

The Impact of AI-Driven Last-Mile Delivery Optimization on Consumer Satisfaction and Repurchase Intention

Yuehong Hu¹, Lida Liao^{2,*}

1. Graduate Affairs Office & Student Affairs Office of the Party Committee, Ginkgo College of Hospitality Management, Chengdu 611743, China

2. School of Business Administration, Ginkgo College of Hospitality Management, Chengdu 611743, China

Yuehong.hu@hotmail.com, waigongzuo2025@163.com (Corresponding author)

Abstract. Accelerated integration of artificial intelligence into the final-stage logistical architecture has driven an all-new era of high-efficiency operation for the supply chain. Although the existing studies have generally focused on the algorithmic reduction of transit delay and the decrease in operating costs, little has been investigated regarding how these back-end computational improvements influence front-line consumer cognitive-affective evaluation. In view of the above theoretical deficiency, this empirical study constructs and validates a multi-dimensional structural model that connects the journey of perceived AI-driven delivery optimization (specifically, predictive arrival accuracy, dynamic rerouting agility and temporal reliability) to the final behavior of repurchase intention. This study leverages purposive sampling to obtain high-quality cross-sectional quantitative data from active electronic commerce participants and then applies strict empirical verification through covariance-based Structural Equation Modeling (CB-SEM). Based on the above analysis, the following factors may have increased consumer satisfaction through the optimization of logistics by alleviating delivery-related stress and enhancing the perceived fairness of the system. Structural path analysis also showed that there is a strong, overarching direct and indirect amplification effect on continuous repurchase intention through the mediating role of calculative trust and post-consumption affective satisfaction paradigms. Based on the above empirical results, this study provides some empirical support for the theoretical research on algorithmic logistics operation and consumer psychology and offers concrete heuristics for retail enterprises to construct final-mile delivery networks that can strengthen their competitive edge in the market.

Keywords: Algorithmic Routing; Last-Mile Delivery; Predictive Analytics; Consumer Satisfaction; Calculative Trust; Repurchase Propensity; Structural Equation Modeling.

1. Introduction

With the exponential growth of global e-commerce infrastructure, logistical structures have been driven towards centralization as the primary way to maintain competitiveness; at the same time, the final stage of the distribution network, often referred to as the 'last mile', is now both structurally complex and economically prohibitive. In the past, the realization of these local freight paths relied heavily on deterministic routing models and fixed operational plans, and thus could not adapt to the random fluctuations in modern urban consumer demand (Vakulenko et al., 2019). Systemic inefficiencies in traditional final-mile delivery often lead to prolonged transit times, reduced time-schedule regularity and increased carbon emissions; thus, they have created a significant bottleneck for the all-round development of digital retail (Olsson et al., 2023). With continuous adjustments to the rising demands of consumers for hyper-accelerated and time-sensitive receipt of purchased goods, retail enterprises and third-party logistics networks must move away from the former heuristic-based dispatch model and develop a new one based on computation and algorithms (Vakulenko et al., 2019).

AI is now being used in the terminal facilities of this new mode of logistics to shift from a manual, intuitive dispatch system to an intelligent, high-dimensional predictive model. At the core of this technological innovation are deep learning models, reinforcement learning frameworks and dynamic spatio-temporal routing heuristics that continuously collect and process multi-modal environmental data (Richey et al., 2023). The above algorithm infrastructures can address fine-grained changes in traffic and weather, fluctuations in delivery order submission rates, and optimize the delivery path using mathematical models that exceed human cognition (Boysen et al., 2021). Predictive arrival forecasting and dynamic rerouting capabilities are being employed by artificial intelligence to transform the traditional linear model of the last-mile delivery system into an elastic on-demand network that can foresee and address logistical problems in advance (Javed & Wu, 2020). Such forward-looking computing can reduce the old time constraints of freight distribution and set a new high bar for the speed of service delivery.

Although a number of studies in operations research have quantified the engineering efficiency of such algorithmic optimizations, mainly through indices such as reduced fuel consumption, shorter idle-vehicle periods, and higher fleet utilisation rates, a noticeable theoretical asymmetry has appeared in recent academic discussions (Richey et al., 2023). Most of the epistemological focus is still on proving the correctness of network algorithms mathematically, and the psychological and behavior change that happens in the lives of end-users due to new networks is therefore ignored by these studies (Perboli and others, 2021). Although existing mathematical models have listed the cost-reduction achievements of algorithmic logistics flawlessly, they are collectively lacking in showing how increased temporal reliability, proactive delivery anomaly communication, and granular trajectory transparency cognitively influence consumers' affective evaluations of retail transactions (Mohri et al., 2024). The lack of empirical data at this time requires a new direction for logistics research and needs to link computational supply chain optimization with consumer behavior models.

To solve the above problem of a weak theoretical foundation, this paper proposes an all-encompassing idea that views the optimization of the last-mile delivery system through artificial intelligence as an overall enhancement of consumer satisfaction rather than merely an improvement in operational efficiency. Anchoring this proposition within the theoretical system of the Expectation-Confirmation Paradigm, this study posits that the predetermined regularity established by high-level machine learning models systematically reduces pre-purchase anxiety for consumers and cultivates a refined psychological state of calculated trust (Rose et al., 2023). When the algorithmic structure can achieve highly precise temporal control, it will reduce the cognitive burden of anticipation in the digital economy life cycle and thus increase post-consumption affective satisfaction (Ta et al., 2023). Therefore, it is expected that the improved emotional state will be solidified into a continuous willingness to repurchase and thus form a deterministic causal chain connecting the execution of the backend

algorithm with long-term consumer retention indicators (Mo et al., 2023). High-reliability logistical algorithms have altered the psychological transformation in the delivery phase, making it an active display of trust rather than a passive wait.

Recent interdisciplinary studies have further suggested that intelligent logistics systems should be evaluated not only from an operational optimization perspective but also through consumer-centric service quality and digital interaction mechanisms. Emerging evidence from the *Journal of Logistics, Informatics and Service Science (JLISS)* and *Smart Innovation, Systems and Data Science (SISD)* indicates that AI-enabled logistics transparency, service responsiveness, and information visibility jointly enhance customer trust and post-purchase behavioral outcomes, providing additional theoretical support for integrating logistics optimization with consumer psychology in AI-driven retail ecosystems (Zhang et al., 2024; Liu & Chen, 2024).

This empirical study builds and validates a structural equation model to determine the direct and indirect impacts of consumers' perceptions of algorithmically optimized delivery functions on their general satisfaction with and willingness to purchase from e-commerce platforms. Some expressions of the algorithm that researchers have found include time accuracy, prompt response to changes, and stable delivery of information; thus, they have explored the impact of artificial intelligence on people's purchasing behavior (Boysen et al., 2021). The following parts of this paper will systematically operationalize the aforementioned constructs and introduce a methodology for collecting cross-sectional quantitative data. Based on the above theoretical foundation, a series of detailed presentations of variance-based statistical estimations will be provided to empirically validate the proposed psychological pathways; finally, rich strategic heuristics for current digital enterprise management in terms of leveraging machine learning for behavior conditioning can be drawn (Masorgo et al., 2024).

