total variance explained by the seven-factor solution (initial and rotation sums).

Component	Initial eigenvalue	% var.	Cumul. %	Rot. eigenvalue	Rot. % var.	Rot. cumul. %
1	9.575	27.36	27.36	3.670	10.49	10.49
2	3.688	10.54	37.89	3.496	9.99	20.48
3	2.317	6.62	44.52	3.320	9.49	29.96
4	2.067	5.90	50.42	3.307	9.45	39.41
5	1.919	5.48	55.90	3.289	9.40	48.81
6	1.813	5.18	61.08	3.242	9.26	58.07
7	1.767	5.05	66.13	2.821	8.06	66.13

Note. Varimax rotation; seven factors with eigenvalues > 1.0 explain 66.13%. n = 550.

Table 11 | Sampling adequacy and sphericity diagnostics

Statistic	Value
Kaiser-Meyer-Olkin measure	0.921
Bartlett's chi-square	9939.146
Degrees of freedom	595
Significance	0.000

Note. KMO = Kaiser-Meyer-Olkin measure; Bartlett's test of sphericity. n = 550.

Table 13 | Condensed post-rotation factor-loading profile (varimax)

Item-set	Loading on intended factor	Highest cross-loading magnitude
IV01-Q1, Q2, Q4, Q5	0.759 - 0.833	≤ 0.16
IV02-Q1 to Q5	0.717 - 0.791	≤ 0.18
IV03-Q1 to Q5	0.718 - 0.795	≤ 0.22
IV04-Q1 to Q5	0.764 - 0.823	≤ 0.17
MED-Q1 to Q5	Strong on Factor 5	≤ 0.17
DV-Q1 to Q5	Strong on Factor 4	≤ 0.16
MODV-Q1 to Q5	Strong negative loadings on Factor 1	≤ 0.07

Note. A factor-loading anomaly on IV01-Q3 (which loaded weakly and inconsistently) was noted; the item was retained on the basis of its acceptable item-total correlation and pre-test CVR, and reliability tests confirm it does not destabilise its construct. n = 550.

Table 14 | Pearson correlations among latent-variable composites (n = 550)

	IV01	IV02	IV03	IV04	MED	DV	MODV
IV01	1						
IV02	0.343**	1					
IV03	0.343**	0.377**	1				
IV04	0.294**	0.340**	0.384**	1			
MED	0.344**	0.357**	0.435**	0.362**	1		
DV	0.372**	0.427**	0.441**	0.362**	0.431**	1	
MODV	-0.073	-0.066	-0.183**	-0.052	-0.287**	-0.135**	1

Note. Pearson correlations among latent-variable composites; ** p < 0.01 (two-tailed). n = 550.

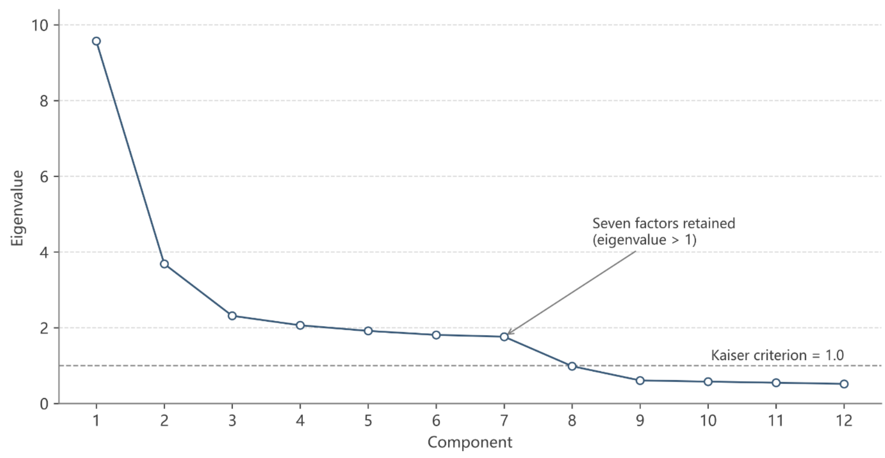

Figure 14 | Scree plot of component eigenvalues; the dashed line marks the Kaiser criterion (eigenvalue = 1.0), supporting a seven-factor solution.

Table 15 | Structural-model fit indices (5,000 bootstrap resamples)

Metric	Model	Original sample	Sample mean	95% bound	99% bound
SRMR	Saturated	0.041	0.034	0.037	0.038
SRMR	Estimated	0.041	0.035	0.037	0.039
d_ULS	Saturated	1.061	0.745	0.840	0.893
d_ULS	Estimated	1.055	0.763	0.879	0.948
d_G	Saturated	0.330	0.307	0.334	0.346
d_G	Estimated	0.327	0.304	0.329	0.341

Note. SRMR < 0.08 indicates acceptable approximate fit; d_ULS and d_G are discrepancy measures. 5,000 resamples. n = 550.

Table 16 | Coefficient-of-determination (R-squared) estimates with bootstrap inference

Construct	R-sq (Original)	R-sq (Mean)	SD	T	p
Continuance intention (DV)	0.342	0.352	0.042	8.24	0.000
Service-quality perception (MED)	0.403	0.418	0.037	10.84	0.000

Note. R-squared with 5,000-resample bootstrap inference. n = 550.

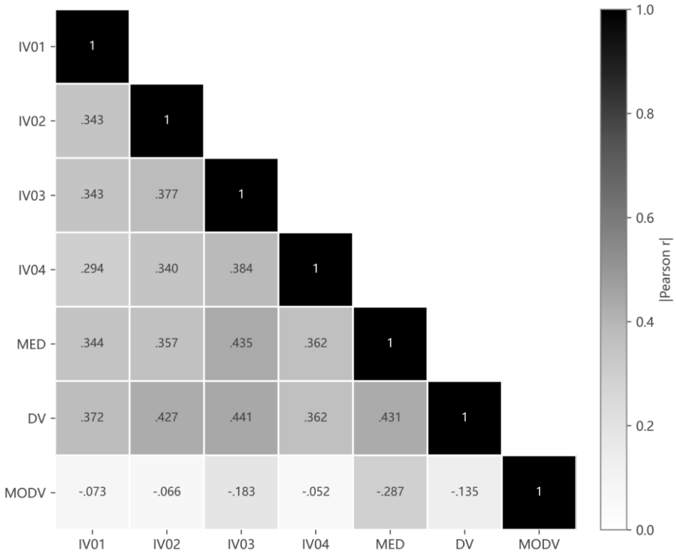

Figure 15 | Pearson correlation matrix among the seven constructs (lower triangle); shade encodes |r| and the signed coefficient is annotated.

