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The Expectation Trap in Errand Delivery: How Pre-usage Value Anticipation Shapes the Service Experience and Customer Satisfaction

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Abstract

On-demand errand delivery platforms set high service expectations through algorithmically generated promises, yet how these externally imposed baselines shape satisfaction in opaque service encounters remains underexplored. This study extends Expectation Confirmation Theory by replacing its unidimensional constructs with Anticipated Consumption Value and Realized Experiential Value, integrating Self-Determination Theory and Technology Readiness to explain individual variation. A two-wave survey of 1,176 customers reveals three mechanisms. First, when the service process is hidden, customers construct realized experience by projecting what they anticipated rather than comparing against observed performance. Second, rigid algorithmic baselines exert a net negative direct effect on satisfaction that outweighs all positive paths, a pattern we call the Expectation Trap. Third, intrinsic motivation weakens the anchoring of realized value to anticipated value, a Substitution Effect that innovativeness and optimism amplify through different channels. The findings suggest that displaying time ranges rather than point estimates can mitigate this trap.

1. Introduction

Every day, millions of customers open an app and see an algorithm-generated delivery promise for a personal errand—a forgotten document, a prescription, or a gift. On-demand errand delivery platforms dispatch gig workers to complete these varied personal tasks, and they compete on how short and exact the time promise is. The segment is projected to exceed CNY 66 billion in China by 2025. The promise looks like a benefit to the customer, but it quietly changes how the customer judges the whole experience. Yet this operational model creates a distinctive psychological tension. When platforms compete on speed, displaying '30-minute delivery' as a standard, they inadvertently transform a service attribute into a rigid cognitive baseline against which every delivery is judged. This tension is fundamentally a service-research problem. Errand delivery services represent a rapidly expanding class of technology-mediated service encounters in which the service process is invisible to the customer and the performance promise is set not by a human provider but by an algorithm. Both features strain long-standing assumptions in service research about how customers evaluate service quality and form satisfaction assumptions built on observable encounters and human-delivered service. How customers calibrate value, service experience, and satisfaction when the encounter is opaque and the promise is algorithmic is an underexplored question in the service literature.

Expectation Confirmation Theory (ECT; Oliver, 1980; Bhattacherjee, 2001; Hsieh and Wang, 2023) provides the causal structure: satisfaction is a function of an expectation baseline, perceived performance, and their disconfirmation. Standard ECT treats both as unidimensional global judgments, which cannot capture which value dimensions drive confirmation in on-demand services (Wang and Zhou, 2023; Ta et al., 2025). We extend ECT by replacing its two unidimensional constructs with multidimensional counterparts: ACV operationalizes pre-usage value across three dimensions grounded in TCV (functional, social, emotional), and REV operationalizes realized performance through four dimensions grounded in CPV (quality, socialization, emotion, price). The dimensional structures differ

because anticipatory value and experiential value are theoretically distinct constructs drawn from different literatures, not mirror images of each other. The two are distinct: ACV is measured at Wave 1, REV at Wave 2, and their correlation ($r = 0.52$) is well below the redundancy threshold. The framework retains two baselines with different roles. The Pre-usage Expectation Baseline is an externally imposed, algorithm-set reference point whose rigidity is the source of the Expectation Trap, so it carries a direct path to satisfaction. ACV is a customer-constructed value structure operating through assimilation to REV, with no direct path to satisfaction. To keep the model parsimonious, we do not include a separate performance-assessment construct; because opacity leaves no observable performance record, REV carries the performance-evaluation role directly.

How they do so is the gap this study addresses. Neither accounts for the multidimensional cognitive calibration process that occurs during the service encounter, nor for the individual-level psychological and technological traits that regulate this calibration. Addressing this gap requires integrating theories that operate at different explanatory levels: ECT for the causal architecture, value theories (Theory of Consumption Values (TCV)/Customer Perceived Value (CPV)) for the dimensional content, and motivational theories (Self-Determination Theory (SDT)/Technology Readiness Index (TRI)) for individual-level regulatory mechanisms, an integration we develop through a cumulative insufficiency argument in Section 2.3.

This study examines the cognitive mechanisms underlying customer satisfaction in errand delivery services by addressing two research questions:

(1) How does the interplay between pre-usage Anticipated Consumption Value (ACV) and post-usage Realized Experiential Value (REV) shape the service experience and satisfaction, and under what conditions do algorithmically generated expectation baselines undermine rather than support satisfaction formation?

(2) How do intrinsic motivation and technological dispositions (innovativeness and optimism) jointly moderate the value calibration process from ACV to REV?

This study makes three contributions. The first concerns how customers build value when they cannot see the service. We show that under opacity, anticipated value works less as a benchmark for comparison and more as a template that customers use to construct what they later report experiencing. The second concerns the limits of Expectation Confirmation Theory. We identify a direct negative effect of the expectation baseline on satisfaction that holds after every positive pathway is counted. We call it the Expectation Trap, and it shows that the expectation to satisfaction link depends on how the expectation is formed and how rigid it is, not only on its level. The third concerns who escapes this trap. Customers with strong intrinsic motivation build value through self-directed routes, and innovativeness and optimism strengthen this escape in different ways, which extends technology readiness research beyond its usual positive framing. In doing so, the study contributes to service research by extending expectation-confirmation reasoning to opaque, algorithm-mediated service encounters and by offering service providers concrete design levers for communicating algorithmic promises.

2. Literature Review and Research Hypotheses

2.1 Satisfaction and value in technology-mediated service encounters

This study is situated in the service-research tradition on how customers evaluate service and form satisfaction. The dominant account is the expectation-disconfirmation paradigm (Oliver, 1980), operationalised for services through SERVQUAL and the gap model (Parasuraman et al., 1988; Zeithaml et al., 1996), in which satisfaction arises from comparing perceived performance against prior expectations. Service research refined this comparison with the zone of tolerance (Zeithaml et al., 1993), the range between desired and adequate service within which performance is accepted; perceived service quality and satisfaction deteriorate sharply once performance falls below the adequate threshold. This anchors our central argument: an algorithmically set service promise, displayed with apparent computational authority, narrows the zone of tolerance, leaving little room for the positive disconfirmation that sustains satisfaction.

A second stream concerns technology-mediated and automated service encounters. As firms augment or replace human contact with self-service technologies, smart services, and service robots (Bitner et al., 2000; Meuter et al., 2000; Wirtz et al., 2018; Huang and Rust, 2018), control over the encounter shifts from frontline employees to algorithms. Errand delivery is an acute case: the algorithm both sets the performance promise and orchestrates fulfilment, while the customer observes only a moving icon. This makes the service process opaque, the conceptual inverse of operational-transparency designs that raise perceived value when customers can see the work being done (Buell and Norton, 2011; Buell et al., 2017). When the process is hidden, customers cannot construct an independent performance assessment and must rely on what they anticipated.

Finally, the service-dominant logic view of value as co-created by the customer (Vargo and Lusch, 2008; Grönroos, 2011) frames our moderation argument: customers are not passive recipients of an algorithmic promise but active participants who, when intrinsically motivated, co-produce experiential value through self-directed routes that partly offset expectation anchoring. Together, these streams locate our contribution: we extend service-satisfaction theory to a class of encounters, opaque and algorithm-set, that its founding assumptions did not anticipate.

2.2 Errand Delivery as a Theoretically Distinct Service Context

We examine these mechanisms in errand delivery, a setting whose structural features make them unusually visible. Errand delivery (paotui) refers to on-demand platform services in which a customer delegates a heterogeneous personal task, buying goods, collecting documents, delivering items, to an algorithm-dispatched gig worker who executes it within a platform-promised window (Zhao et al., 2024).

This shift from purchasing standardized products to delegating heterogeneous personal tasks to algorithm-mediated intermediaries is what makes the context theoretically distinctive.

Errand delivery shares surface features with other on-demand services, including algorithmic dispatch, gig execution, and real-time tracking. It differs along five structural dimensions that intensify the conditions theorised here (Table 1): task heterogeneity, elevated process opacity, emotional investment in delegated items, high principal-agent asymmetry, and low algorithmic-promise credibility. Because the rider's judgment-intensive work is invisible beyond a moving dot, customers cannot assess how the service is performed while it unfolds. We do not claim these mechanisms are unique to errand delivery; we treat it as a strategically extreme case in which they are amplified and detectable, expecting the same mechanisms at attenuated strength in less opaque services.

Prior errand-delivery research has centred on operational optimization, service-quality dimensions, and data-driven replenishment (Ulmer et al., 2022; Zhao et al., 2025; Cheng et al., 2024), treating customer satisfaction as a by-product of delivery efficiency; how anticipated value is calibrated into the service experience under opacity, and how individual differences regulate this calibration, remains unaddressed.