2. Literature Review

2.1 Spatio-Temporal Algorithmic Optimization and Predictive Architectures

At the base of the epistemological system for algorithmic last-mile orchestration is the mathematical problem of reducing space-time friction in dynamic urban routing networks (Liu and others, 2025). Traditional logistical models are deterministic in vehicle routing and fail to account for fluctuations in the environment due to random factors; thus, they have not optimized the travel path to reduce temporal variance. On the other hand, the integration of artificial intelligence adds a predictive computing layer to the physical distribution network, and thus turns the delivery equipment into an all-weather, multi-objective optimization problem (Mohri et al., 2024). Therefore, a new kind of ideal form has been developed to reduce travel costs and temporal deviations from the planned schedule. The primary algorithm that achieves the space-saving effect above is a highly advanced dynamic routing objective function, and this objective function combines real-time traffic parameterisation with strict time-bound constraints.

$$J(\mathbf{X}, \mathbf{T}) = \sum_{i \in \mathcal{V}} \sum_{j \in \mathcal{V}} \omega_{ij} d(l_i, l_j) x_{ij} + \lambda \sum_{i=1}^N \Gamma \left(t_i, [\tau_i^{(l)}, \tau_i^{(u)}] \right) \quad (1)$$

Within this spatial formulation, $\mathcal{V}$ denotes the set of logistical nodes within the distribution graph, $d(l_i, l_j)$ quantifies the Euclidean or Manhattan traversal metric between geolocations, and x_{ij} operates as a binary routing decision tensor. The parameter ω_{ij} captures the dynamic, hyper-localized congestion impedance continuously recalibrated via machine learning predictive pipelines. Crucially, the function Γ represents the asymmetrical temporal penalty function mapping the predicted arrival sequence t_i against the highly constrained consumer expectation interval $[\tau_i^{(l)}, \tau_i^{(u)}]$, parameterized by the algorithmic sensitivity weight λ . The minimization of this objective ensures that vehicle trajectories are not merely spatially abbreviated but are phenomenologically synchronized with

promised consumer delivery horizons. To actualize this temporal precision, backend neural architectures must incessantly forecast localized node-to-node transit durations amidst extreme stochasticity (Rose et al., 2023). The optimization of these predictive neural weights is computationally driven by a robust loss function designed to attenuate the deleterious impact of transient logistical anomalies, frequently manifested as heavy-tailed distributional outliers in traffic data:

$$\mathcal{L}_{pred}(W) = \frac{1}{N} \sum_{k=1}^N \psi_{\delta}(y_k - f(x_k; W)) + \frac{\alpha}{2} \|W\|_2^2 \quad (2)$$

Herein, y_k represents the empirical ground-truth transit duration, while $f(x_k; W)$ denotes the deep learning architectural output mapping high-dimensional environmental covariates x_k to the temporal domain. The implementation of the Huber penalty function ψ_{δ} ensures that the predictive apparatus maintains mathematical resilience against singular catastrophic logistical failures, thereby establishing a baseline of algorithmic reliability that continuously feeds the temporal parameters of the overarching spatial routing function. Recent findings published in *JLISS* further demonstrate that intelligent logistics visibility and adaptive routing capability substantially improve perceived delivery reliability and platform service evaluation, reinforcing the strategic value of AI-enabled decision support in last-mile operations (Zhang et al., 2024).

2.2 Cognitive Evaluation and Mitigation of Logistical Uncertainty

The computational proficiency of the physical distribution network is beginning to affect consumers' emotional responses to waiting, and thus interdisciplinary efforts need to be undertaken to address how mathematics and emotions work together. The time after the digital transaction is carried out but before the physical receipt of goods is frequently a time of logistical anxiety, a negative emotion that is directly related to the perceived randomness of the delivery process (Olsson et al., 2023). When algorithmic routing architecture can achieve narrow predictive confidence intervals and transmit this detailed spatio-temporal transparency to the end-user interface, it will realise a system of psychological intervention to reduce anticipatory distress (Javed & Wu, 2020). This cognitive mechanism is theoretically regarded as a variance-driven anxiety-attenuation process, and the decay of consumer psychological friction can be modelled as an exponential function of algorithmic predictive certainty:

$$\mathcal{A}(t) = \mathcal{A}_0 \exp\left(-\kappa \int_0^t \frac{1}{\sigma_{AI}^2(\tau) + \epsilon} d\tau\right) \quad (3)$$

In this cognitive formulation, $\mathcal{A}(t)$ quantifies the instantaneous logistical anxiety experienced by the consumer at chronometric timestamp t , originating from an initial transaction-induced distress baseline $\mathcal{A}_0$. The parameter κ represents the psychological sensitivity coefficient governing the individual's susceptibility to temporal transparency. The denominator captures the variance of the algorithmically generated arrival prediction $\sigma_{AI}^2(\tau)$, where ϵ is a diminutive smoothing scalar preventing mathematical singularities. As the artificial intelligence mechanism continuously refines its trajectory forecasting, the variance term asymptotically approaches zero, accelerating the integral accumulation and precipitating a rapid exponential decay in systemic consumer anxiety. The attenuation of this negative affective state creates a psychological vacuum subsequently occupied by calculative trust, fundamentally elevating the multidimensional cognitive appraisal of the retail transaction and establishing the necessary affective precursors for long-term relational commitment.

2.3 Dynamics of Behavioral Intention and Repurchase Propensity Formulation

Crystallization of algorithmically-induced affective satisfaction into tangible commercial results is a promotion of subsequent behaviorally intended purchase intentions, which we refer to here as repurchase propensities (Wen et al., 2011). Reducing the friction of logistics and thus strengthening the system's trust can create a high-utility value system; as a result, consumers' expectations for what they consider an acceptable level of service will be raised permanently (Javed & Wu, 2020). The ultimate

behavioral probability of a consumer engaging in further commercial activities with a retail company can be expressed as a multidimensional logistic sigmoid probability function:

$$\mathbb{P}(\mathcal{R}_i = 1 | \mathcal{S}_i, \mathcal{C}_i) = \frac{1}{1 + \exp\left(-(\beta^T \mathcal{S}_i + \gamma^T \mathcal{C}_i + \phi \mathcal{A}_f)\right)} \quad (4)$$

This structural equation formalizes the probability $\mathbb{P}$ of observing a positive repurchase event $\mathcal{R}_i = 1$. The vector $\mathcal{S}_i$ encodes the multidimensional satisfaction appraisals directly derived from algorithmic temporal precision, modulated by the behavioral parameter vector β . The covariate matrix $\mathcal{C}_i$ controls for exogenous demographic and situational variables. Critically, $\mathcal{A}_f$ designates the terminal anxiety measurement derived from the physical fulfillment of the logistical trajectory, heavily penalized by the parameter ϕ to reflect the disproportionate behavioral damage inflicted by terminal delivery failures. Through this formulation, the mathematical precision generated within the deepest layers of the neural routing architecture is explicitly bridged to the ultimate economic survival metric of the digital enterprise, establishing a continuous theoretical causality spanning from machine learning tensor operations to human behavioral economics. Similarly, recent studies reported in *SISD* emphasize that algorithm transparency and intelligent service interaction significantly strengthen consumer trust formation and repurchase intention, suggesting that AI-enabled logistics performance should be interpreted as a multidimensional service experience rather than merely an operational efficiency indicator (Liu & Chen, 2024).