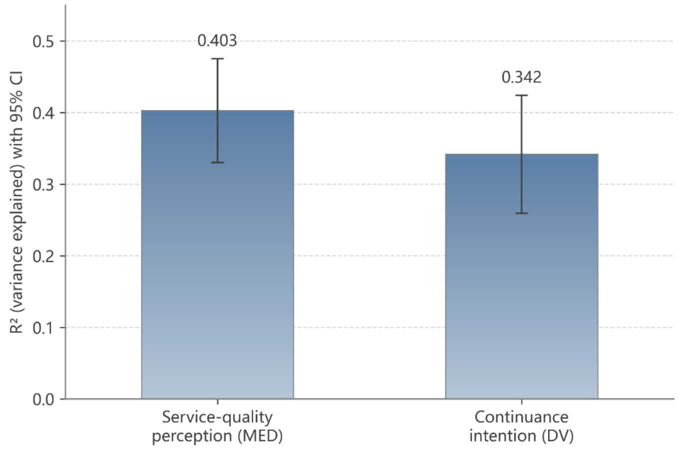

Figure 16 | Coefficient of determination (R^2) for the two endogenous constructs, with 95% confidence intervals.

on a single factor in the exploratory solution (all primary loadings on one factor, cross-loadings ≤ 0.16; Table 13), with Cronbach's α = 0.873, composite reliability ρc = 0.908, and average variance extracted above 0.50, and the construct is discriminant from all others (HTMT ≤ 0.505; Table 10). We therefore retain continuance intention as a unidimensional construct, consistent with extended expectation-confirmation treatments that bundle repurchase, preference, and advocacy intentions (Bhattacherjee, 2001). We nonetheless acknowledge that the recommendation (word-of-mouth) item taps an advocacy facet that future work could model as a separate outcome.

Inter-construct correlation patterns (Table 14) align with the hypothesised relations: each engagement strand correlates positively with both service-quality perception and continuance intention; service-quality perception correlates positively with continuance intention; and technology-related apprehension correlates negatively with service-quality perception (-0.287), with effort expenditure (-0.183), and (more weakly) with continuance intention (-0.135).

Figure 15 visualises the correlation matrix as a heat map; the cell shade encodes the absolute correlation and the signed value is annotated, so the uniformly weak negative correlations of technology-related apprehension are visible at a glance.

Structural-model evaluation

Structural-model fit indices fall within recommended ranges (Table 15). The SRMR for both saturated and estimated models is 0.041, well under the conservative 0.08 threshold. The geodesic distance (d_G) is 0.327 (estimated model), and the unweighted least-squares discrepancy (d_{ULS}) is 1.055.

R-squared statistics indicate moderate explanatory strength: 40.3% of the variance in service-quality perception and 34.2% of the variance in continuance intention are explained by their respective predictors (Table 16). Both R-squared values are significant at $p < 0.001$.

Figure 16 plots the two R^2 values with their 95% confidence intervals; both endogenous constructs show moderate, statistically significant explanatory power.

Effect-size (f-squared) estimates (Table 17) are predominantly in the weak-to-small range, with two exceptions: the direct effect of technology-related apprehension on service-quality perception (f-sq = 0.114, approaching medium) and

Table 17 | Effect-size (f-squared) estimates for structural relations and interaction terms

Path	f-sq	T	p
IV01 to DV	0.020	1.42	0.156
IV01 to MED	0.019	1.43	0.153
IV02 to DV	0.051	2.19	0.029
IV02 to MED	0.033	1.97	0.049
IV03 to DV	0.039	1.84	0.066
IV03 to MED	0.067	2.56	0.010
IV04 to DV	0.015	1.25	0.212
IV04 to MED	0.034	1.93	0.054
MED to DV	0.037	1.65	0.099
MODV to MED	0.114	2.89	0.004
MODV x IV01 to MED	0.004	0.47	0.641
MODV x IV02 to MED	0.047	2.09	0.037
MODV x IV03 to MED	0.000	0.00	0.997
MODV x IV04 to MED	0.009	0.84	0.400

Note. Effect sizes f² (Equation (3)); 0.02/0.15/0.35 = small/medium/large. The effects are predominantly small, so substantive claims are kept correspondingly measured. n = 550.

Table 18 | Structural-model path coefficients with bootstrap inference (5,000 resamples)

Path	Original	Mean	SD	T	p	Decision
IV01 to DV	0.129	0.131	0.042	3.077	0.002	Significant
IV01 to MED (H1a)	0.122	0.121	0.041	3.006	0.003	Supported
IV02 to DV	0.209	0.209	0.046	4.579	0.000	Significant
IV02 to MED (H1b)	0.165	0.165	0.041	4.022	0.000	Supported
IV03 to DV	0.192	0.193	0.049	3.958	0.000	Significant
IV03 to MED (H1c)	0.239	0.239	0.044	5.482	0.000	Supported
IV04 to DV	0.112	0.113	0.042	2.688	0.007	Significant
IV04 to MED (H1d)	0.162	0.162	0.040	4.055	0.000	Supported
MED to DV (H2)	0.185	0.183	0.052	3.530	0.000	Supported
MODV to MED	-0.280	-0.282	0.044	6.385	0.000	Significant
MODV × IV01 to MED (H3a)	-0.052	-0.052	0.047	1.103	0.270	Not supported
MODV × IV02 to MED (H3b)	-0.178	-0.180	0.041	4.381	0.000	Supported
MODV × IV03 to MED (H3c)	-0.004	-0.003	0.048	0.077	0.939	Not supported
MODV × IV04 to MED (H3d)	-0.082	-0.083	0.047	1.761	0.078	Not supported

Note. Standardised path coefficients with 5,000-resample bootstrap inference. * p < .05, ** p < .01, *** p < .001. n = 550.