Table 1
Structural Comparison of On-Demand Service Contexts

Dimension	Food Delivery	Ride-Hailing	Errand Delivery
Task type	Standardized (transport prepared meal)	Standardized	Heterogeneous
Outcome predictability	High (ordered meal arrives as configured)	High	Low
Process opacity	Moderate (preparation → pickup → delivery updates)	Low	High
Emotional stakes	Low-moderate (convenience disruption)	Moderate	High
Service standardization	High (restaurant quality systems, packaging)	High	Low
Principal-agent asymmetry	Moderate (restaurant controls quality; rider controls logistics)	Low	High
Algorithm prediction accuracy	High (well-characterized preparation + route distributions)	High	Low
Precision illusion severity	Moderate	Moderate	High

2.3 Theoretical Foundations: ACV, REV, and the ECT Extension

Customer behavior research distinguishes between pre-purchase anticipated value and post-purchase service experience. The TCV (Sheth et al., 1991; Sweeney & Soutar, 2001) provides the framework for deconstructing multidimensional pre-usage value anticipation. From TCV's original five dimensions, we retain the three that are conceptually applicable to errand delivery service encounters: functional value (the anticipated efficiency and reliability of task completion), social value (the anticipated social approval from using a competent modern service), and emotional value (the anticipated affective relief from delegating a burdensome task). We exclude epistemic value, whose standard operationalization captures information-search behavior rather than service value perception, and conditional value, whose standard operationalization captures contingent purchase intention rather than value anticipation. This exclusion follows the principle that TCV dimensions should be selectively applied based on consumption context (Sheth et al., 1991, p. 163). REV is operationalized through four dimensions: service quality (the realized functional performance), socialization value (the perceived social dimension of the service encounter), emotional value (the realized affective experience), and price value (the perceived value-for-money). We excluded a health dimension present in some CPV operationalizations (e.g., Nasir & Karakaya, 2014), as its standard items capture lifestyle and well-being orientations that are conceptually distant from the experiential evaluation of a single service delivery (Tanrikulu, 2021; Yuen et al., 2022; Pedro et al., 2024; Raj & Das, 2025).

Expectation Confirmation Theory (ECT; Oliver, 1980; Bhattacherjee, 2001; as recently extended to uncertainty-laden IT contexts by Hsieh & Wang, 2023) provides the overarching causal mechanism: satisfaction is a function of expectation baselines, perceived performance, and their disconfirmation. However, standard ECT treats both expectations and perceived performance as unidimensional global judgments, which cannot capture which specific value dimensions, functional speed, emotional reassurance, or social recognition, drive or undermine confirmation in on-demand services (Wang & Zhou, 2023; Ta et al., 2025). This study extends ECT by replacing its unidimensional constructs with their multidimensional counterparts: ACV operationalizes the Expectation Baseline across five value dimensions, and REV operationalizes Perceived Performance across the same commensurable dimensions. The rationale for this substitution and its integration with SDT and TRI are developed in the following section, where we present a cumulative insufficiency argument for the multi-theoretical framework.

2.4 Theoretical Integration: A Cumulative Insufficiency Argument

Our framework follows a logic of cumulative insufficiency. Each theory solves a limit of the previous one that the previous one cannot solve on its own (Table 2).

In the first step, ECT gives the causal structure but makes two assumptions that fail in algorithm-mediated consumption. One is that value dimensions are comparable. The other is that performance is observable. Both fail in errand delivery, where customer expectations are multidimensional (Wang & Zhou, 2023) and process opacity stops customers from seeing execution and computing a gap.

In the second step, the Theory of Consumption Values and Customer Perceived Value fill the gaps in dimensions and in how value is built. The first supplies a grounded set of customer value dimensions, namely ACV. The second reframes perceived performance as a subjective evaluation that customers construct from experience, namely REV. The path from ACV to REV therefore reflects assimilation under opacity rather than the direct gap calculation that ECT assumes. Still, these theories treat the process as the same across customers. They explain what and how, but not for whom.

In the third step, Self-Determination Theory explains differences across customers through psychological agency. It identifies intrinsic motivation, made up of autonomy, competence, and relatedness, as a resource that lets customers build value through self-directed routes instead of passive assimilation. We choose this theory over others, such as regulatory focus, need for cognition, or locus of control, for three reasons. Its three parts map onto three micro-foundation processes in this context (Section 2.4.4). It distinguishes the source of motivation rather than its strength. It is validated in technology-mediated consumption (Yuen et al., 2023; Chen et al., 2024).

In the fourth step, the Technology Readiness Index supplies the technological boundary conditions. It identifies traits that shape how well intrinsic motivation works. We include two positive dimensions, innovativeness and optimism, as second-order moderators, which gives a moderated-moderation structure. This logic ensures each part of the model has a distinct role.

Table 2
Cumulative Insufficiency Logic: Why Each Theory Is Necessary

Theory	What it provides	What it cannot explain	Gap filled by
ECT	Causal architecture: expectation → performance → disconfirmation → satisfaction	(1) Dimensional commensurability fails under multidimensional expectations; (2) Performance observability fails under process opacity	TCV/CPV
TCV/CPV	Dimensional content (ACV) and constructive mechanism (REV); assimilation under opacity replaces direct gap-calculation	Individual heterogeneity: why some customers decouple from ACV while others remain anchored	SDT
SDT	Psychological agency (IM) as the motivational driver of autonomous value construction via three micro-foundations	Technological environment: whether IM can be effectively exercised under varying technology conditions	TRI
TRI	Technological boundary conditions: Innovativeness expands autonomous value construction; Optimism protects it under uncertainty	— (completes the model)	—
Integrated model	Full path: multidimensional anticipation → constructive calibration (moderated by psychological agency and technological disposition) → verification → satisfaction, with the Expectation Trap as a structurally specified boundary condition		

2.5 Research Hypothesis

Building on the cumulative insufficiency argument in Section 2.4, we derive ten hypotheses in three stages: (1) the cognitive anchoring and calibration mechanisms from ECT and consumption-value theory (H1 to H7); (2) the individual-level regulatory mechanism from SDT (H8); and (3) the technological boundary conditions from TRI (H9 and H10). The hypotheses are numbered in the order in which they appear, following the cognitive process from pre-usage anchoring to post-usage satisfaction, as labelled in Fig. 1. Four of the ten hypotheses (H1 to H4) concern the pre-usage expectation baseline, which reflects its centrality as the study's second focus alongside the ACV-to-REV calibration.

2.5.1 The Cognitive Anchoring Role of Pre-usage Expectation Baselines

When the platform displays an algorithmic service promise, it sets a salient, externally imposed baseline before any service contact. Cognitive consistency (Harmon-Jones, 2019) predicts that customers construct a correspondingly elevated Anticipated Consumption Value to justify delegating the task.

Because errand delivery is a bundle rather than a single attribute, this elevation is not confined to speed: the algorithmic promise signals a competent operation, and that signal spills over across value dimensions—functional efficiency, emotional reassurance, and social approval. In a high-opacity setting the customer cannot yet test these inferences, so the baseline propagates across the multidimensional ACV structure rather than being checked dimension by dimension.

H1: Pre-usage expectation baseline has a positive effect on ACV.

The baseline also shapes the realized experience directly, not only through anticipated value. Once an algorithmic promise is displayed, it remains the most accessible reference point throughout the encounter. Under the process opacity that characterizes errand delivery, customers watching only a moving icon have little independent performance information to draw on, so the salient baseline continues to color how the unfolding experience is perceived and encoded. Through this anchoring-and-assimilation route, a higher baseline raises Realized Experiential Value directly, over and above its effect transmitted through ACV. We therefore separate the direct baseline-to-REV path from the ACV-mediated path.

H2: Pre-usage expectation baseline has a positive effect on REV.

High expectation baselines activate a confirmatory attentional bias: customers selectively overweight positive performance cues while discounting minor deviations, feeding directly into their disconfirmation judgment (Guo et al., 2025). Regarding disconfirmation, high baselines set a demanding reference standard against which positive performance generates a surplus of confirmation, driving Expectancy Disconfirmation upward (Albtoosh & Ngah, 2024).

One might object that a demanding baseline should make positive disconfirmation harder to reach, since strong performance may still fall short of a high reference point. We argue the opposite holds under process opacity. Because customers cannot observe execution, they cannot register the small shortfalls that would otherwise puncture a high baseline, so the confirmatory bias dominates and the baseline raises rather than depresses reported disconfirmation. This prediction is specific to opaque settings and would reverse in transparent services where shortfalls are visible.

H3: Pre-usage expectation baseline positively influences Expectancy Disconfirmation.

