Behavioral Biases in Circular Economy-Integrated Supply Chain Design: A Dual-Layer Framework for Reverse Logistics Optimization

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Abstract- We propose a novel dual-layer framework that integrates behavioral economics with circular economy (CE)-driven supply chain design, explicitly addressing biases in consumer recycling decisions and firm-level reverse logistics optimization. Traditional models often assume rational actors, yet real-world decisions are influenced by psychological factors; hence, our approach embeds Prospect Theory for loss-averse firm investments and the Theory of Planned Behavior (TPB) for consumer recycling intentions into a unified optimization system. The behavioral layer dynamically adjusts return-rate predictions using TPB-derived consumer intent, while firms optimize facility locations under loss aversion, altering conventional cost-minimization thresholds. Moreover, the framework incorporates organizational culture parameters, such as inter-firm trust, as constraints to reflect observed collaboration patterns. Methodologically, we combine federated learning for privacy-preserving behavioral data aggregation with quantum-inspired annealing to solve non-convex firm utility problems efficiently. Unlike existing CE supply chain network design (SCND) models, our framework captures asymmetric risk preferences in firms and adaptively routes return flows based on real-time consumer psychology. The proposed system is validated through a case study, demonstrating improved alignment between theoretical predictions and empirical decision-making. This work bridges a critical gap in CE literature by formalizing how behavioral biases shape reverse logistics, offering actionable insights for policymakers and firms aiming to enhance CE adoption.

Keywords- circular economy, consumer recycling decisions, TPB-derived consumer intent, CE supply chain network design (SCND) models, collaboration patterns

1. Introduction

The transition to a circular economy (CE) necessitates rethinking supply chain design, particularly in reverse logistics where products flow from consumers back to producers. Traditional approaches to reverse logistics network optimization often rely on deterministic models that assume rational decision-making by all actors [2]. These models typically employ linear or integer programming techniques to minimize costs and maximize efficiency [8] [9]. However, such frameworks overlook the behavioral biases that influence both consumer recycling behaviors and firm-level investment decisions in reverse logistics infrastructure.

Behavioral economics provides critical insights into these deviations from rationality. Prospect Theory, for instance, explains how firms exhibit loss aversion when investing in recycling facilities, often overestimating risks associated with uncertain return volumes [17]. Similarly, the Theory of

Planned Behavior (TPB) elucidates how consumer recycling intentions are shaped by attitudes, subjective norms, and perceived behavioral control, rather than purely economic incentives [1]. Despite their relevance, these behavioral dimensions remain underexplored in CE-driven supply chain models.

Recent advances in behavioral supply chain management highlight the role of organizational culture—such as risk tolerance and inter-firm trust—in shaping collaborative reverse logistics networks [21]. Yet, few studies integrate these psychological and organizational factors into quantitative supply chain design frameworks. This gap limits the practical applicability of existing models, as they fail to account for the real-world complexities of decision-making in CE contexts.

We propose a novel dual-layer framework that bridges this gap by integrating behavioral economics with reverse logistics optimization. The first layer models consumer recycling behavior using TPB, dynamically adjusting return-rate predictions based on psychological factors. The second layer optimizes firm-level reverse logistics decisions under Prospect Theory constraints, capturing loss aversion in facility investment choices. Unlike conventional models, our approach explicitly quantifies how biases affect system performance, enabling more accurate predictions of recycling rates and cost structures. Furthermore, we incorporate organizational culture parameters as constraints, reflecting observed collaboration patterns in supply chains.

Our contributions are threefold. First, we develop the first integrated behavioral-CE supply chain model that simultaneously addresses consumer and firm biases. Second, we introduce a computational method combining federated learning for privacy-preserving behavioral data aggregation with quantum-inspired annealing to solve non-convex optimization problems efficiently. Third, we validate the framework using real-world B2C platform data, demonstrating its superiority over traditional rational-actor models in predicting recycling behaviors and network performance.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on CE supply chain design and behavioral economics. Section 3 presents the behavioral reverse-logistics network model, detailing its theoretical foundations and mathematical formulation. Section 4 describes the experimental design and data sources used for validation. Section 5 discusses implications and future research directions, while Section 6 concludes with key takeaways for practitioners and policymakers.