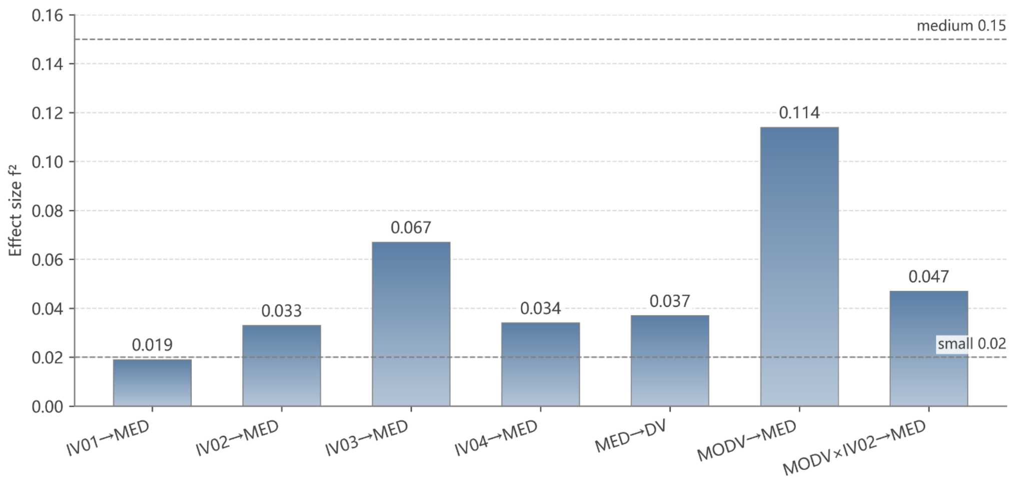

Figure 17 | Effect sizes (f²) for the structural relations, against the 0.02 (small) and 0.15 (medium) benchmarks.

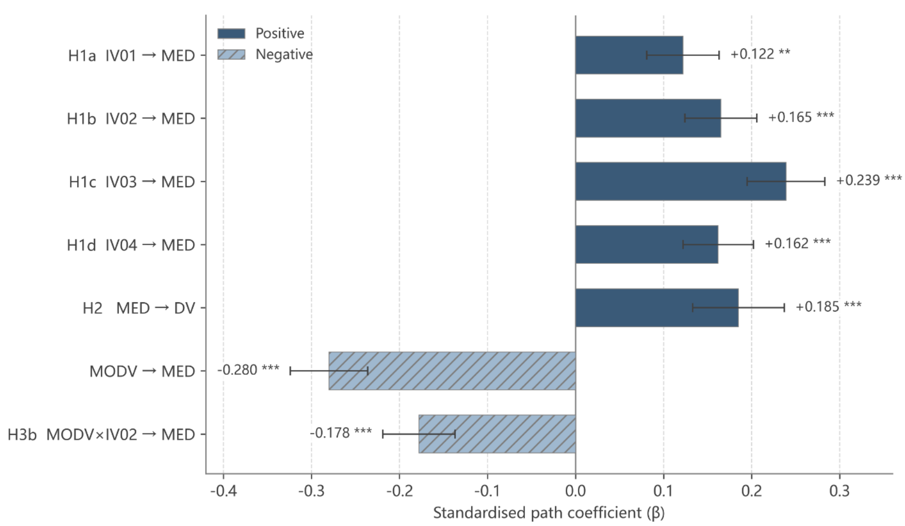

Figure 18 | Standardised structural path coefficients with bootstrap standard errors. Positive coefficients are solid, negative coefficients hatched (p < .01, *** p < .001)**

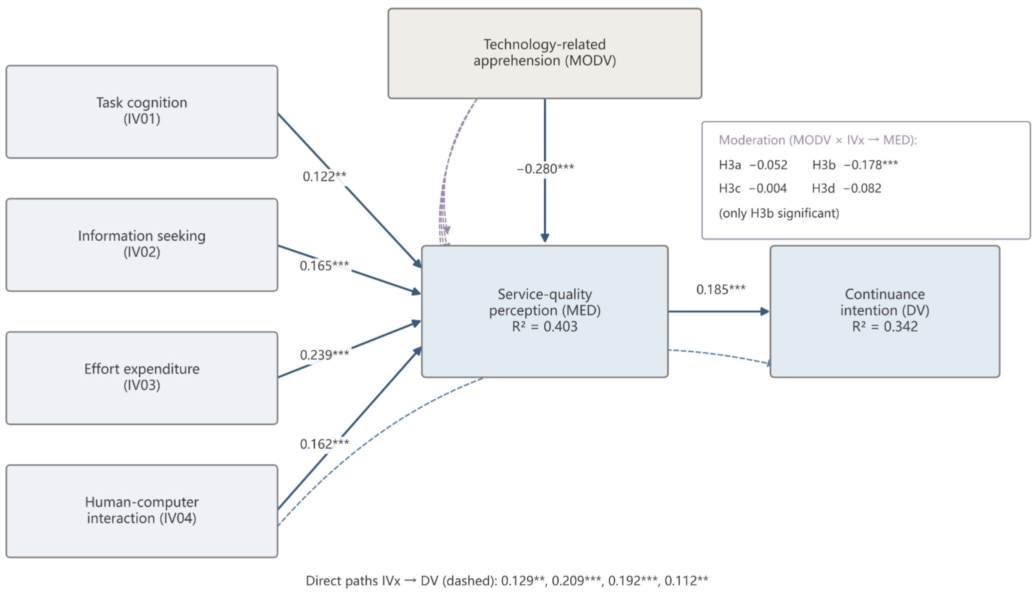

Figure 19 | Structural model with standardised path coefficients, R^2 for the two endogenous constructs, the direct technology-related-apprehension effect, and the four moderating interaction terms (only H3b significant). Dashed arrows denote moderation and the additional direct engagement→continuance paths.

Note: ** $p < .01$, *** $p < .001$. Solid arrows = hypothesised paths; dashed = moderation and additional direct paths.

the effect of effort expenditure on service-quality perception (f-sq = 0.067). The interaction term MODV by IV02 on MED reaches f-sq = 0.047, a weak but statistically significant moderation.