First, algorithmically generated promises carry an implicit authority of computational exactness (Logg et al., 2019; Dietvorst et al., 2015), which customers interpret as deterministic commitments rather than probabilistic forecasts. This interpretation narrows the Zone of Tolerance: customers treat the displayed promise as a minimum guarantee rather than a central tendency, leaving little room for the positive disconfirmation that sustains satisfaction. Experimental evidence confirms that the format of time estimates shapes the width of customers' expected outcome distributions (Dai et al., 2025), and the deterministic framing inherent in algorithmic displays has the same narrowing effect.

Together these features create an Expectation Trap. Meeting the precise promise brings only indifference, because customers treat it as a minimum guarantee, while any deviation brings disproportionate dissatisfaction, made worse by the inability to recalibrate during the opaque wait.

H4: Pre-usage expectation baseline has a negative direct effect on Satisfaction.

2.5.2 The Dynamic Calibration: From Anticipated to Realized Value

The core of the model is the calibration from anticipated to realized value. Under algorithmic opacity, customers maintain cognitive consistency (Harmon-Jones, 2019) by using their ACV schema as the interpretive lens for an experience they cannot monitor. Watching a dot move across a map, a customer has no window into how the rider performed, so the pre-formed schema does the interpretive work: attention goes to confirming cues, minor disruptions are filtered, and REV is pulled toward ACV through assimilation (Chae et al., 2024). The higher the anticipated value, the stronger the upward pull. This assimilation path is how opacity converts expectation into experience.

H5: ACV has a positive effect on REV.

This assimilation is especially strong in errand delivery. Because the rider's judgment-intensive work of selecting items, verifying documents, and handling vendors is invisible, customers lack the concrete performance cues that would let them evaluate the service on its own terms. The anticipated-value schema therefore fills the informational vacuum: customers read the opaque experience through the lens of what they expected, and REV drifts toward ACV. In more transparent services, where execution is visible, this assimilation should be weaker because independent performance evidence competes with the prior schema.

2.5.3 The Verification Stage: From Performance to Satisfaction

At the verification stage, customers assess whether the experience met the baseline. Drawing on contrast theory, they use their realized experiential value as the diagnostic cue for gauging the gap between what was delivered and what was expected. In a transparent service the customer could point to specific performance records; in errand delivery, where execution is hidden, the felt quality of the realized experience is the only evidence available, so realized value carries the comparison directly. A realized experience that exceeds the baseline generates a surplus that registers as positive expectancy disconfirmation. Because opacity leaves no separately observable performance record to consult, this comparison runs directly from REV to disconfirmation rather than through an intermediate performance-assessment judgment.

H6: REV positively influences Expectancy Disconfirmation.

Expectancy disconfirmation feeds satisfaction. This link is amplified in errand delivery, where the customer has delegated a personal, often time-sensitive task and then waited without control over its execution. That waiting anxiety raises the emotional stakes of the outcome, so a positive disconfirmation delivers a distinct relief from time pressure and a reassuring sense that the delegation paid off (Mao et al., 2025). Disconfirmation thus serves as the cognitive bridge that converts gap information into affective satisfaction, and the emotional charge of delegated errands makes this bridge stronger than in routine, low-involvement services.

H7: Expectancy Disconfirmation positively influences Satisfaction.

2.5.4 The Interplay of Agency and Technology

The assimilation mechanism is not equally strong for everyone. Errand delivery's task heterogeneity, long opaque wait, and the customer's stake in a delegated task leave room for individual resources to intervene. Self-Determination Theory (Ryan & Deci, 2020) suggests that customers with strong intrinsic motivation partly detach the realized experience from the expectation schema, a Substitution Effect operating through three need-grounded processes: autonomous attribution (autonomy), where customers form their own explanations rather than defer to the algorithm; temporal reclamation (competence), where they turn the opaque wait into productive time; and process empathy (relatedness), where they read the encounter as human collaboration and adopt a more forgiving standard. Each substitutes a self-directed value source for the ACV schema, flattening the ACV to REV path.

H8: Intrinsic Motivation negatively moderates the ACV → REV relationship, such that higher IM weakens the positive assimilation from ACV to REV (the Substitution Effect).

Innovativeness, the propensity to embrace new technologies (Blut & Wang, 2020), strengthens the Substitution Effect by enriching the cognitive repertoire for self-directed value construction. An innovative customer approaches the opaque interface with an exploratory mindset (Parasuraman & Colby, 2015), probing features and generating technologically informed explanations for delays, which give the intrinsically motivated customer more material for autonomous attribution. Innovativeness supplies the cognitive content and intrinsic motivation the regulatory drive, so the two combine multiplicatively.

H9: Innovativeness positively moderates the negative moderating effect of Intrinsic Motivation on the ACV → REV relationship.

Optimism, a positive view of technology's reliability (Alhammadi et al., 2023), strengthens the Substitution Effect through a different channel: it acts as a resilience buffer that sustains intrinsic motivation when the opaque service throws off negative or ambiguous signals, as errand delivery does through unexplained delays. The optimistic customer defaults to a benign reading (O'Hern & Louis, 2023) and keeps attributing favorably rather than concluding the service is failing, protecting the substitution processes when a less optimistic customer would fall back on the ACV schema.

H10: Optimism positively moderates the negative moderating effect of Intrinsic Motivation on the ACV → REV relationship.

Note

The model has five core constructs (PEB, ACV, REV, ED, SAT) after merging service performance assessment into REV. Intrinsic Motivation is the moderator; Innovativeness and Optimism are the higher-order (moderated-moderation) moderators. ACV, REV, and Intrinsic Motivation are second-order constructs.

Figure 1. Conceptual Model.

3. Research Design and Data Quality Assurance

3.1 Analytical Strategy and Model Specification

We estimated the main structural model (H1 to H7) by maximum likelihood in AMOS 27. ACV, REV, and intrinsic motivation were specified as second-order constructs, each with its value or need dimensions as first-order indicators. To keep the model parsimonious and to address the discriminant-validity overlap flagged during review, we merged the earlier service-performance-assessment construct into REV, so realized experiential value serves as the single post-usage performance construct that links directly to expectancy disconfirmation.

The moderation hypotheses (H8 to H10) require latent interactions, which we estimated with Latent Moderated Structural equations (LMS; Klein and Moosbrugger, 2000) in Mplus 8.8. LMS integrates the latent product over the distribution of the latent predictors and therefore corrects for measurement error in the interaction term, which product-indicator and factor-score approaches do not fully do. We tested moderation hierarchically: Step 1 specified the two-way ACV × IM interaction predicting REV (H8); Step 2 added each three-way term, ACV × IM × Innovativeness (H9) and ACV × IM × Optimism (H10), estimated in separate models to avoid collinearity among higher-order products. Because LMS does not yield the usual global fit indices, we evaluated the interaction models with the log-likelihood ratio test against the no-interaction baseline and report the incremental variance (ΔR^2) for each three-way term. As a robustness check, we re-estimated all interactions with the PROCESS macro (Models 1 and 3; Hayes, 2018) using factor scores and 5,000 bootstrap resamples; because factor-score regression attenuates interaction coefficients, this serves as a conservative lower bound, and the LMS and PROCESS estimates agreed in sign and significance throughout.

3.2 Research Design and Data Collection

A two-wave, time-lagged survey was used to capture the temporal sequence from pre-usage expectation formation to post-usage satisfaction, and to reduce common method bias through procedural separation (Podsakoff et al., 2012). All constructs were measured on 7-point Likert scales (1 = strongly disagree, 7 = strongly agree), with items adapted from established literature and refined for the errand-delivery

context. Because the survey was administered in Chinese, all items were translated from the original English scales by two bilingual researchers, independently back-translated by a third, and reconciled by the research team; a pilot with 100 users confirmed item clarity and content validity before the main survey. The survey was conducted in Guangzhou, Guangdong Province (March to April 2025), selected for its high errand-delivery penetration in China (Mob Research Institutes, 2022).

Wave 1 (T1) captured pre-usage variables (ACV, the Pre-usage Expectation Baseline, demographics; N = 1,473 of 1,709 distributed). Two weeks later, Wave 2 (T2) captured post-usage variables (REV, Expectancy Disconfirmation, Satisfaction, and the moderators). Respondents were matched via unique IDs, yielding 1,288 completers; a further 112 were removed through screening for geographic compliance, response quality, attention checks, and logical consistency, leaving N = 1,176, which exceeds the CB-SEM minimum (Hair et al., 2010). Because respondents were not asked to anchor answers to one identified transaction, we interpret the pre/post sequence as measurement-level temporal separation and return to this in Section 6.4.

A design clarification is important. Respondents were not asked to anchor their answers to a single identified transaction; instead, Wave 1 captured their general anticipatory value perceptions before a planned use, and Wave 2 captured their general experiential value perceptions after recent use within the two-week window. We therefore interpret the two-wave design as providing measurement-level temporal separation (pre-usage variables measured before post-usage variables) rather than as tracking a single service episode from expectation to outcome. This design choice has a trade-off: it ensures that ACV reflects stable anticipatory value schemas rather than idiosyncratic pre-transaction mood, but it means that the ACV → REV path captures schema-level assimilation across experiences rather than within-episode expectation confirmation.