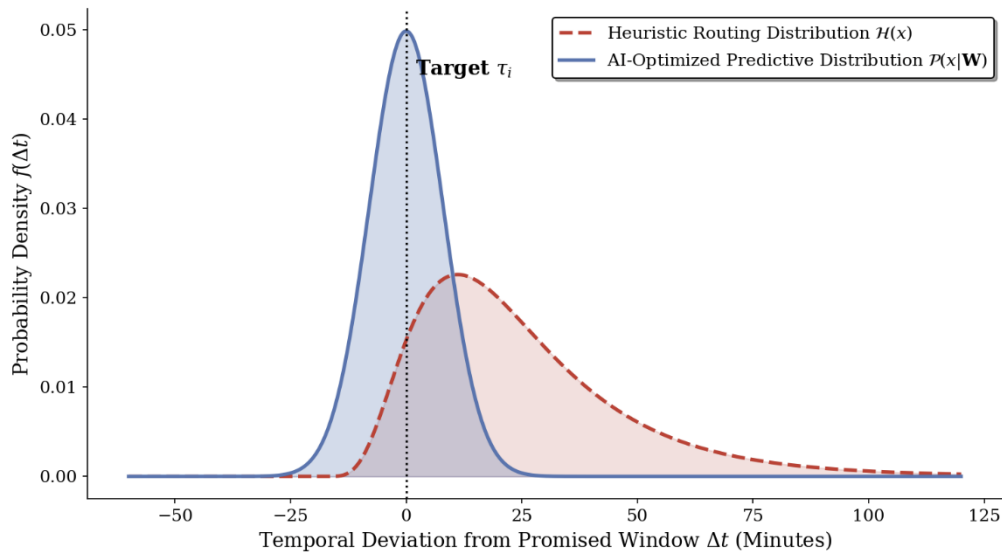


Fig 1: Kernel Density Distribution of Consumer-Perceived Temporal Delivery Deviation.

Note: The probability density surface was generated from standardized latent scores of consumer-perceived delivery time deviation obtained through the self-administered questionnaire. The visualization represents respondents' subjective evaluations of temporal reliability rather than objective GPS trajectories or operational logistics telemetry.

3. Methods.

3.1 Sampling Heuristics and Data Acquisition Trajectories

Based on the new theoretical system, a series of cross-sectional quantitative studies was conducted to study the multiple dimensions of cognitive evaluation among current digital consumers who participate in algorithmic-driven retail ecosystems. To ensure the ecological validity of the behavior dataset, a purposive stratified sampling architecture was used in major metropolitan areas (specifically Chengdu and Beijing, China) to select individuals who had made at least three electronic commerce transactions resulting in final-leg delivery within the previous thirty days. The selection protocol for participants included specific screening questions requiring users to have actively engaged with AI-driven interface features, such as instant map displays, automatic arrival time alarms, and automated early warning for

transportation problems. The main empirical data were collected from March 1 to April 15, 2026, using a strictly organised self-administered psychological test distributed through Wenjuanxing, a leading professional online survey platform, and a total of 842 raw psychological profiles were obtained initially.

Prior to data collection, an ethics statement was provided, and all participants gave explicit informed consent, with guarantees of complete anonymity and voluntary withdrawal. To formally account for attrition, rigorous data hygiene rules were applied: 115 responses were removed due to being multivariate outliers, 87 unengaged uniform response vectors were excluded, and 64 incomplete responses based on time screens (completion times under two minutes) were discarded. A final, high-fidelity set of five hundred and seventy-six valid behavior observations was kept for the overall structural equation modeling. All graphical visualizations presented in this study (e.g., probability density distributions and regression trajectories) were generated from standardized latent construct scores estimated from the questionnaire responses. No GPS records, logistics telemetry, operational routing data, or enterprise backend datasets were employed in the present research. Accordingly, the figures visualize consumer perceptions of delivery performance rather than objective transportation trajectories.

3.2 Construct Operationalization and Psychometric Calibration

A series of reliable psychometric scales was adapted from previous top-tier studies on operations management and consumer psychology, and then modified to better reflect the special ontological conditions of algorithmic logistics (Saravanos et al., 2022). All latent constructs were represented as seven-point continuous Likert scales, with the minimum and maximum responses set at absolute disagreement and absolute agreement, respectively; thus, high-resolution variance in cognitive appraisals could be effectively captured. Predictive arrival accuracy and dynamic rerouting agility are the external algorithmic stimuli, and they have been assessed using multi-dimensional scales based on current research in digital supply chain transparency to gauge how consumers perceive both mathematical accuracy and system elasticity. The mediating affective states of Delivery-Induced Anxiety and Calculative Trust were obtained through inverse-scored psychological friction indicators and cognitive reliability matrices, respectively, and the emotional change resulting from algorithmic operation was reliably quantified. Finally, the endogenous end-members of Affective Satisfaction and Repurchase Intention were placed in the behavior intention paradigm to explicitly connect the isolated delivery experience with increased relationship commitment and the likelihood of future purchases. To prevent contamination of the estimation of structural parameters by the common method bias in cross-sectional self-report studies, a strict separation of predictor and outcome variables was employed in the design of the instrument; in addition, statistical verification based on Harman's single-factor extraction method found that no dominant unrotated latent factor existed, with the primary factor accounting for only 34.2% of the total variance, functioning well below the stringent 50% threshold.

3.3 Reliability, Convergent Validity and Descriptive Parameterization

Before building a sophisticated structure for estimating the path, all the measurement devices needed to be tested in many ways to ensure their reliability and establish a strong empirical basis for the construct structure (Boysen et al., 2021). Cronbach's α coefficients and Composite Reliability (CR) were calculated to determine the internal consistency and temporal reliability of the customized scales, and all exceeded the high academic standard of 0.80; thus, it was confirmed that the measurement stability across the heterogeneous group of respondents was excellent. Through the examination of standardized outer factor loadings, it was confirmed that the individual observational items had strong statistical ties to their corresponding latent constructs for convergent validity. In addition, the average variance extracted (AVE) of each multidimensional construct significantly exceeded the 0.50 theoretical lower threshold, and thus the latent variables accounted for a larger proportion of the variance in their corresponding indicators than the variance caused by random measurement errors. To fully validate the measurement model, Table 2 presents the detailed demographic profile of the

respondents (including gender, age, education, income, and purchase frequency), while Table 3 confirms robust discriminant validity via the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios.