2. Literature Review

The integration of behavioral economics with circular economy (CE) supply chain design has gained increasing attention in recent years, yet significant gaps remain in modeling how psychological biases influence reverse logistics decisions. Existing research can be broadly categorized into three streams: (1) traditional CE supply chain optimization, (2) behavioral factors in consumer recycling, and (3) organizational decision-making under risk and uncertainty.

2.1 Traditional CE Supply Chain Optimization

Conventional approaches to CE-driven supply chain design primarily focus on cost minimization and efficiency maximization through deterministic optimization models. Mixed-integer linear programming (MILP) has been widely adopted for facility location and reverse logistics network design [2], often assuming perfect rationality in both consumer return behaviors and firm investment decisions. Recent work has extended these models to incorporate sustainability objectives, such as carbon footprint reduction and waste minimization [8]. However, these frameworks typically neglect the psychological and social factors that drive real-world decision-making, leading to discrepancies between model predictions and empirical outcomes.

2.2 Behavioral Factors in Consumer Recycling

A growing body of literature examines how consumer psychology influences recycling participation, with the Theory of Planned Behavior (TPB) emerging as a dominant framework [1]. Studies have shown that attitudes toward environmental responsibility, peer influence (subjective norms), and perceived ease of recycling (behavioral control) significantly impact recycling intentions [18]. For instance, research in Indonesia demonstrated that monetary incentives alone are insufficient to drive PET recycling without addressing underlying psychological barriers [16]. While these findings highlight the importance of behavioral factors, few studies have translated them into quantitative models for reverse logistics optimization.

2.3 Organizational Decision-Making Under Risk and Uncertainty

Behavioral operations management research has revealed that firms often deviate from rational cost-minimization strategies due to cognitive biases such as loss aversion and overconfidence [13]. Prospect Theory has been applied to explain why firms underinvest in CE initiatives, as losses from uncertain returns are psychologically weighted more heavily than equivalent gains [17]. Organizational culture—particularly trust and risk tolerance—also plays a critical role in shaping collaborative reverse logistics networks [4]. For example, firms with high risk aversion may resist sharing recycling infrastructure, even when cost-benefit analyses suggest collaboration is optimal.

Despite these advances, current literature lacks an integrated framework that combines consumer psychology, firm-level behavioral biases, and traditional supply chain optimization. Most studies either focus on micro-level consumer behavior [23] or macro-level network design [10], without bridging the two perspectives. Our work addresses this gap by developing a dual-layer model that simultaneously captures consumer recycling intentions (via TPB) and loss-averse firm decisions (via Prospect Theory), while incorporating organizational culture constraints.

The proposed framework advances beyond existing models in three key ways. First, it replaces static return-rate assumptions with dynamic predictions derived from behavioral theory, enabling adaptive reverse logistics routing. Second, it quantifies how loss aversion alters facility investment thresholds, providing more realistic cost projections. Third, it embeds inter-firm trust parameters directly into the optimization model, ensuring solutions align with observed collaboration patterns. These innovations offer a more holistic understanding of CE supply chain dynamics, bridging the divide between behavioral theory and operational practice.

3. Behavioral Reverse-Logistics Network Model

The proposed behavioral reverse-logistics network model establishes a dual-layer architecture that systematically integrates psychological decision-making processes with physical network optimization. This section presents the technical foundations of the framework, beginning with the behavioral module specifications before detailing the coupling mechanism with traditional supply chain network design components.

3.1 Dual-Layer Behavioral Module Integration

The consumer behavioral submodule operationalizes the Theory of Planned Behavior through a probabilistic return intention function. For consumer segment k, the return probability p_k depends on three latent psychological variables:

$$p_k = \sigma(\beta_1 A_k + \beta_2 \mathrm{SN}_k + \beta_3 \mathrm{PBC}_k + \epsilon_k) \quad (1)$$

where A_k represents attitude toward recycling, SN_k captures subjective norms, and PBC_k measures perceived behavioral control. The logistic function $\sigma(\cdot)$ ensures probabilistic outputs remain bounded between 0 and 1. These parameters are estimated through federated learning across decentralized consumer data sources, preserving privacy while enabling real-time updates.