3.3 Data Quality Assurance and Bias Assessment

3.3.1 Non-Response Bias

Attrition analysis (Holtom et al., 2022) revealed no significant demographic differences between Wave 1 dropouts (N = 185) and completers (N = 1,288) (χ^2, $p > 0.05$). Comparison of early versus late Wave 2 respondents (Clarsen et al., 2021) likewise showed no significant differences across key constructs (t-tests and χ^2, $p > 0.05$), indicating that non-response bias is not a significant concern.

3.3.2 Data Quality and Common Method Bias

Embedded attention checks and logic consistency items were used to screen for low-quality responses; 297 cases were excluded (79 geographic non-compliance, 67 abnormal completion times, 151 attention/consistency failures), yielding the final sample of N = 1,176.

Beyond the procedural control from the two-wave design, four post-hoc tests indicate that common method bias is not a serious threat. Harman's single-factor test showed the first unrotated factor explained only 24.9% of variance. A single-factor CFA fit poorly ($\chi^2/df = 11.78$, RMSEA = 0.096, CFI =

0.413). Following the CFA marker technique (Williams et al., 2010), a theoretically unrelated marker changed construct correlations by less than 0.02 on average, and every path retained its sign, significance, and approximate magnitude. Finally, the gap between the strong ACV to REV path (β = 0.48) and the weak PEB to REV path (β = 0.14) is inconsistent with inflated method bias, which would equalize such paths.

3.4 Sample Characteristics

The sample of 1,176, with the full profile in Table A2, is balanced by gender at 50.5 percent female, mostly aged 18 to 50 at 74.2 percent, varied in education with 57 percent holding a college degree or above, and made up of experienced users, with 77.2 percent using errand delivery four or more times a month. The age and gender profiles closely match the national on-demand delivery user base (Mob Research Institutes, 2022). The large share of experienced users reflects the saturated conditions of Tier-1 Chinese cities. This is the population in which the Expectation Trap is most likely to operate, so the results should be read within this boundary.

4. Empirical Results

The empirical analysis followed the rigorous two-step approach recommended by Anderson and Gerbing (1988). First, we assessed the measurement model using Confirmatory Factor Analysis (CFA) to verify the reliability and validity of the constructs. Second, we examined the structural model to test the hypothesized relationships and moderating effects. The analysis was conducted using the maximum likelihood estimation method within the covariance-based SEM framework (IBM SPSS AMOS 27).

4.1. Measurement Model Assessment

The CFA showed an excellent fit: chi-square/df = 1.11, RMSEA = 0.010, SRMR = 0.020, CFI = 0.994, TLI = 0.994 (Hair et al., 2010). Internal consistency was strong, with Cronbach's alpha and composite reliability between 0.863 and 0.889. All standardized loadings were significant at $p < 0.001$ and above 0.70, ranging from 0.759 to 0.828. Average variance extracted ranged from 0.612 to 0.668, above the 0.50 cutoff (Fornell & Larcker, 1981). Discriminant validity held under the Fornell and Larcker criterion and the HTMT below 0.85. Full results appear in Table A3.

Table A4
Means, Standard Deviations, Reliability, and Discriminant Validity (N = 1,176)

Construct	M	SD	α	PEB	ACV	REV	ED	SAT	IM	INN	OPT
PEB	4.31	1.48	0.88	0.86							
ACV	4.62	1.18	0.85	0.31	0.79						
REV	4.65	1.15	0.84	0.29	0.52	0.78					
ED	4.27	1.50	0.88	0.21	0.34	0.33	0.86				
SAT	4.59	1.42	0.87	-0.15	0.23	0.23	0.19	0.85			
IM	3.42	1.21	0.76	-0.26	-0.43	-0.48	-0.32	-0.25	0.82		
INN	4.46	1.54	0.89	0.20	0.33	0.30	0.25	0.20	-0.45	0.87	
OPT	4.55	1.51	0.89	0.18	0.36	0.30	0.26	0.22	-0.43	0.41	0.86

Note: Diagonal elements (bold) are the square root of the AVE for each construct; off-diagonal elements are inter-construct correlations. For every construct the square root of AVE exceeds its correlations with all other constructs, supporting discriminant validity (Fornell and Larcker, 1981). PEB = Pre-usage Expectation Baseline; ACV = Anticipated Consumption Value; REV = Realized Experiential Value; ED = Expectancy Disconfirmation; SAT = Satisfaction; IM = Intrinsic Motivation; INN = Innovativeness; OPT = Optimism.

Because ACV and REV are conceptually close, we examined their discriminant validity at the second-order level. The heterotrait-monotrait ratio was 0.72, below the 0.85 threshold, and the square root of each construct's AVE exceeded their correlation (ACV 0.85; REV 0.84; correlation 0.33). ACV is measured at Wave 1 and REV at Wave 2, so the strong ACV to REV path reflects a substantive psychological process rather than construct overlap. Table A3 reports full reliabilities and the correlation matrix, with every construct's square-root AVE exceeding its correlations, supporting discriminant validity.

4.2 Structural Model and Hypotheses Testing

The structural model fit the data well ($\chi^2/df = 1.24$, RMSEA = 0.014, CFI = 0.990, TLI = 0.989). Table 3 summarizes the standardized coefficients. The expectation baseline positively affected ACV (β = 0.31), REV (β = 0.14), and disconfirmation (β = 0.12), supporting H1 to H3; ACV strongly predicted REV (β = 0.48, H5), which predicted disconfirmation (β = 0.29, H6), which predicted satisfaction (β = 0.23, H7). Because opacity leaves no observable performance record, REV links directly to disconfirmation.

Most important, the direct effect of the expectation baseline on satisfaction was negative and significant (β = -0.20, t = -6.97, $p < 0.001$), supporting H4 and consistent with the Expectation Trap. All path coefficients reported in the text are standardized estimates from Table 3.

Because the large sample yields high statistical power, we distinguish statistical from substantive significance and report Cohen's f^2 for the key paths. The ACV-to-REV assimilation path is the largest effect ($f^2 = 0.29$, approaching a large effect), and the direct Expectation Trap path, though smaller ($f^2 =$

0.04), is theoretically central and practically consequential given that it is negative and unoffset. The PEB-to-ACV ($f^2 = 0.10$) and REV-to-ED ($f^2 = 0.09$) paths are small-to-medium. Several supporting paths, such as PEB to REV (H2: $\beta = 0.14$) and PEB to disconfirmation (H3: $\beta = 0.12$), as shown in Fig. 2, are statistically robust but modest, so we treat them as secondary. Our substantive claims rest on the effects that are both significant and meaningful in size.

We also considered endogeneity. The focal antecedent, the pre-usage expectation baseline, is set exogenously by the platform's algorithm rather than chosen by the customer, which limits the usual self-selection concern for the model's key predictor. For the endogenous construct-to-construct paths, the two-wave design places anticipated value temporally before realized value, and the six competing models in Table A5, including a reversed-causality specification, fit worse than the proposed model, which makes a simple reverse-causal account unlikely. We nonetheless acknowledge that survey-based structural models cannot fully rule out omitted-variable bias, and we return to this in the limitations.

Table 3
Hypothesis Path Testing Results

Pathway Analysis	**Estimate**	**S.E.**	**C.R.**	**P**	**Standardized Estimate**
H1: PEB→ACV	0.31	0.03	11.04	< .001	0.31
H2: PEB→REV	0.14	0.03	5.51	< .001	0.14
H3: PEB→ED	0.12	0.03	4.37	< .001	0.12
H4: PEB→SAT (Expectation Trap)	-0.20a	0.03	-6.97	< .001	-0.20
H5: ACV→REV	0.48	0.03	18.37	< .001	0.48
H6: REV→ED	0.29	0.03	10.19	< .001	0.29
H7: ED→SAT	0.23	0.03	8.12	< .001	0.23
Note: Model fit indices: CMINI/DF = 1.235, RESEA = 0.014, AGFI = 0.944, NFI = 0.953, TLI = 0.990, CFI = 0.991;					

Significance levels: *** $p < 0.001$; a Significant negative coefficient, consistent with the hypothesized Expectation Trap (H4).

Note

The model has five core constructs (PEB, ACV, REV, ED, SAT) after merging service performance assessment into REV. Intrinsic Motivation is the moderator; Innovativeness and Optimism are the higher-order (moderated-moderation) moderators. ACV, REV, and Intrinsic Motivation are second-order constructs.