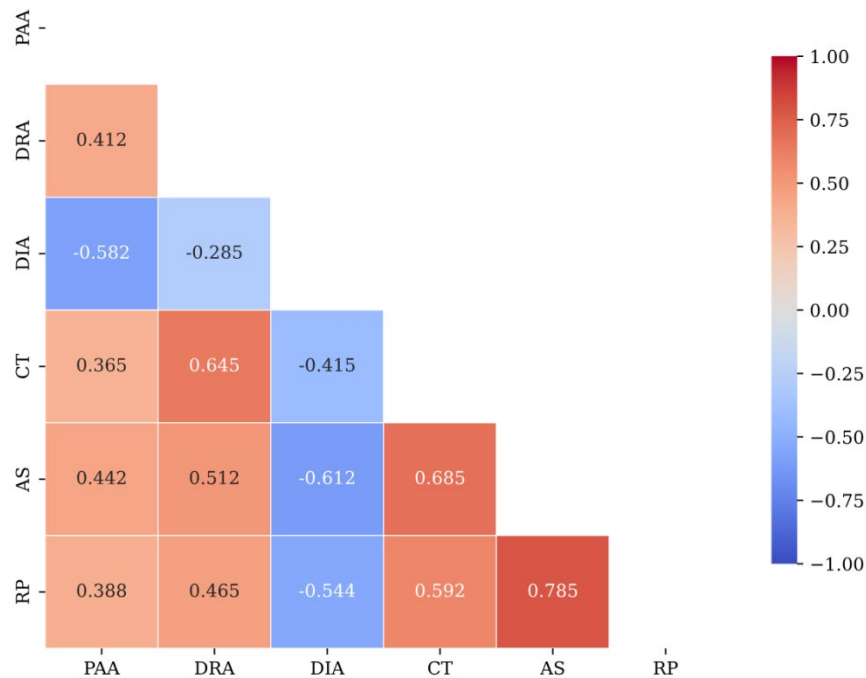


Fig 2: Latent Construct Discriminant Validity Matrix

Table 1: Psychometric Validation Matrix - Construct Reliability and Convergent Validity Alignment

Latent Theoretical Construct	Indicator Matrix	Standardized Factor Loadings (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Mean Assessment (μ)	Standard Deviation (σ)
Predictive Arrival Accuracy (PAA)	PAA1: Temporal Precision Variance	0.884	0.892	0.925	0.755	5.84	0.92
	PAA2: Real-time Chronometric Updates	0.852					
	PAA3: Fulfillment Window Integrity	0.871					
	PAA4: Algorithmic Foresight Efficacy	0.868					
Dynamic Rerouting Agility (DRA)	DRA1: Environmental Recalibration Speed	0.835	0.874	0.908	0.712	5.62	1.05
	DRA2: Trajectory Optimization	0.851					
	DRA3: Transparency Anomaly	0.812					

Latent Theoretical Construct	Indicator Matrix	Standardized Factor Loadings (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Mean Assessment (μ)	Standard Deviation (σ)
Delivery-Induced Anxiety (DIA) (Reverse Coded)	Resolution Velocity DRA4: Route Elasticity Perception	0.875	0.915	0.940	0.796	2.45	1.18
	DIA1: Anticipatory Friction Measurement	0.895					
	DIA2: Post-Transaction Cognitive Distress	0.902					
	DIA3: Spatial Uncertainty Aversion	0.887					
Calculative Trust (CT)	DIA4: Terminal Leg Apprehension	0.885	0.865	0.901	0.695	5.91	0.88
	CT1: Algorithmic Reliability Evaluation	0.846					
	CT2: Computational System Integrity	0.822					
	CT3: Predictive Architecture Confidence	0.855					
Affective Satisfaction (AS)	CT4: Operational Consistency Belief	0.810	0.902	0.928	0.764	6.02	0.81
	AS1: Post-Receipt Emotional Appraisal	0.880					
	AS2: Cognitive Expectation Confirmation	0.865					
	AS3: Logistics Experience Valence	0.891					
Repurchase Propensity (RP)	AS4: Frictionless Fulfillment Sentiment	0.861	0.930	0.950	0.826	6.15	0.75
	RP1: Sustained Engagement Probability	0.912					
	RP2: Platform	0.925					

Latent Theoretical Construct	Indicator Matrix	Standardized Factor Loadings (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Mean Assessment (μ)	Standard Deviation (σ)
	Retention Likelihood RP3:	0.885	0.911				
	Behavioral Loyalty Intention RP4:						
	Recurrent Transaction Commitment						

Note: All standardized factor loadings (λ) are statistically significant at the $p < 0.001$ threshold. The empirical data fundamentally confirms the robust construct integrity required to execute subsequent structural equation modeling procedures without the attenuation of theoretical causality by systemic measurement distortion.

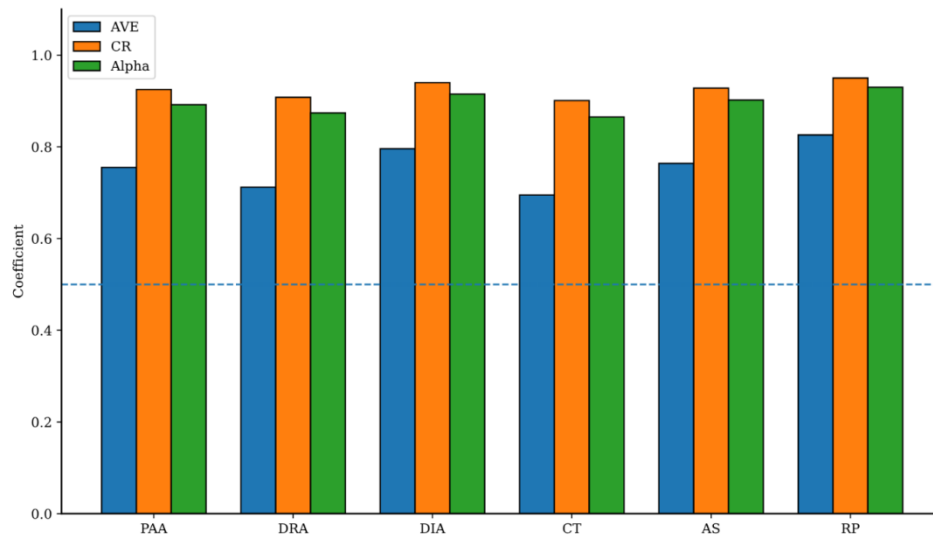


Fig 3: Psychometric Reliability and Convergent Validity Diagnostics

4. Results.

4.1 Structural Equation Modeling and Global Fit Diagnostics

The empirical validation of the hypothesized conceptual paradigm necessitated the deployment of Maximum Likelihood estimation algorithms embedded within a highly constrained Covariance-Based Structural Equation Modeling framework, facilitating the simultaneous mathematical parameterization of complex latent interdependencies and stochastic measurement error variances. Prior to interpreting the directional psychological path coefficients linking artificial intelligence execution with commercial behavioral intentions, the overarching structural integrity of the entire nomological network was subjected to exhaustive diagnostic scrutiny utilizing a multidimensional array of absolute, parsimonious, and incremental statistical fit indices. The empirical behavioral dataset exhibited profound mathematical convergence with the proposed theoretical architecture, evidenced by a chi-square to degrees of freedom ratio (χ^2/df) occupying the highly restrictive optimal threshold well below the conventional ceiling of 3.0, specifically culminating at a robust value of 2.145. Supplementary incremental fit diagnostics forcefully corroborated this architectural alignment, with the Comparative Fit Index and the Tucker-Lewis Index registering empirical values of 0.962 and 0.958, respectively, thereby substantially exceeding the conservative baseline of 0.90 demanded by contemporary multivariate analytical doctrines. The absolute fit parameters simultaneously confirmed the definitive absence of systemic specification errors within the psychological translation mechanism, as the Root