Effect sizes were computed as f^2 (Equation (3)), where R^2_incl and R^2_excl are the explained variances of the dependent construct with and without the focal predictor; values of 0.02, 0.15, and 0.35 denote small, medium, and large effects.

$$f^2 = \frac{R^2_{\text{incl}} - R^2_{\text{excl}}}{1 - R^2_{\text{incl}}} \tag{3}$$

Path-coefficient estimates (Table 18) speak directly to the hypotheses. All four engagement strands raised service-quality perception, with the strongest single contribution from effort expenditure (beta = 0.239), followed by information seeking (beta = 0.165), human-computer interaction (beta = 0.162), and task cognition (beta = 0.122). Service-quality perception raised continuance intention (beta = 0.185). Technology-related apprehension exerted a sizable direct depressing effect on service-quality perception (beta = -0.280) and a single significant moderating effect on the information-seeking route (beta = -0.178); the other three moderating effects were directionally negative but not statistically significant. Figure 19 visualises the full structural model.

Mediation analysis

To test the mediating role of perceived service quality directly, rather than inferring it from the pattern of direct paths, we estimated the specific indirect effect of each engagement dimension on continuance intention through service-quality perception. Following the product-of-coefficients approach, the indirect and total effects are defined in Equation (4), where a_k is the engagement→MED path, b the MED→DV path, and c'_k the direct engagement→DV path; the proportion mediated is the indirect effect divided by the total effect. Confidence intervals were obtained from 5,000 resamples of the coefficient distribution, a Monte Carlo / bootstrap approximation that does not assume a normal sampling distribution for the product term (Preacher & Selig, 2012).

$$\text{Indirect}_k = a_k b, \qquad \text{Total}_k = c'_k + a_k b \tag{4}$$

All four indirect effects are positive and significant (95% confidence intervals excluding zero), and all four direct effects remain significant. Perceived service quality therefore complementarily but partially mediates the engagement-to-continuance relationships, accounting for approximately 13–21% of each total effect. The largest indirect effect runs through effort expenditure (a×b = 0.044), consistent with its dominant path to service-quality perception.

Table 19 | Specific indirect, direct, and total effects on continuance intention via service-quality perception

Engagement dimension	Indirect (a×b)	95% CI	Direct (c′)	Total	% mediated	Mediation type
Task cognition	0.023	[0.006, 0.045]	0.129	0.152	14.9%	Complementary partial
Information seeking	0.031	[0.011, 0.056]	0.209	0.240	12.7%	Complementary partial
Effort expenditure	0.044	[0.018, 0.077]	0.192	0.236	18.7%	Complementary partial
Human-computer interaction	0.030	[0.011, 0.055]	0.112	0.142	21.1%	Complementary partial

Note. Indirect = a×b; total = c′ + a×b (Equation (4)); 95% CIs from 5,000 Monte Carlo / bootstrap resamples (Preacher & Selig, 2012). All indirect effects are positive with CIs excluding zero and all direct effects remain significant, indicating complementary partial mediation. n = 550.

Table 20 | Hypothesis-testing summary

Hypothesis	Statement	beta	p	Outcome
H1a	Task cognition to Service-quality perception	0.122	0.003	Supported
H1b	Information seeking to Service-quality perception	0.165	0.000	Supported
H1c	Effort expenditure to Service-quality perception	0.239	0.000	Supported
H1d	Human-computer interaction to Service-quality perception	0.162	0.000	Supported
H2	Service-quality perception to Continuance intention	0.185	0.000	Supported
H3a	Apprehension moderates Task cognition route	-0.052	0.270	Not supported
H3b	Apprehension moderates Information seeking route	-0.178	0.000	Supported
H3c	Apprehension moderates Effort expenditure route	-0.004	0.939	Not supported
H3d	Apprehension moderates Human-computer interaction route	-0.082	0.078	Not supported
H4a	Task cognition to Continuance intention	0.129	0.002	Supported
H4b	Information seeking to Continuance intention	0.209	0.000	Supported
H4c	Effort expenditure to Continuance intention	0.192	0.000	Supported
H4d	Human-computer interaction to Continuance intention	0.112	0.007	Supported

Note. β = standardised coefficient; p from 5,000 bootstrap resamples. H4a–H4d are the additional direct engagement→continuance paths. n = 550.

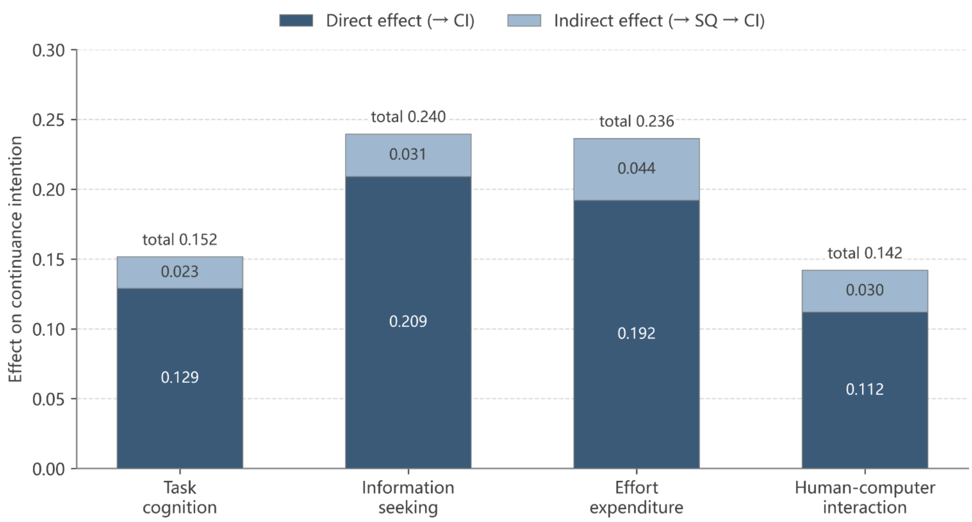

Figure 20 | Decomposition of each engagement dimension's total effect on continuance intention into direct and indirect (via service-quality perception) components.