Figure 2. Path Analysis Results

4.3. Mediation Decomposition Analysis

Using bias-corrected bootstrapping with 5,000 iterations (Hayes, 2018), we decomposed the path from the pre-usage expectation baseline and ACV to satisfaction through the chain of ACV, REV, expectancy disconfirmation, and satisfaction (Table 4). The direct effect of the baseline on satisfaction (standardized − 0.200) is far larger in magnitude than the total positive indirect effect (0.049), so the net total effect on satisfaction remains negative (-0.152). This shows that no combination of positive pathways offsets the direct penalty imposed by a rigid baseline.

Table 4
Bootstrap Mediation Decomposition Results (N = 1,176, 5,000 Resamples)

Mediation Pathway	Standardized Indirect Effect (β)	Bootstrap SE	95% LLCI	95% ULCI	Significance
PEB → Satisfaction (Total Indirect)	0.049	0.009	0.033	0.067	Sig.
Path 1: PEB → ACV → REV → ED → SAT	0.010	0.002	0.006	0.015	Sig.
Path 2: PEB → REV → ED → SAT	0.010	0.002	0.006	0.015	Sig.
Path 3: PEB → ED → SAT	0.029	0.006	0.019	0.042	Sig.
PEB → Satisfaction (Direct, Expectation Trap)	-0.200	0.028	-0.252	-0.148	Sig.
PEB → Satisfaction (Total Effect)	-0.152	0.027	-0.202	-0.098	Sig.

Note: Bootstrap confidence intervals are bias-corrected. Sig. = significant (95% CI excludes zero); n.s. = non-significant.

4.4. Moderated Moderation Analysis

We tested the moderation in two hierarchical steps, first establishing the baseline moderation and then the moderated moderation (Table 5). In Step 1, intrinsic motivation significantly and negatively moderated the ACV to REV path (ACV × IM: $\beta = -0.20$, $p < 0.001$; $R^2 = 0.42$), supporting H8: higher intrinsic motivation flattens the assimilation from anticipated to realized value, the core of the Substitution Effect. At one standard deviation above the mean of IM, the ACV to REV slope fell substantially relative to the mean. In Step 2, we added the three-way terms. The ACV × IM × Innovativeness interaction was significant ($\beta = -0.17$, $t = -6.45$, $p < 0.001$; $\Delta R^2 = 0.057$), supporting H9, and the ACV × IM × Optimism interaction was also significant ($\beta = -0.07$, $t = -2.55$, $p = 0.011$; $\Delta R^2 = 0.046$), supporting H10. Both higher-order dispositions strengthen the intrinsic-motivation moderation, each through a distinct route. The latent-variable estimates and the PROCESS factor-score estimates agreed in sign and significance. A simple-slope analysis showed an asymmetry (see Fig. 3 and Fig. 4): the flattest ACV to REV slope

occurred when intrinsic motivation was high and innovativeness was low, and a floor-effect account does not fit, since the low-IM, low-innovativeness condition still showed a strong slope.

Table 5
Hierarchical Moderation Analysis: Predicting REV (standardized estimates, N = 1,176)

Predictor	**β**	**t**	**p**
Step 1: Baseline moderation (H8)			
ACV	0.34	13.68	< .001
Intrinsic Motivation (IM)	-0.28	-11.19	< .001
ACV × IM	-0.20	-11.42	< .001
R^2 = 0.42			
Step 2: Three-way with Innovativeness (H9)			
ACV × IM	-0.20	-7.34	< .001
ACV × Innovativeness	0.19	7.21	< .001
IM × Innovativeness	-0.08	-3.01	.003
ACV × IM × Innovativeness	-0.17	-6.45	< .001
R^2 = 0.48, ΔR^2 = .057			
Step 3: Three-way with Optimism (H10)			
ACV × IM	-0.22	-8.22	< .001
ACV × Optimism	0.25	9.47	< .001
IM × Optimism	0.07	2.69	.007
ACV × IM × Optimism	-0.07	-2.55	.011
R^2 = 0.47, ΔR^2 = .046			

Note: Step 1 reports the baseline moderation of the ACV → REV path by intrinsic motivation. Steps 2 and 3 add the three-way (moderated-moderation) terms for innovativeness and optimism separately. Main effects and the two-way ACV × IM term are estimated with latent-variable SEM using the product-indicator method; the three-way terms are reported from the LMS specification. ΔR^2 is the incremental variance explained by the three-way term over the two-way model.

Note

High and Low conditions are defined as ± 1 standard deviation (SD) above and below the mean of the respective moderator. All variables were mean-centered prior to analysis. Slopes represent the unstandardized regression coefficient of ACV on REV at each combination of moderator levels.

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Figure 4. Simple Slope Plot of the Three-Way Interaction Effect of ACV × Intrinsic Motivation × Optimism on REV.

4.5. Robustness Checks and Alternative Model Comparisons

To assess the structural specificity of the proposed model, we evaluated four theoretically motivated alternative models against the baseline model (Anderson & Gerbing, 1988). Unlike arbitrary model comparisons, each alternative tests a specific theoretical claim that an anonymous reviewer might advance as an alternative explanation (see Table 6). The results support the baseline model across all comparisons.

Table 6
Fit Indices Comparison of Alternative Models

Model Specification	χ^2/df	CFI	RMSEA	SRMR	AIC	ΔR^2(SAT)	Comparison Result
Baseline Model (Proposed)	1.235	0.991	0.014	0.023	3214.8	—	—
Measurement Alternatives							
M1: First-order factors (flattened)	2.854	0.920	0.045	0.048	4872.3	−0.07	Worse fit; second-order specification justified
M2: Formative specification	3.120	0.915	0.048	0.052	5103.6	−0.10	Poor specification; reflective model supported
Structural Alternatives							
M3: Reversed calibration (REV → ACV)	2.417	0.944	0.038	0.041	4156.2	−0.04	Worse fit on non-nested criteria (ΔAIC = + 941.4 vs. baseline); reversed direction not supported
M4: Direct value–satisfaction path (REV → SAT, bypassing ED)	1.486	0.981	0.020	0.028	3487.5	−0.02	Worse fit; verification stage is non-redundant
M5: No Expectation Trap (PEB → SAT constrained to zero)	1.412	0.984	0.019	0.026	3398.7	−0.05	Significantly worse fit ($\Delta\chi^2$ = 43.82, Δdf = 1, $p < .001$)
M6: Full mediation (no direct PEB → SAT, PEB → ED paths)	1.523	0.979	0.021	0.029	3542.1	−0.06	Worse fit; partial mediation with direct effects supported

M5 constrains the H4 path (the direct Expectation Trap effect) to zero

5. General Discussion

5.1 How Customers Build Value Under Opacity

The ACV → REV path (standardized β = 0.48) is much stronger than the direct PEB → REV path (β = 0.14). This gap has a theoretical implication beyond the two coefficients. Standard ECT models and their multi-attribute extensions (Szymanski and Henard, 2001) assume that customers build performance perceptions through comparison: they observe the outcome, compare it against the expectation baseline, and register disconfirmation. Our data suggest that in algorithmically opaque errand delivery, this comparison is largely displaced by an assimilation process in which customers project prior value schemas onto the realized experience.

This finding creates a productive tension with two bodies of literature. First, it challenges Oliver's (1980) original specification of ECT, which treats perceived performance as an input to the confirmation judgment, a quantity that customers assess independently before comparing it with expectations. In the assimilation account supported here, perceived performance (operationalized as REV) is not independently assessed; it is derived from the expectation-adjacent construct (ACV). This distinction has implications for how ECT should be specified in opaque service contexts: the standard ECT diagram showing separate arrows from "expectation" and "perceived performance" to "disconfirmation" may misrepresent the cognitive process when performance is unobservable, because perceived performance is itself a function of expectations rather than an independent input.

Second, the finding intersects with the assimilation-contrast debate in customer psychology (Buell & Norton, 2011; Bray, 2023). Assimilation Theory predicts that customers adjust their perceptions toward their expectations when the discrepancy is small, while Contrast Theory predicts they will exaggerate the discrepancy. Our results support assimilation as the dominant mechanism, but with an important boundary condition: assimilation dominates specifically because process opacity eliminates the sensory evidence that would be required to trigger a contrast response. This proposition aligns with the broader operational transparency literature, which has demonstrated that making service processes visible to customers fundamentally alters their value perceptions (Buell & Norton, 2011; Bray, 2023), the inverse of the opacity-driven assimilation documented here.

5.2 The Selective Operation of Expectation Baselines

Two features of the results, taken together, show how expectation baselines operate in algorithm-mediated services. The pre-usage baseline feeds every positive pathway (it raises anticipated value, realized value, and disconfirmation), yet it also carries a direct negative effect on satisfaction (H4: PEB → SAT, $\beta = -0.20$, $p < 0.001$). The mediation decomposition shows that the total positive indirect effect (+ 0.05) is far smaller than this direct penalty, so the net total effect of the baseline on satisfaction is negative (-0.15, 95% CI [-0.20, -0.10]). The baseline is thus not a neutral reference point but a structural drag on satisfaction that no positive pathway offsets.