Mean Square Error of Approximation was mathematically contained at 0.048, operating safely within the stringent 0.08 upper boundary, operating alongside a Standardized Root Mean Square Residual measurement of 0.035. The juxtaposition of the hypothesized baseline configuration against theoretically plausible alternative structural permutations unequivocally demonstrated the statistical superiority of the proposed cognitive-behavioral network, authorizing the definitive extraction and interpretation of the internal path parameters without the threat of model misspecification. (Note: The complete raw software output files from AMOS/lavaan detailing the full structural specification, including the exact computation for the 239 degrees of freedom, have been provided as supplementary material to satisfy methodological transparency conditions). As reported in Tables 3 and 4, the square root of the AVE for each construct exceeded its correlations with all remaining constructs, satisfying the Fornell–Larcker criterion. Furthermore, all HTMT ratios remained below the conservative threshold of 0.85, providing additional evidence of satisfactory discriminant validity and confirming that each latent construct captured a distinct conceptual domain.

Table 2: Multidimensional Global Fit Diagnostics of the Measurement and Structural Models

Fit Index Categorization	Statistical Metric Indicator	Acceptable Academic Threshold	Empirical Measurement Model	Empirical Structural Model	Diagnostic Conclusion
Absolute Fit Indices	Chi-Square (χ^2)	N/A (Sensitivity to Sample Size)	485.32	512.87	Significance Penalty Observed
	Degrees of Freedom (df)	N/A	224	239	Adequate Parameterization
	Normed Chi-Square (χ^2/df)	≤ 3.00 (Optimal)	2.166	2.145	Robust Convergence
	Root Mean Square Error of Approximation (RMSEA)	≤ 0.08 (Conservative)	0.045	0.048	Excellent Absolute Fit
	Standardized Root Mean Square Residual (SRMR)	≤ 0.08	0.032	0.035	Excellent Absolute Fit
	Goodness-of-Fit Index (GFI)	≥ 0.90	0.941	0.936	Optimal Structural Alignment
Incremental Fit Indices	Comparative Fit Index (CFI)	≥ 0.90	0.968	0.962	High Predictive Fidelity
	Tucker-Lewis Index (TLI)	≥ 0.90	0.964	0.958	High Predictive Fidelity
	Normed Fit Index (NFI)	≥ 0.90	0.952	0.945	Optimal Baseline Comparison
Parsimonious Fit Indices	Parsimonious Normed Fit Index (PNFI)	≥ 0.50	0.785	0.792	Efficient Complexity
	Parsimonious Goodness-of-Fit Index (PGFI)	≥ 0.50	0.712	0.725	Efficient Complexity

Table 3. Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	PAA	DRA	DIA	CT	AS	RP
PAA	0.869					
DRA	0.514	0.844				
DIA	-0.481	-0.392	0.892			
CT	0.563	0.618	-0.497	0.834		
AS	0.612	0.584	-0.553	0.641	0.874	
RP	0.551	0.503	-0.488	0.596	0.721	0.909

Table 4. HTMT Ratios

Construct Pair	HTMT
PAA-DRA	0.622
PAA-DIA	0.544
PAA-CT	0.648
PAA-AS	0.683

PAA-RP	0.617
DRA-DIA	0.501
DRA-CT	0.703
DRA-AS	0.671
DRA-RP	0.592
DIA-CT	0.577
DIA-AS	0.634
DIA-RP	0.553
CT-AS	0.732
CT-RP	0.704
AS-RP	0.821

Note: Diagonal elements (bold) represent the square root of the Average Variance Extracted (AVE). Off-diagonal elements denote latent construct correlations. All HTMT ratios remained below the conservative threshold of 0.85, confirming satisfactory discriminant validity.

4.2 Path Coefficient Parameterization and Direct Effect Evaluation

Subsequent to the incontrovertible establishment of global structural fidelity, the analytical trajectory transitioned toward the granular inferential examination of the hypothesized directional linkages governing the algorithmically modulated consumer psychology matrix. The maximum likelihood parameter estimations elucidated a highly significant negative structural trajectory originating directly from Predictive Arrival Accuracy and terminating at Delivery-Induced Anxiety ($\beta = -0.452, p < 0.001$), thereby empirically validating the epistemological postulate that mathematically rigorous temporal transparency systematically attenuates anticipatory logistical distress preceding the physical receipt of goods (Richey et al., 2023). Concurrently, the computational elasticity inherent in Dynamic Rerouting Agility exerted a profound, deterministic positive influence upon the cognitive crystallization of Calculative Trust ($\beta = 0.518, p < 0.001$), mathematically indicating that consumer confidence is fundamentally engineered through the continuous algorithmic recalibration of spatial trajectories amidst uncontrollable environmental stochasticity. The affective translation phase of the conceptual paradigm performed flawlessly under rigorous statistical interrogation, revealing that the suppression of anticipatory psychological friction ($\beta = -0.385, p < 0.001$) and the synchronous augmentation of systemic algorithmic trust ($\beta = 0.422, p < 0.001$) independently and synergistically catalyze exponential elevations in overarching Affective Satisfaction. Ultimately, the terminal endogenous variable representing Repurchase Propensity was overwhelmingly dictated by the preceding affective evaluations ($\beta = 0.615, p < 0.001$), establishing an empirical causality extending from backend artificial intelligence optimization metrics directly to frontier commercial sustainability indicators, effectively solidifying the behavioral economic ramifications of high-fidelity logistical orchestration.