Simple-slope analysis of the significant interaction

To interpret the single significant moderation (H3b), we probed the information-seeking × technology-related-apprehension interaction. The simple slope of information seeking on service-quality perception, conditional on apprehension, is given by Equation (5), where $\beta_{IV}2$ is the information-seeking main effect and γ_2 the interaction coefficient.

$$\frac{\partial \mathrm{MED}}{\partial \mathrm{IV}_2} = \beta_{\mathrm{IV}2} + \gamma_2 \mathrm{MODV} \tag{5}$$

Figure 21 plots this slope at low (−1 SD), mean, and high (+1 SD) apprehension. The information-seeking slope falls from +0.343 at low apprehension to +0.165 at the mean and to a non-significant −0.013 at high apprehension. Substantively, the quality-enhancing return to information seeking is

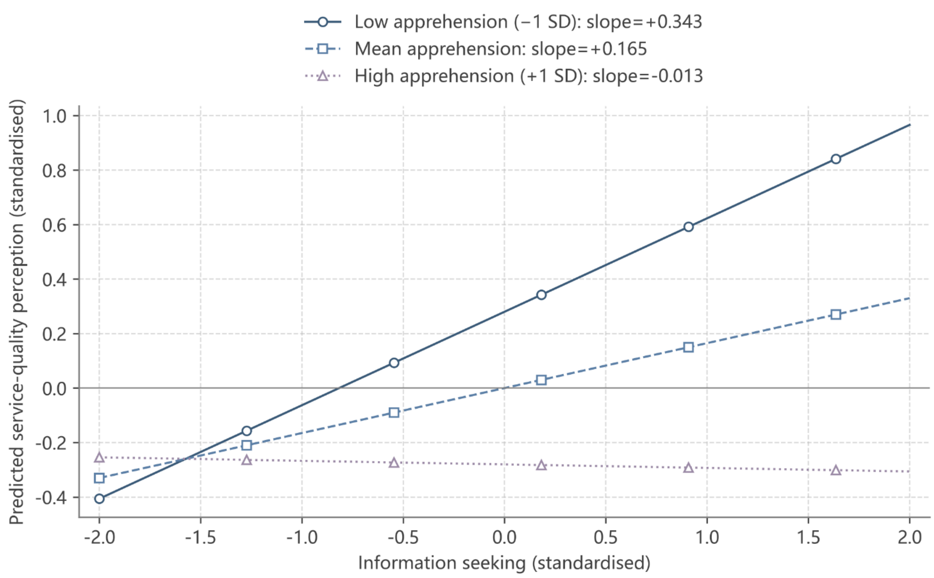

Figure 21 | Simple slopes of information seeking on service-quality perception at low (−1 SD), mean, and high (+1 SD) technology-related apprehension

concentrated among users with low-to-moderate apprehension and effectively disappears for highly apprehensive users. We present this as an empirical finding specific to the present model and sample rather than as a general property of technology-related apprehension.

Hypothesis-testing summary

Of the thirteen hypotheses, ten are supported and three are not (**Table 20**). The four engagement-to-perception relations (H1a–H1d) and the perception-to-intention link (H2) are all supported, as are the four direct engagement-to-continuance relations (H4a–H4d). Among the four moderation hypotheses, only the information-seeking moderation (H3b) is supported; technology-related apprehension does not significantly dampen the cognitive (H3a), effort (H3c), or interaction (H3d) routes.

Figure 22 summarises the outcome of all thirteen hypotheses, showing each standardised coefficient with its 95% confidence interval and whether it is supported.

Discussion

What the engagement architecture tells us

The clearest empirical signal in the data is that the four engagement strands carry different weights inside the same model. Effort expenditure does the heaviest lifting (beta = 0.239), followed by information seeking, human-computer interaction, and task cognition. That hierarchy is theoretically informative for at least three reasons.

First, the dominance of effort expenditure is consistent with co-production accounts in which the user's own behavioural investment becomes part of the perceived service value (Wu & Chen, 2017; Sadighha et al., 2025). A user who invests time selecting a delivery window, who tolerates a small product imperfection, who participates in a review programme, is not merely consuming the platform's service but co-producing it. That co-production posture biases the resulting service evaluation upward, because the user has psychological stake in the outcome. Substantively this means that retention strategy in the fresh-grocery channel should not be organised around minimising user effort but around making user effort feel productive - a different objective from the conventional "frictionless commerce" emphasis.

Second, information seeking lands in the middle of the hierarchy. This makes sense given the unusually high pre-purchase uncertainty of perishable goods: a user who reads provenance labels, compares freshness ratings, and parses delivery-slot logistics enters into the purchase with calibrated expectations, but the marginal benefit of additional information seeking diminishes once a baseline of confidence has been reached (Qi et al., 2024; Wang & Li, 2025).

Third, human-computer interaction has a near-equivalent direct effect to information seeking, despite being a property of the platform's design rather than the user's behaviour. This is the strongest evidence in the model that perceived service quality is not merely a function of user behaviour or platform behaviour but of the joint configuration - the same user can experience the same platform very differently depending on the smoothness of filtering, the helpfulness of intelligent search, and the responsiveness of in-app customer service (Tarafdar et al., 2019; Huang & Benyoucef, 2013).

Task cognition is the foundational rather than the dominant strand. Its beta of 0.122 is the smallest of the four but still significant. Conceptually, task cognition is best understood as a prerequisite for the other three strands; without it, the user cannot effectively deploy information seeking,