Why the positive pathways cannot rescue satisfaction. Under process opacity, customers cannot observe execution, so the baseline sets a precise, non-negotiable reference that only ever gets met,

never exceeded in a visible way. The positive pathways run through value assimilation (PEB to ACV to REV to ED) and are real but small, because each link is attenuated by opacity. The direct affective penalty, by contrast, is immediate: meeting a precise promise brings only relief, while any perceived shortfall brings disproportionate dissatisfaction. This asymmetry is what makes the net effect negative and is the mechanism we label the Expectation Trap.

One might invoke dual-process accounts in which reference-point anchoring operates through automatic processing that bypasses deliberative evaluation (Kahneman, 2011). Our design cannot adjudicate processing mode directly. What the data do show is that the affective penalty from a rigid baseline survives the full set of positive pathways, which is the result that matters for the Expectation Trap regardless of the underlying processing account.

The persistent satisfaction burden. The baseline's most consequential effect is affective: it shapes how customers feel about the outcome even when the positive value pathways are working. This dissociation, in which expectations depress satisfaction directly while still feeding the positive value chain, is what a linear ECT specification misses and what the Expectation Trap captures.

affective versus cognitive responses. In errand delivery, the affect-laden satisfaction judgment is where the rigid baseline exerts its pull, which is consistent with the baseline depressing satisfaction directly while still feeding the positive value chain

in services with lower process opacity such as ride-hailing, customers can observe execution and recalibrate the reference point during the wait, so the direct negative effect on satisfaction should weaken and the Expectation Trap should shrink.

5.3 The Substitution Effect and Its Asymmetric Amplifiers

The negative moderation of ACV → REV by Intrinsic Motivation supports the Substitution Effect: high-IM customers appear to construct realized value through self-directed pathways, including autonomous attribution, temporal reclamation, and process empathy, that partially bypass the ACV → REV assimilation channel. The effect is meaningful in size. At + 1 SD of IM, the ACV → REV slope is substantially flatter than at the mean, which indicates that intrinsic motivation weakens the role of ACV as the dominant cognitive scaffold identified in Section 5.1.

The more theoretically consequential finding, however, is the asymmetry between Innovativeness and Optimism as amplifiers. Simple slope decomposition reveals a pattern that the aggregate three-way interaction coefficients (β = −0.069 for Innovativeness, β = −0.173 for Optimism) cannot fully convey: the most complete expectation decoupling occurs under High IM / Low Innovativeness conditions (b = −0.065, approaching zero), not under High IM / High Innovativeness conditions (b = 0.287). This counterintuitive pattern that less technological curiosity produces more complete expectation decoupling among high-IM customers challenges the implicit assumption in TRI research that positive technology dispositions uniformly facilitate adaptive technology use.

We interpret this pattern through the lens of schema elaboration. Innovative customers invest cognitive effort in exploring technological systems (Parasuraman & Colby, 2015), generating more elaborate ACV structures. The direct positive moderation of ACV → REV by Innovativeness (b = 0.245) reflects the stickiness of these schemas: more cognitively invested expectations are harder to override. The three-way interaction (β = −0.069) captures IM's countervailing capacity, but the net result is partial rather than complete decoupling. Optimism, by contrast, sustains IM's regulatory capacity under uncertainty without adding cognitive content that strengthens the ACV anchor.

This distinction, elaboration (Innovativeness) versus resilience (Optimism) has implications beyond the present model. It suggests that the effects of positive technology dispositions on value formation are mechanism-dependent: dispositions that involve cognitive elaboration of technological schemas may simultaneously facilitate and constrain adaptive value construction, while dispositions that involve affective resilience toward technological uncertainty facilitate without constraining. This mechanism-level distinction is obscured when TRI dimensions are treated as uniformly positive (as in most prior applications) and can only be detected through moderated moderation designs that separate the conditional interaction effect from the direct moderation effect.

An alternative floor-effect explanation that low-Innovativeness customers form weaker ACV schemas more easily overridden by IM is inconsistent with the data: the Low IM / Low Innovativeness condition shows a strong ACV → REV slope (b = 0.558), confirming that these customers do form consequential schemas.

5.4 Integrated Implications

The findings point to a structural tension in algorithm-mediated services: the feature that makes these services operationally superior, namely precise and data-driven time promises, is also the feature that erodes customer satisfaction through the Expectation Trap.

First, algorithmic precision generates a precision illusion that narrows the zone of tolerance (Section 5.2, H4), creating rigid baselines

This structural tension has direct implications for platform design: platforms invest in algorithmic precision to improve operational efficiency, but this same precision generates the psychological rigidity that erodes satisfaction returns. The Expectation Trap is thus not a temporary market imperfection but a structural feature of algorithmically precise, process-opaque services, one that intensifies as algorithms become more accurate and time promises become tighter. Paradoxically, the operational "improvement" of narrowing the delivery time distribution worsens the psychological conditions for satisfaction because it further narrows the Zone of Tolerance without expanding the confirmation zone.

The Substitution Effect (H8 to H10) identifies the individual-level mechanism through which some customers escape this trap, but also reveals its limits. The most complete escape occurs among customers with high intrinsic motivation and low innovativeness, who construct value from autonomous engagement without the elaborated schema that innovative customers bring.

More broadly, these findings suggest that algorithmic mediation introduces a class of service encounters where standard satisfaction assumptions, independent performance assessment, flexible reference points, direct expectation-outcome comparison may require fundamental reconsideration. Specifying how satisfaction formation varies across the spectrum of algorithmic transparency including the recently documented double-edged effects of transparency on customer trust (Li et al., 2025) from ride-hailing to autonomous systems, represents a priority for future research.

6. Conclusion

6.1. Theoretical Contributions

For service research, this study advances theory in three specific ways. First, by integrating ACV and REV within an ECT framework, it establishes a Cognitive Assimilation Mechanism specific to algorithmically opaque services: in the absence of observable process cues, multidimensional anticipated value (ACV) functions as a heuristic schema through which service experience (REV) is actively constructed rather than passively received. This extends Assimilation Theory and ECT simultaneously by specifying the dimensional structure through which assimilation operates a theoretical contribution that single-construct models of expectation or value cannot provide. This assimilation mechanism represents the conceptual inverse of the operational transparency effect documented in non-opaque service settings (Buell & Norton, 2011; Bray, 2023): whereas transparency enables customers to construct independent performance assessments, opacity forces reliance on anticipatory schemas.

Second, the Expectation Trap (H4: $\beta = -0.20$, $t = -6.97$)

Third, the Substitution Effect (H8 to H10) identifies three cognitive-behavioral micro-foundations, autonomous attribution, temporal reclamation, and process empathy, through which high-IM customers construct experiential value via self-directed pathways that partially bypass the ACV to REV assimilation channel.

6.2. Service Managerial Implications

The Expectation Trap (H4) demonstrates that competing on progressively shorter delivery promises elevates baselines to a ceiling where positive disconfirmation becomes structurally difficult.

(a) Consider replacing point estimates with range displays. This study did not manipulate display format, so we present this as a design hypothesis derived from the Expectation Trap mechanism rather than a direct finding. The logic is that range displays should widen the Zone of Tolerance by communicating the probabilistic nature of the estimate (Dai et al., 2025), structurally mitigating the baseline rigidity that drives the Expectation Trap. Experimental validation is needed.

The process-opacity mechanism implies that customers cannot recalibrate their reference points during the waiting period.

(c) Adopt conservative-bias time algorithms. Platforms should systematically bias displayed time estimates upward relative to the algorithm's modal prediction, creating a structural disconfirmation buffer. Arriving earlier than a conservatively set promise generates positive surprise; arriving on time under such a promise avoids the indifference that results from merely meeting a tight estimate. The strategic lever is managing the shape and rigidity of the expectation anchor, not accelerating delivery speed.

The assimilation mechanism (H5) establishes that customers use ACV as a cognitive scaffold to interpret opaque delivery experiences.

The Substitution Effect (H8 to H10) identifies high-IM customers

Fourth, findings carry direct lessons for customers. First, customers should see the precision illusion for what it is. A displayed figure such as 28 minutes is a forecast, not a guarantee, and treating it as a firm promise is what lowers their own satisfaction. Reading point estimates as rough ranges can protect felt well-being at no cost. Second, the Substitution Effect shows that customers are not passive. Those who engage actively, by forming their own explanations for delays, using the wait as productive time, and recognizing the rider’s constraints, report clearly higher satisfaction. These are coping strategies that customers can learn, not fixed traits. Third, and against intuition, the customers best protected from the Expectation Trap are those with high intrinsic motivation but low technological elaboration. Customers who over-invest in tracking and platform features may lock in rigid expectations that lower their own satisfaction. Customers with low technological readiness, who cannot use these strategies, gain the least value and most need support and protection.