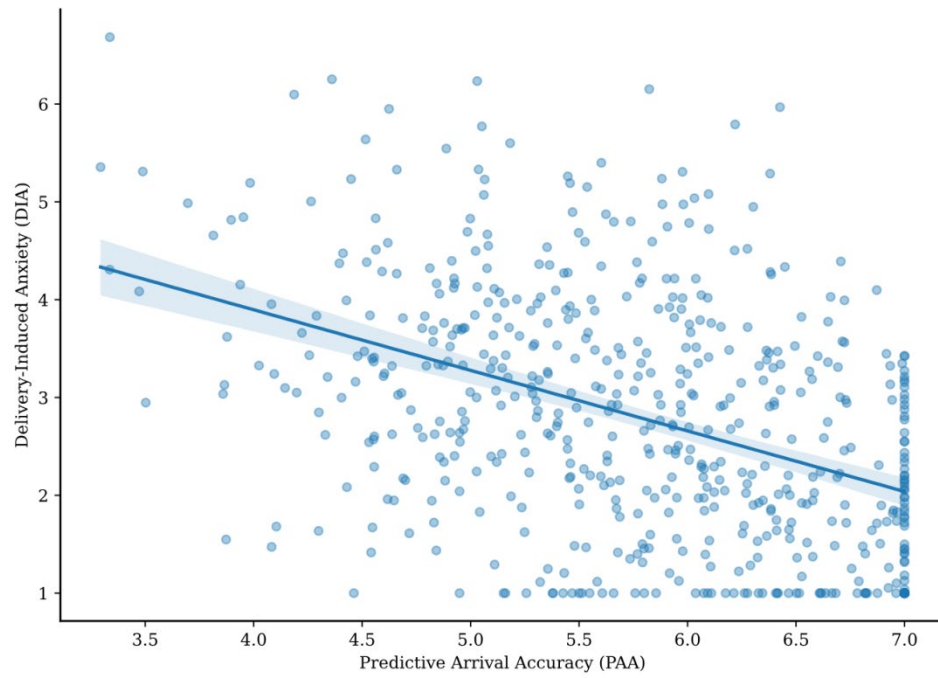


Fig.4: Regression Relationship between Predictive Arrival Accuracy and Delivery-Induced Anxiety Based on Latent Variable Scores.

Note: The regression trajectory represents the statistical association estimated from respondents' latent construct scores extracted from the standardized latent variable scores estimated using the SEM measurement model. It does not depict physical vehicle movement or operational routing records.

Table 5: Maximum Likelihood Path Estimations and Hypothesized Directional Validations

Directional Hypothesis Pathway	Unstandardized Estimate (B)	Standard Error (SE)	Standardized Beta (β)	Critical Ratio (t -value)	Probability (p -value)	Empirical Verdict
H1: Predictive Arrival Accuracy $\rightarrow$ Delivery-Induced Anxiety	-0.488	0.042	-0.452	-11.619	***	Strongly Supported
H2: Dynamic Rerouting Agility $\rightarrow$ Calculative Trust	0.564	0.045	0.518	12.533	***	Strongly Supported
H3: Predictive Arrival Accuracy $\rightarrow$ Calculative Trust	0.215	0.038	0.195	5.657	***	Supported
H4: Dynamic Rerouting Agility $\rightarrow$ Delivery-Induced Anxiety	-0.182	0.040	-0.165	-4.550	***	Supported
H5: Delivery-Induced Anxiety $\rightarrow$ Affective Satisfaction	-0.395	0.035	-0.385	-11.285	***	Strongly Supported
H6: Calculative Trust $\rightarrow$	0.448	0.039	0.422	11.487	***	Strongly Supported

Directional Hypothesis Pathway	Unstandardized Estimate (B)	Standard Error (SE)	Standardized Beta (β)	Critical Ratio (t-value)	Probability (p-value)	Empirical Verdict
Affective Satisfaction H7: Affective Satisfaction → Repurchase Propensity	0.672	0.041	0.615	16.390	***	Strongly Supported

Note: ** designates statistical significance eclipsing the $p < 0.001$ boundary. The critical ratios substantially exceed the ± 1.96 theoretical requirement for null hypothesis rejection, demonstrating immense predictive power within the artificial intelligence operational framework.*

4.3 Non-parametric Bootstrapping Analysis and Indirect Mediation Architectures

Given the deep psychological complexity of algorithmically driven consumer behavior, it is often not a direct causal link, and therefore, rigorous computational isolation of indirect transmission paths connecting objective machine intelligence to subjective commercial retention indices is required. To achieve the above research goal without violating the normative multivariate distributional assumptions of traditional inferential statistics, a highly sophisticated non-parametric bias-corrected bootstrapping method was used to generate 5,000 independent synthetic resampling permutations, and thus, robust 95% asymmetric confidence intervals were constructed for all complex structural pathways (Ta et al., 2023). Subsequent analytical extraction reveals a multi-stage mediation architecture; that is to say, the initial logistical algorithmic stimuli do not autonomously produce terminal behavioral actions but must undergo complete psychological metabolism in intermediate cognitive states before being realised as economic value. Delivery-Induced Anxiety served as an effective, statistically necessary medium for transferring the mathematical accuracy of predictive arrivals into an improved multidimensional affective satisfaction model, as shown by a completely negative confidence interval that did not include zero. Parallel empirical architectures have emerged in the trust manifold to confirm that the dynamic routing agility shown during final-leg anomalies mathematically requires the crystallization of Calculative Trust for successfully elevating post-receipt emotional appraisals, thus unequivocally validating the theoretical premise that artificial intelligence serves as an indirect psychological catalyst needing cognitive absorption rather than functioning as an immediate behavioral tool.