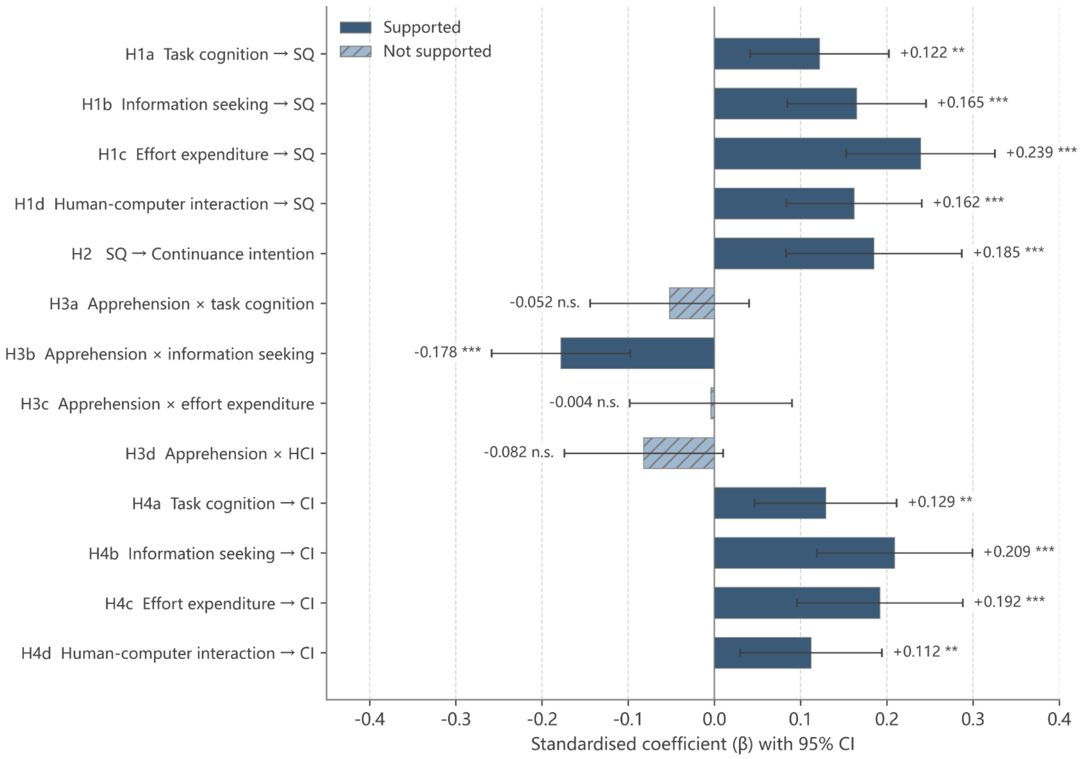

Figure 22 | Outcome of all thirteen hypotheses: standardised coefficients with 95% confidence intervals. Solid bars are supported hypotheses; hatched bars are not supported (* $p < .05$, ** $p < .01$, *** $p < .001$).

cannot calibrate effort, and cannot translate interface design into smooth task completion. A simple test of this interpretation is that the f-squared estimates for the higher-weight strands are concentrated in MED rather than DV, indicating that engagement strands chiefly route through perceived service quality rather than directly through behavioural intention - consistent with the S-O-R logic of the model.

The mediating role of perceived service quality

The H2 result (beta = 0.185, $p < 0.001$) confirms that perceived service quality is the proximate antecedent of continuance intention in this setting. Combined with the four supported H1 paths and the consistent direction of the indirect effects, this constitutes evidence that perceived service quality is the principal route through which engagement reaches retention. Service quality is the organism in the S-O-R chain, and it is a load-bearing organism: even when engagement strands have direct effects on continuance intention, these are best understood as engagement-as-stimulus translating into perception-as-organism translating into intention-as-response.

The substantive implication is that retention strategy cannot bypass service-quality perception. A platform that successfully boosts user effort but fails to convert that effort into perceptible quality (because of inconsistent freshness, irregular delivery times, opaque information, or unresponsive after-sales support) will see the input dissipate. Conversely a platform that consistently delivers high perceived quality will see retention emerge as the path of least resistance, even when its competitor offers a marginally lower price.

This is also where the SERVQUAL-as-mediator move makes its theoretical contribution. Classical SERVQUAL is descriptive (it measures quality across five dimensions); positioning it as a mediating mechanism makes it explanatory (it identifies the cognitive translation step between engagement and behavioural outcome). Doing so moves SERVQUAL into closer dialogue with behavioural-intention theories (Monoarfa et al., 2024; Espino-Rodriguez & Rodriguez-Diaz, 2021), and it lets the model produce hypothesis-driven predictions about which engagement design choices will and will not move the retention needle.

Why apprehension moderates only the informational route

The asymmetric moderation result is, within this model, a notable and theoretically suggestive finding. Technology-related apprehension exerts a substantial direct negative effect on service-quality perception (beta = -0.280, $p < 0.001$), confirming the well-established baseline that apprehensive users see the platform less favourably. But the interaction term is significant only for information seeking (beta = -0.178, $p < 0.001$). It is not significant for task cognition, effort expenditure, or human-computer interaction.

We interpret this pattern as follows. Apprehension is a cognitive-affective load. It depresses the user's ability to process platform-provided information efficiently. Where the engagement strand is itself cognitively demanding - as information seeking is, requiring evaluation, comparison, and integration across multiple information sources - apprehension exerts a measurable dampening influence, because the user simply cannot extract as much quality-relevant signal from the same engagement effort. Where the engagement strand is behavioural rather than cognitive (effort expenditure), or where the strand depends on the platform's design rather than the user's cognitive bandwidth (human-computer interaction), or where the strand pre-supposes rather than generates rule comprehension (task cognition), apprehension's marginal influence is comparatively muted.

This finding has two consequences. Theoretically, it is consistent with, rather than proof of, a path-conditional view, and it qualifies, in this single setting, treatments of technology-related apprehension as a uniformly generalised inhibitor (Tarhini et al., 2021; Tarafdar et al., 2019). Practically, it suggests that apprehension-sensitive design should focus on the informational interface, simplifying search and filtering, providing visual rather than purely textual information, and offering decision-support tools that reduce the cognitive cost of information seeking, rather than on uniformly reducing all engagement demands. Because the interaction effect is modest ($f^2 = 0.047$) and observed in one cross-sectional sample, these interpretations require replication before being generalised.

Direct engagement-to-intention paths

A subsidiary observation is worth noting: the four direct engagement-to-continuance-intention paths are all significant (beta between 0.112 and 0.209). This implies that the mediation through perceived service quality is partial rather than full. Engagement strands have both a routed effect (via perception) and a residual direct effect on intention. The residual direct effect is consistent with habit-formation accounts in which repeated platform usage develops into a behavioural routine that bypasses explicit cognitive evaluation (Liu et al., 2023; Sharma et al., 2024). For platforms, this means that even before service-quality perception fully consolidates, sustained engagement can begin to build the habits that anchor retention.

Theoretical and Practical Implications

Theoretical implications

Four theoretical implications follow.