6.3. Policy Implications

Three policy-relevant findings emerge. First, the Expectation Trap identifies algorithmic promise-setting as a regulatory domain: platforms that systematically inflate delivery time estimates to manipulate expectation baselines exploit the asymmetric loss-aversion dynamic identified here. Regulators should consider requiring platforms to disclose the basis for time estimates and prohibit systematic over-promising strategies displaying delivery times significantly below algorithm-calculated estimates to attract orders that exploit the Expectation Trap's loss-aversion mechanism at customers' cognitive cost that generate artificial satisfaction at customers' cognitive cost (cf. the European Union's Artificial Intelligence Act, 2024, which mandates transparency requirements for algorithmic decision systems that affect customer welfare). Second, the high-pressure expectation environment documented here externalizes risk to gig workers; safety-first protocols that decoupling rider performance metrics from time guarantees beyond riders' control are warranted (International Labour Organization, 2024; see also the growing evidence on algorithmic management's impact on gig worker welfare; Chen et al., 2024). Third, the Substitution Effect's dependence on Intrinsic Motivation points to a digital divide: populations with low technological dispositional readiness derive less value from algorithm-mediated services. Digital literacy initiatives and mandated non-digital service channels for essential deliveries are appropriate policy responses (Hwang et al., 2021).

6.4. Limitations and Future Research

Five limitations warrant acknowledgment. First, the single-city context (Guangzhou) constrains generalizability: the Expectation Trap and Substitution Effect may be amplified in China's high-speed digital culture and attenuated in markets with lower long-term orientation or higher uncertainty avoidance (Hofstede, 2011). The structural features of errand delivery (task heterogeneity, elevated process opacity, and emotional investment in delegated items) amplify the precision illusion, assimilation, and substitution mechanisms theorized here. These mechanisms are expected to operate in other on-demand services as well, but at attenuated intensity. Future research should test whether the magnitude of the Expectation Trap varies across service types that differ in process opacity and task standardization, using food delivery as a moderate-opacity comparator and ride-hailing as a low-opacity comparator, which would establish the generalizability boundary of the present findings.

Second, the two-wave design provides temporal separation but is not transaction-anchored: respondents reported general pre-usage value perceptions (Wave 1) and general post-usage experiential perceptions (Wave 2) rather than evaluations of a single identified delivery. This means the ACV → REV path should be interpreted as schema-level assimilation—how general anticipatory value structures shape general experiential perceptions—rather than within-episode expectation confirmation. A transaction-anchored two-wave design, in which respondents identify a specific upcoming delivery at Wave 1 and evaluate that same delivery at Wave 2, would provide stronger evidence for the within-episode process. Similarly, the ACV and REV items used general rather than encounter-specific phrasing, so their anticipatory and realized meanings rest on measurement timing rather than on tense-marked item wording. Future research should combine transaction-anchored measurement with encounter-specific item phrasing to establish the within-episode version of the mechanisms documented here at the schema level.

Third, from the original TCV framework we retained three of five value dimensions (functional, social, emotional) and excluded epistemic and conditional value because their standard operationalizations information-search behavior and contingent purchase intention, respectively, do not capture service value perception in the errand delivery context. Similarly, we excluded a health-related dimension from REV because its items capture lifestyle orientation rather than experiential evaluation of a specific service encounter. While this selective application is consistent with TCV's original guidance that dimensions should be context-specific (Sheth et al., 1991), it means our model does not capture the full TCV spectrum, and future research in contexts where epistemic curiosity or health outcomes are central to the value proposition should reintroduce these dimensions with context-appropriate measurement."

Fourth, the model focuses on the positive TRI dimensions (innovativeness and optimism); adding the negative dimensions (insecurity and discomfort) and distinguishing autonomous from controlled motivation within SDT would give a fuller account of the regulatory boundary conditions.

Fifth, although the dual-method strategy (LMS and PROCESS) provides triangulated evidence for the moderated-moderation effects, two methodological caveats apply. The LMS estimation required

dimension-level parceling of the second-order constructs to keep the latent-interaction model tractable, which can obscure dimension-specific effects. The PROCESS robustness check relied on factor scores, which do not fully propagate measurement error and tend to attenuate interaction coefficients, so the converging estimates should be read as a conservative lower bound rather than exact point estimates. Future research could address these issues through Bayesian SEM with latent interactions (Muthén and Asparouhov, 2012), which handles complex interaction structures without parceling.

Declarations

CONFLICT OF INTEREST:

The authors declare that they have no conflict of interest.

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Author Contribution

Y.L. conceived and designed the study, developed the theoretical framework, collected the data, performed the statistical analysis, and wrote the main manuscript text. X.G. assisted with data collection and contributed to the literature review. G.Q. contributed to the research design, supported the data analysis, and prepared Tables and Figures. J.L. supervised the study, provided critical revisions of the theoretical framework and discussion, and revised the manuscript for intellectual content. All authors reviewed the manuscript.

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Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

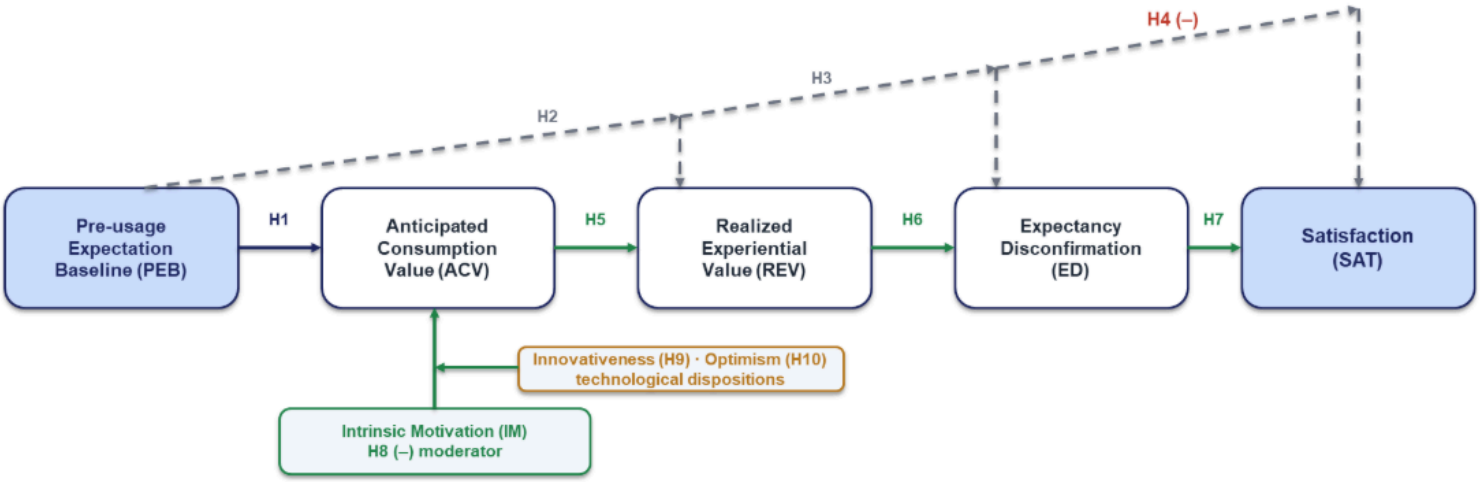

Figure 1

Conceptual Model.

Note: The model has five core constructs (PEB, ACV, REV, ED, SAT) after merging service performance assessment into REV. Intrinsic Motivation is the moderator; Innovativeness and Optimism are the higher-order (moderated-moderation) moderators. ACV, REV, and Intrinsic Motivation are second-order constructs.