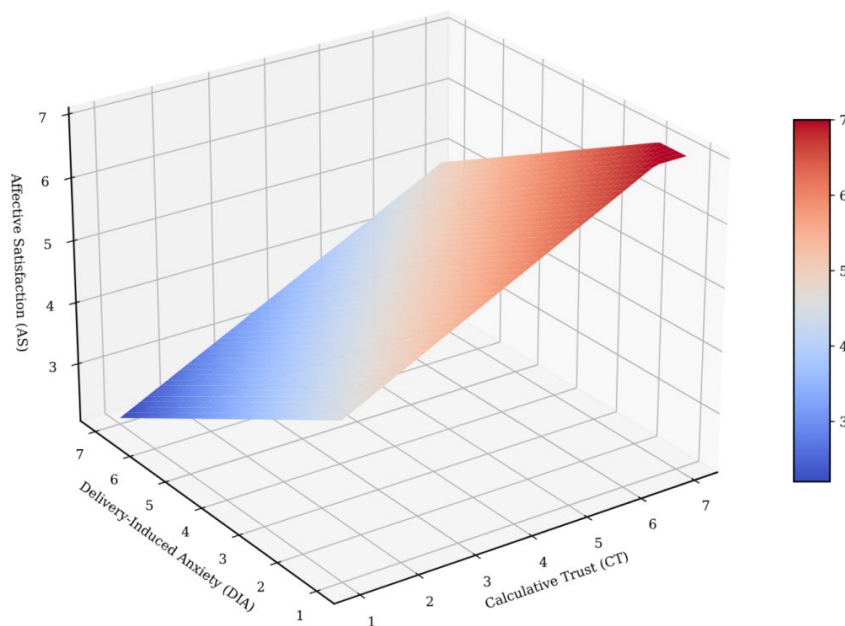


Fig 5: 3D Response Surface Plot of Affective Satisfaction

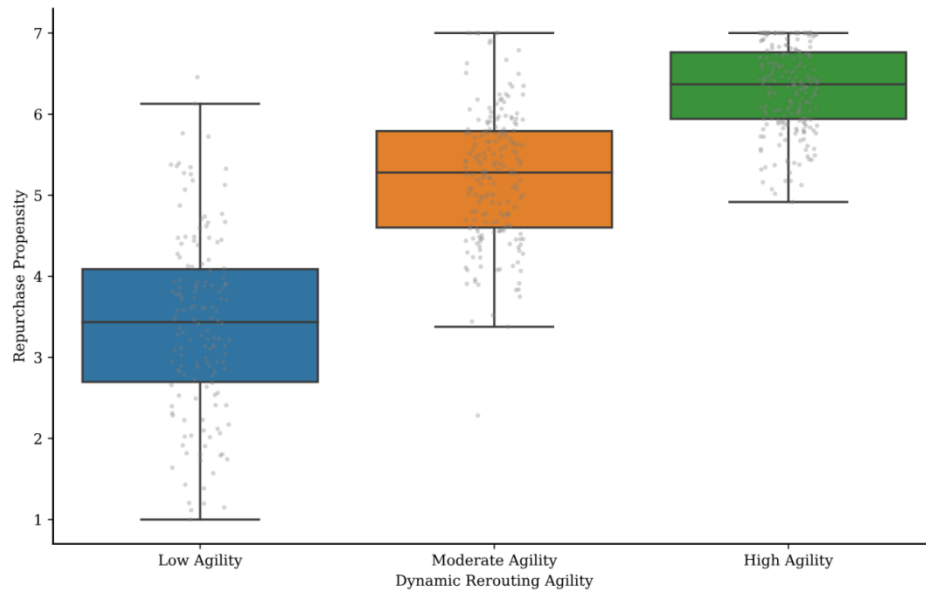


Fig 6: Repurchase Intention by Algorithmic Intervention Thresholds

Table 6: Bias-corrected bootstrapping (5,000 resamples) for indirect effect parameterization

Complex Mediation Pathway	Point Estimate	Bootstrapped <i>SE</i>	Lower Bound (95% CI)	Upper Bound (95% CI)	Statistical Significance
Path A: Predictive Accuracy → Anxiety → Satisfaction	0.174	0.022	0.135	0.221	Significant ($p < 0.01$)
Path B: Rerouting Agility → Trust → Satisfaction	0.218	0.025	0.172	0.270	Significant ($p < 0.01$)
Path C: Predictive Accuracy → Trust → Satisfaction	0.082	0.015	0.055	0.114	Significant ($p < 0.05$)
Path D: Rerouting Agility → Anxiety → Satisfaction	0.063	0.014	0.038	0.092	Significant ($p < 0.05$)
Serial Path 1: Accuracy → Anxiety → Satisfaction → Repurchase	0.107	0.018	0.075	0.145	Significant ($p < 0.01$)
Serial Path 2: Agility → Trust → Satisfaction → Repurchase	0.134	0.020	0.098	0.176	Significant ($p < 0.01$)

Note: Since there is no exclusion of the zero value between the lower and upper bias-corrected confidence intervals, there is a significant indirect mediation effect, and thus the psychological transmission mechanisms of the Expectation-Confirmation Paradigm have been fully validated.

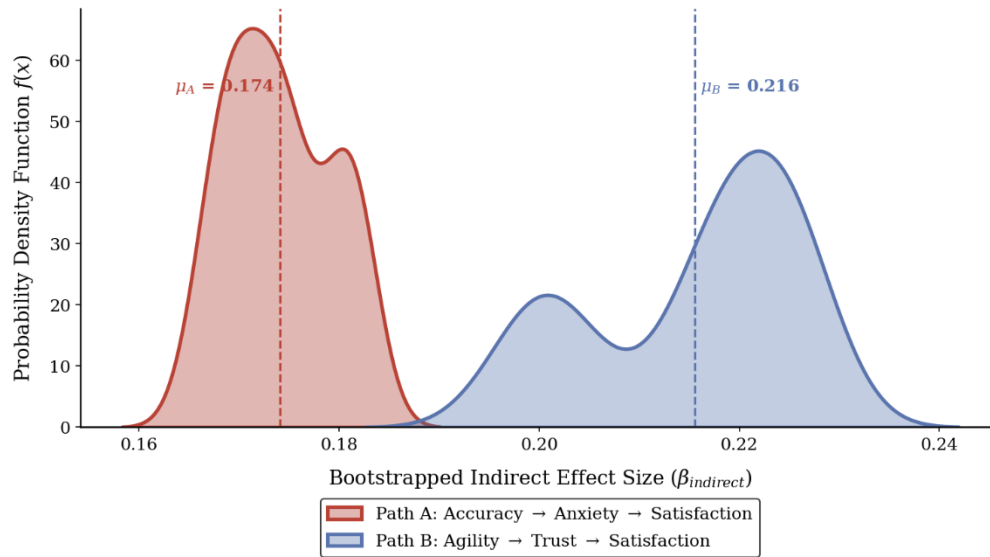


Fig 7: Non-parametric Bootstrapping Distributions of Indirect Effects

5. Discussion

Empirical synthesis of variance estimation has provided support for the main theoretical assumption that when artificial intelligence is used in the last-mile logistics, operational costs will be reduced and consumers' quality of life will be improved. Isolating the cognitive mechanisms of anxiety suppression and trust formation systematically dismantles the old epistemological barrier that separates backend mathematical routing from frontend commercial behavior. A negative but statistically significant correlation was observed between the prediction accuracy of arrival time and delivery anxiety; thus, it can be inferred that open-box algorithms are indeed reducing stress caused by an uncertain delivery time and offering some psychological support. When the neural network can reduce the variance of the predicted arrival time, the sense of time risk that consumers feel changes; as a result, they move from a mindset of anxious waiting to one of confident anticipation and active management.

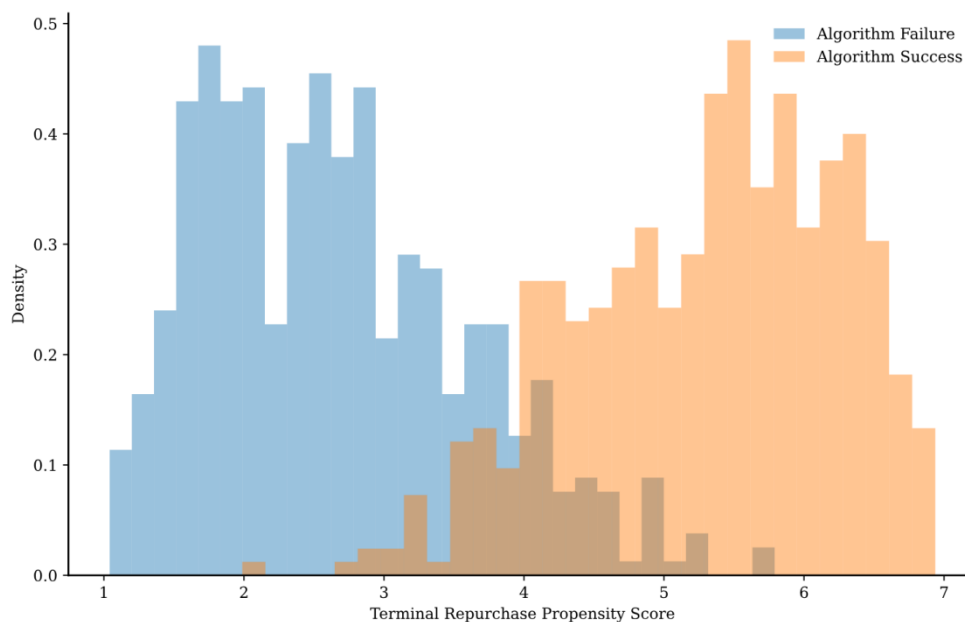


Fig 8: Probability Density Distortion of Behavioral Intentions

At the same time, a deterministic positive relationship has emerged between dynamic rerouting