Disaggregation matters. Treating user engagement as an aggregated construct masks substantial heterogeneity in how engagement reaches retention. The four-strand decomposition advanced here - task cognition, information seeking, effort expenditure, human-computer interaction - is empirically defensible (distinct factor structure, distinct path weights, distinct moderation patterns) and theoretically meaningful (each strand corresponds to a different cognitive-behavioural resource). Future research in digital-platform settings should resist the temptation to lump.

Perceived service quality is a mechanism, not an endpoint. The traditional SERVQUAL apparatus has tended to position service quality either as an antecedent of satisfaction or as an outcome of design choices. The mediation result here, in concert with prior work in adjacent settings (Monoarfa et al., 2024), suggests instead that perceived service quality is the cognitive bridge between user-side stimulus and behavioural response, with implications for how the construct is theorised and measured going forward.

Participatory stimuli enrich the S-O-R framework. The S-O-R framework has been applied widely in digital commerce but most often with platform-side stimuli (interface design, information quality, environmental cues). Treating user engagement as a stimulus - a co-productive stimulus that the user supplies through their own activity - is consistent with service-dominant logic and aligns S-O-R with the participatory turn in contemporary marketing theory (Cheng et al., 2024; Gao et al., 2015).

Technology-related apprehension is path-conditional. The result that apprehension moderates only the cognitively demanding route invites theoretical refinement. The technostress literature increasingly distinguishes between techno-eustress and techno-distress and emphasises that distress is task-specific rather than person-specific (Tarafdar et al., 2019). The present finding extends that argument into a domain-specific empirical context and provides a falsifiable mechanism (cognitive-load competition) for why path-conditional moderation should occur.

Practical implications for platform operators

For fresh-grocery platform operators, the results are consistent with effort engineering, complementing, rather than simply minimising, the work asked of the user, as a design orientation. Because effort expenditure carries the largest path to service-quality perception ($\beta = 0.239$) and a significant direct path to continuance intention, designing the platform so that each tap surfaces relevant information, each filter usefully narrows the option set, and each interaction yields a tangible benefit is likely to convert user effort into perceived quality. Given the modest effect sizes, however, these implications are offered as directional guidance rather than firm prescriptions.

A second implication concerns the management of perceived service quality. Operators tend to monitor objective performance metrics - fulfilment time, return rates, app crash counts - but the data here suggest they should equally invest in perception-measurement infrastructure: brief in-app surveys after delivery, sentiment analysis of review text, response-quality scoring for chat interactions. Perceived service quality is the variable that converts performance into retention, and it cannot be measured purely through backstage metrics.

A third implication concerns segmentation. Apprehensive users do not need a different platform but they do need a different informational interface: simpler search, more visual product representation, guided checkout flows, clear and unambiguous promotion explanations, decision-support tools that pre-process comparison information. The current results suggest that these interventions will have measurable returns precisely on the informational-acquisition route (which is where apprehension's moderation bites) and will likely yield smaller returns when targeted at effort-side or interaction-side bottlenecks.

Practical implications for merchants and supply-side operators

For merchants and supply-side operators, the model implies that product-information quality and fulfilment reliability are not merely operational metrics but inputs into the user's perception-formation process. Provenance disclosure, accurate product descriptions, traceable freshness indicators, transparent pricing, and post-purchase responsiveness all feed into the perceived service quality that mediates retention. Investments in supply-side coordination - cold-chain reliability, last-mile efficiency, return-handling responsiveness - are most likely to translate into retention when they are made visible to the user through information presentation.

Practical implications for policymakers and the industry ecosystem

Because the estimated effects are modest, the following are offered as directions for governance rather than firm prescriptions. For policymakers, the model suggests that regulatory attention could expand beyond transaction security toward an integrated framework addressing platform accountability, service-quality standards, consumer experience, and digital inclusion: **1)** industry-level service-quality standards for fresh-grocery platforms (product quality, fulfilment reliability, after-sales remediation, information transparency, interface usability) could help shift competition from price-based to service-based dynamics; **2)** consumer-information governance could require not only formal disclosure but substantive comprehensibility, given the documented role of information seeking and the moderating role of apprehension on that route; **3)** digital-inclusion measures (interface design for older users, accessible payment, low-friction onboarding) could help address the apprehension-related inequality the model points to; and **4)** cross-stakeholder governance could help institutionalise the experience-monitoring infrastructure the model implies.

For the wider industry ecosystem, the model offers a pivot from traffic-driven competition toward relationship-driven operation, in line with growing evidence that sustainable growth in digital retail depends increasingly on user repurchase, relationship quality, service stability, and ecosystem synergy rather than on traffic acquisition alone.

Limitations and Future Research

The study has limitations that bear on interpretation and on the design of subsequent investigations.

Cross-sectional design. Because all variables were measured at a single point in time, causal sequencing - even with a tightly specified S-O-R structural model - is supported by theory rather than confirmed by design. Longitudinal or panel-data designs could track the same cohort of users across multiple platform interactions and identify how engagement strands accumulate into perception and habit over time.

Self-reported instrumentation. All constructs were measured via respondent self-report. Despite Harman's test, anonymity assurances, and reverse-coded items, residual common-method variance cannot be ruled out completely. Triangulating survey responses with platform-side behavioural data (click paths, time-on-page, transaction logs, review histories) would strengthen inference by combining subjective perception with objective behavioural signal.

Self-reported instrumentation and common-method variance. All constructs were measured via respondent self-report from the same individuals at a single time point. Despite Harman's single-factor test, the full-collinearity assessment (all VIFs < 3.3), anonymity assurances, and reverse-coded items, residual common-method variance cannot be fully excluded. Triangulating survey responses with platform-side behavioural data (click paths, time-on-page, transaction logs, review histories), or separating the measurement of predictors and outcome across occasions or sources, would strengthen inference.

Mono-method analytical strategy. PLS-SEM is well suited to the structural complexity of the model but does not produce the global-fit machinery of covariance-based SEM. Cross-validation against CB-SEM, hierarchical regression, or Bayesian SEM would help adjudicate whether the substantive results are method-sensitive. Sensitivity analyses across sample subsets and alternative model specifications would similarly help assess robustness.