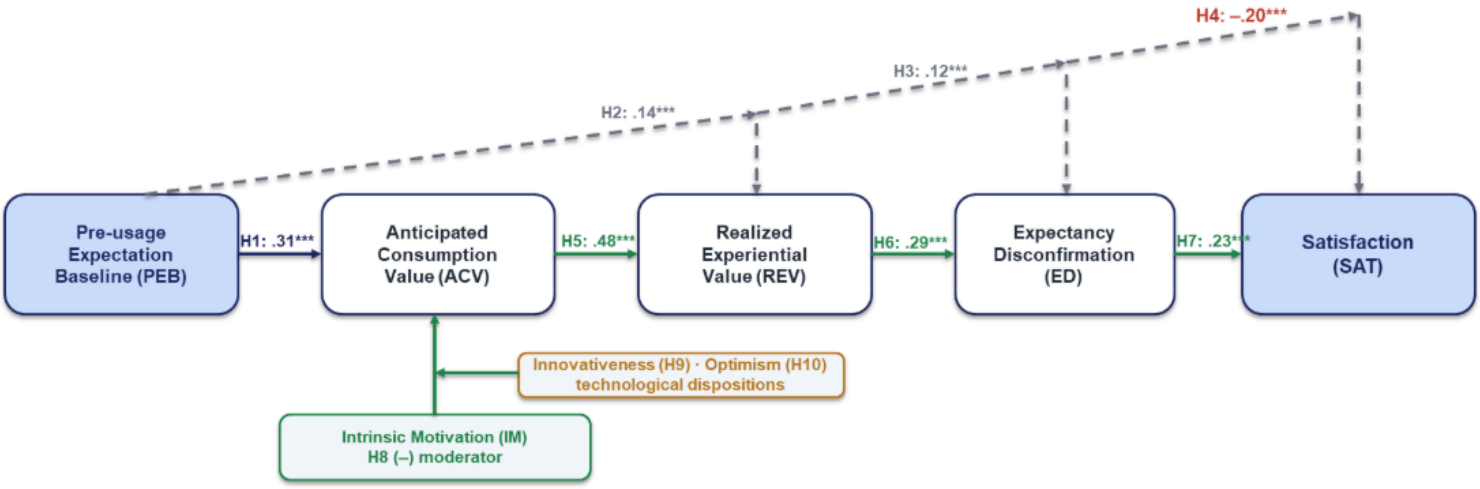

Figure 2

Path Analysis Results

Note: The model has five core constructs (PEB, ACV, REV, ED, SAT) after merging service performance assessment into REV. Intrinsic Motivation is the moderator; Innovativeness and Optimism are the higher-order (moderated-moderation) moderators. ACV, REV, and Intrinsic Motivation are second-order constructs.

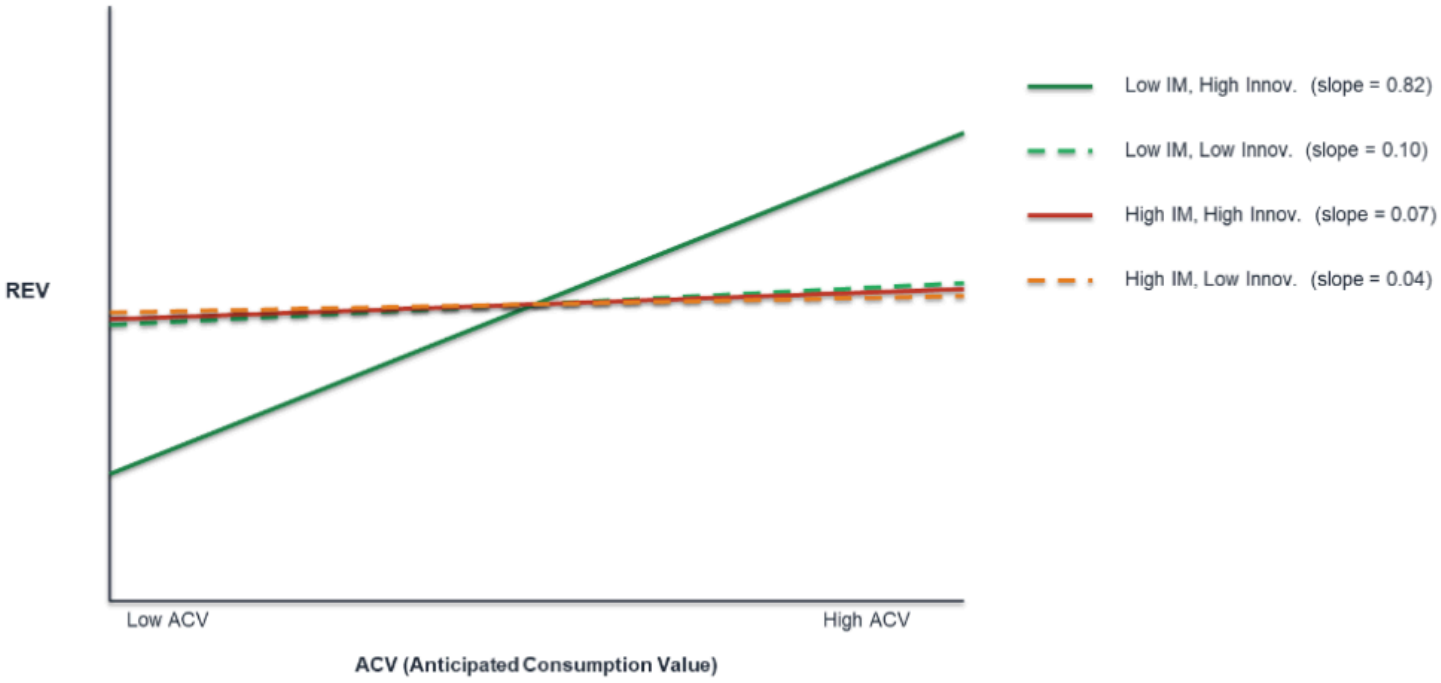

Figure 3

Simple Slope Plot of the Three-Way Interaction Effect of ACV × Intrinsic Motivation × Innovativeness on REV

Note: High and Low conditions are defined as ±1 standard deviation (SD) above and below the mean of the respective moderator. All variables were mean-centered prior to analysis. Slopes represent the unstandardized regression coefficient of ACV on REV at each combination of moderator levels.

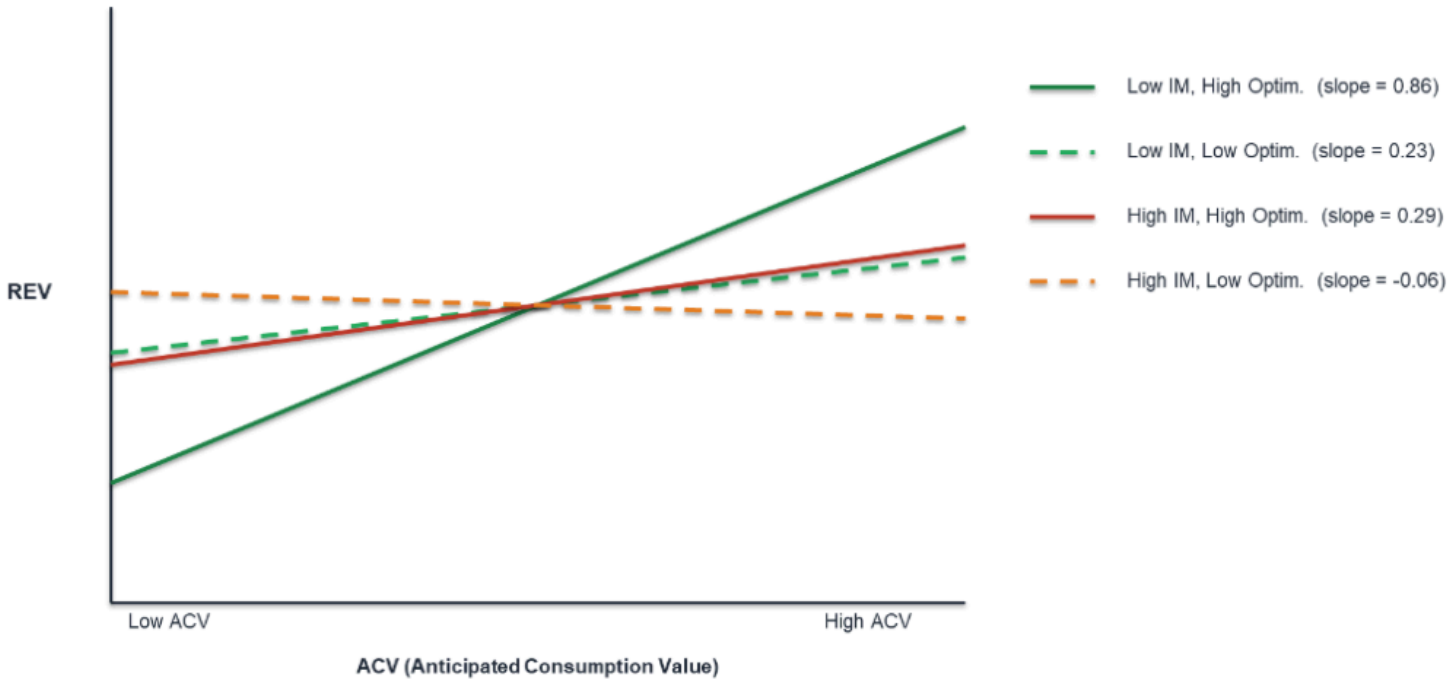

Figure 4

Simple Slope Plot of the Three-Way Interaction Effect of ACV × Intrinsic Motivation × Optimism on REV.

Note: High and Low conditions are defined as ±1 standard deviation (SD) above and below the mean of the respective moderator. All variables were mean-centered prior to analysis. Slopes represent the unstandardized regression coefficient of ACV on REV at each combination of moderator levels.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- OnlineAppendix.docx