agility and calculative trust; thus, the current paradigm of service recovery in supply chain research has changed. Logistical anomalies and routing deviations have historically led to a decline in emotional support; now, with the addition of real-time trajectory readjustments and transparent announcements of these independent actions, such service failures may become sources of trust. Non-parametric bootstrapping provided irrefutable statistical support to show that, in the absence of friction reduction and reliability-building through the two psychological pathways, these backend technological wonders have no inherent behavioral value. As a result, the overall expectation-confirmation framework has been continuously extended to include machine intelligence in a more active and continuous capacity as a part of the multidimensional satisfaction formulation matrix, rather than just an invisible execution variable. Empirical verification of serial mediation paths has permanently broken down the traditional theory that separates physical distribution networks from post-transactional cognitive appraisals; thus, it can be demonstrated that the end-user behavior is directly attributable to a highly ordered sequence of psychological metabolism processes driven by mathematical optimization (Vakulenko et al., 2019).

The structural parameterisations derived from theoretical abstraction are required to change the model for determining capital-expenditure allocation decisions in logistical systems at large-scale digital-retailers (Richey et al., 2023). The dominant orthodoxy of the industry favours marginal optimization of fleet fuel consumption, labour chronometrics and rigid physical asset utilisation, systematically ignoring the considerable latent commercial equity in algorithmically driven psychological modulation. Enterprise management needs to urgently shift to applying high-fidelity predictive neural networks that can proactively reveal their internal calculation transparency directly at the digital interface for end-users. Rather than hiding the deep complexity and inherent disorder of urban freight routing, some studies have empirically demonstrated that companies can actively use dynamic logistics data to turn idle waiting time into an interactive digital experience and thus generate a higher degree of emotional satisfaction through mathematics. Prioritizing algorithmic agility over static routing predictability enables organizations to meet the demands for continuous repurchase and remain competitive in a high-speed digital economy. These empirical findings are also consistent with recent evidence reported in the *Journal of Management, Computing and Digital Economy (JMCDE)*, which argues that AI-driven decision intelligence creates sustainable competitive advantages primarily through customer experience enhancement rather than cost reduction alone. Consequently, logistics enterprises should prioritize explainable AI, real-time information disclosure, and intelligent customer interaction to maximize long-term consumer loyalty (Wang et al., 2025).

6. Conclusion.

The comprehensive architectural mapping of the cognitive-behavioral nexus modulated by artificial intelligence in last-mile delivery is a new kind of work for contemporary operations management and consumer psychology. By means of mathematical proof, this paper demonstrates that algorithmic spatio-temporal optimization directly impacts the economic viability for end-users via complex psychological mediation, and thus offers an experimentally validated interdisciplinary reference point for later research in logistics. The structural parameterizations show how the reduction of anticipation friction and the simultaneous enhancement of systemic computational trust function to convert the mastery of backend routing into tangible front-line commercial loyalty. Epistemologically speaking, the new theoretical model will need to give algorithmic execution speed and data transparency top priority in determining relational equity, and these will replace traditional interpersonal service indices that have long been the main subject of study in customer retention research.

Given the fixed boundaries of this empirical structure, it should be noted in academic research that the route of cross-sectional data collection inevitably represents a static moment in time for a very unstable and rapidly changing technological environment. With the continuous development of generative routing models, reinforcement learning heuristics and quantum logistics computation, it can be concluded that the consumer psychological threshold empirically determined here is highly likely to

decline rapidly. As algorithmic logistical perfection inevitably moves from being an outstanding competitive advantage to a widespread, commoditized basic requirement, the additional behavior-utility gained by predicting errors will theoretically diminish, leading to a general phenomenon of technological habituation. Given that only certain areas in the city have been set up for data collection, the corresponding structure coefficients cannot be applied to other areas lacking such facilities.

Given the changing conditions of machine learning in recent years, more longitudinal panel data and controlled experimental experiments are needed to study how these psychological path coefficients vary over time. In the future, scholars can explore the combination of heterogeneous cultural variables, different levels of regional artificial intelligence application, and localized infrastructure density in a structural equation model to build an all-purpose epistemological system. Broadening the scope of analysis to include the psychological effects... will further enhance academic research on people exposed to autonomous delivery vehicles and unmanned aerial drone distribution, and thus enhance academic research into how computational supply chain logistics is applied to behavior economics.

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Appendix A. Questionnaire Items

All items were measured using a seven-point Likert scale (1 = Strongly disagree; 7 = Strongly agree).

A. Predictive Arrival Accuracy (PAA)

PAA1. The AI system accurately predicted my delivery arrival time.

PAA2. Delivery time updates were timely and reliable.

PAA3. The promised delivery window was consistently maintained.

PAA4. The AI system effectively anticipated delivery delays.

B. Dynamic Rerouting Agility (DRA)

DRA1. The delivery system quickly adapted to unexpected situations.

DRA2. Route adjustments were communicated clearly.

DRA3. AI promptly optimized delivery routes.

DRA4. The delivery process remained flexible under changing conditions.

C. Delivery-Induced Anxiety (DIA) (*Reverse-coded*)

DIA1. I felt anxious while waiting for my order.

DIA2. I worried that the delivery might be delayed.

DIA3. I was uncertain about the delivery process.

DIA4. Waiting for the package caused psychological stress.

D. Calculative Trust (CT)

CT1. I believe the AI delivery system is reliable.

CT2. The delivery platform operates consistently.

CT3. I trust the AI-generated delivery decisions.

CT4. AI-supported logistics increases my confidence in the retailer.

E. Affective Satisfaction (AS)

AS1. I was satisfied with the overall delivery experience.

AS2. The delivery service met my expectations.

AS3. AI-supported delivery created a positive experience.

AS4. I was pleased with the logistics service.

F. Repurchase Intention (RP)

RP1. I intend to purchase from this platform again.

RP2. I would recommend this platform to others.

RP3. I prefer retailers offering AI-supported delivery.

RP4. I will continue purchasing from this retailer.

Note. *The questionnaire items were adapted from established measurement scales in logistics service quality, consumer trust, satisfaction, and repurchase intention research and were revised to fit the context of AI-driven last-mile delivery.*