Linearity assumption. The structural model is linear-in-parameters. Real consumer responses may exhibit threshold effects, diminishing marginal returns, or asymmetric reactions to losses and gains. Nonlinear regression, quantile regression, or fuzzy-set qualitative comparative analysis (fsQCA) could surface configurational patterns invisible to a purely linear model (Pu et al., 2025).

Geographic and platform-segment scope. The empirical setting is one province (Guangdong) and one segment (fresh-grocery), albeit a province and segment chosen for their representativeness and dynamism. Cross-provincial and cross-segment replication would help establish where the model's parameter estimates remain stable and where regional, infrastructural, or category-specific moderators come into play.

Geographic, platform-segment, and sampling scope. The empirical setting is one province (Guangdong) and one segment (fresh-grocery). Equally important, the sample was recruited through purposive and convenience-based online channels and is therefore non-probabilistic; the parameter estimates should be generalised with caution and re-examined on probability-based and cross-provincial samples before broad claims of representativeness are made.

Construct scope. The model intentionally focused on a four-strand engagement decomposition, a single mediator, and a single moderator. Other plausible drivers of continuance intention - price sensitivity, brand trust, perceived value, social influence, platform stickiness, habit - were excluded for analytical clarity. Future work could extend the model to integrate digital-psychology variables (technology self-efficacy, digital trust, perceived privacy risk, technology fatigue) and platform-ethics variables (algorithmic transparency, recommender-system fairness, data-governance perceptions) (Tarafdar et al., 2019).

Mixed-methods complement. The structural model identifies patterns but not the textured, situational micro-experience that produces them. Pairing the structural-model evidence with qualitative interviews, focus groups, or user-experience tracking would deepen interpretation, especially around the asymmetric moderation result and the apparent dominance of effort expenditure.

Continuance-intention measurement. The continuance-intention construct bundles continued use, preference, recommendation, and primary-channel intentions. Although these items are empirically unidimensional in this sample, the recommendation (word-of-mouth) facet is conceptually distinct from repurchase, and future research could model advocacy as a separate behavioural outcome.

Conclusion

This study has examined how the user-side architecture of platform engagement translates into continued use of fresh-grocery e-commerce, taking the Guangdong market as its empirical setting. The four-strand decomposition of engagement - task cognition, information seeking, effort expenditure, and human-computer interaction - is documented here as an expanded account of the same core model and dataset reported by Yue et al. (2026). Each strand raises the user's perception of service quality; effort expenditure shows the largest effect; perceived service quality in turn translates into continuance intention; and technology-related apprehension acted, in this sample, as a path-conditional rather than a uniformly generalised inhibitor, weighing principally on the cognitively demanding information-acquisition route. These results contribute to ongoing theoretical conversations about the architecture of customer participation, the mediating role of perceived quality, the participatory reframing of stimulus-organism-response logic, and the path-specificity of technostress; they also provide cautious, design-oriented guidance for platform operators, merchants, and policymakers attempting to convert engagement into durable retention in a maturing and increasingly contested digital-retail segment. These conclusions should be read in light of the study's cross-sectional, single-region, non-probability design and the modest magnitude of the estimated effects.

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Appendix A. Measurement Instrument

All items were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) and were adapted from the sources listed in Table 1 and contextualised to the fresh-grocery platform setting. Reverse-coded items, marked (R), were recoded before analysis.

Table A1 | Full measurement instrument by construct

Construct	Code	Item wording
Task cognition (IV01)	WC1	I understand how this fresh-grocery platform's ordering and delivery process works.
	WC2	I am familiar with the navigation and category structure of the platform.
	WC3	I know how the platform's promotion and discount rules are applied.
	WC4	I understand the steps required to turn browsing into a confirmed delivery order.
	WC5	I can correctly interpret the platform's delivery time-slot and fulfilment information.
Information seeking (IV02)	IS1	Before buying, I actively read product provenance and freshness information on the platform.
	IS2	I compare supplier ratings and user reviews before selecting fresh products.
	IS3 (R)	I rarely check delivery-window or logistics information before placing an order.
	IS4	I look up promotion details and price comparisons within the app before purchasing.
	IS5	When needed, I seek additional product information from sources outside the platform.
Effort expenditure (IV03)	EF1	I am willing to spend time selecting the most suitable delivery time-slot.
	EF2	I make the effort to write custom notes or special requests for my fresh-grocery orders.
	EF3	I am willing to adjust my schedule to receive fresh deliveries on time.
	EF4	I actively participate in the platform's review or feedback programmes.
	EF5	I tolerate minor product imperfections and follow up rather than abandoning the platform.
Human-computer interaction (IV04)	HCI1	The platform's filtering and category tools respond smoothly to my actions.
	HCI2	The intelligent search returns results that match what I am looking for.
	HCI3 (R)	I often find the in-app customer-service interaction unresponsive or confusing.
	HCI4	Moving from browsing to cart to checkout feels seamless on the platform.
	HCI5	The platform interface makes it easy for me to complete my fresh-grocery tasks.
Service-quality perception (MED)	SQ1	The packaging and delivery presentation of my fresh orders are of high quality.
	SQ2	Products arrive fresh and on time as promised.
	SQ3	The platform responds quickly and effectively to after-sales problems.
	SQ4	I trust the provenance disclosure and payment security of the platform.
	SQ5	The platform offers regionally tailored options and flexible delivery windows that suit me.
Continuance intention (DV)	CI1	I intend to keep purchasing fresh groceries from this platform.
	CI2	I will continue to use this platform rather than switch to alternatives.
	CI3	I prefer this platform over other fresh-grocery options.
	CI4	I would recommend this platform to others.
	CI5	I regard this platform as my primary channel for buying fresh groceries.
Technology-related apprehension (MODV)	TA1	I feel uneasy when using new features on the fresh-grocery platform.
	TA2	I worry about making mistakes when operating the platform's technology.
	TA3	Interacting with the platform's digital tools makes me nervous.
	TA4 (R)	I feel confident and at ease when trying the platform's new technological features.
	TA5	I am concerned about data privacy and security when using the platform.

Note. (R) = reverse-coded item (recoded before analysis). Five-point Likert response (1 = strongly disagree, 5 = strongly agree). Items adapted from the sources in Table 1 and contextualised to the fresh-grocery setting (e.g., "delivery time-slot", "freshness inspection").