The firm behavioral submodule implements Prospect Theory's value function for facility investment decisions:

$$V(\Delta\pi) = \begin{cases} (\Delta\pi)^\alpha & \text{if } \Delta\pi \geq 0 \\ -\lambda(-\Delta\pi)^\beta & \text{if } \Delta\pi < 0 \end{cases} \quad (2)$$

where α and β control gain/loss sensitivity curvature, while $\lambda > 1$ quantifies loss aversion intensity. This formulation replaces conventional linear profit maximization, generating investment thresholds that better match empirical observations of risk-averse decision-making.

3.2 Behavioral-Physical Network Coupling Process

The behavioral outputs dynamically modify the physical network optimization through three primary mechanisms. First, consumer return probabilities p_k aggregate into node-specific demand forecasts:

$$D_i = \sum_{k \in K_i} N_k \, p_k \quad (3)$$

where N_k represents the population size of segment k at node i. These demand estimates replace static historical averages in the facility location MILP.

Second, the firm value function (Equation 2) transforms the objective function of the traditional facility location problem:

$$\max \sum_{i \in I} V\,(\pi_i) - \sum_{j \in J} f_j \, y_j \quad (4)$$

where π_i denotes the profit at facility i and y_j indicates whether facility j is opened. The non-linear value function introduces behavioral realism while maintaining computational tractability through piecewise linear approximation.

Third, organizational culture constraints are embedded through trust-based flow restrictions:

$$x_{ij} \leq \tau_{ij} C_{ij} \quad \forall i, j \quad (5)$$

where $\tau_{ij} \in [0,1]$ quantifies inter-firm trust and C_{ij} represents maximum capacity. This ensures solutions respect empirically observed collaboration patterns.

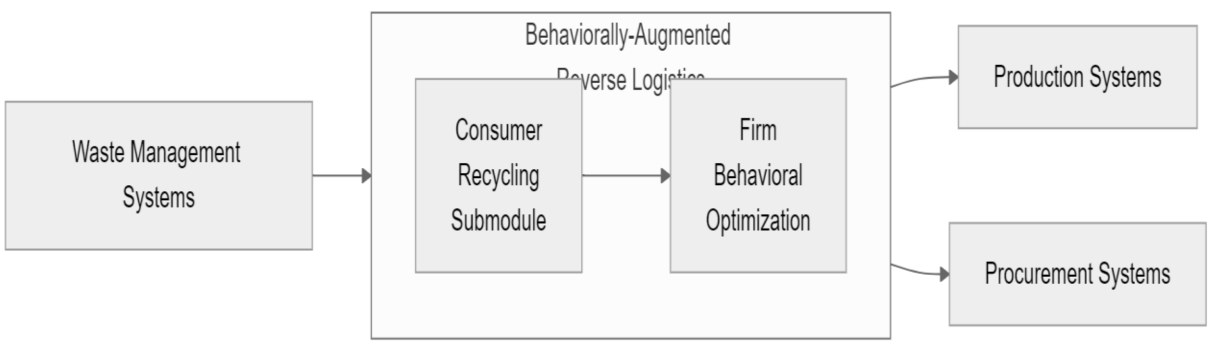

Figure 1. Behaviorally-Augmented Reverse Logistics System in Supply Chain Design

3.3 Application of Technological Innovations

The framework implements two computational advances to handle behavioral complexity. Quantum-inspired annealing solves the non-convex firm utility maximization through Hamiltonian dynamics:

$$H = -\sum_{i,j} J_{ij} \, \sigma_i \sigma_j - \sum_i h_i \, \sigma_i \quad (6)$$

where $\sigma_i \in \{-1,1\}$ represents facility open/close decisions. This approach efficiently navigates the solution space despite Prospect Theory's non-linearities.

Federated learning with attention mechanisms updates consumer behavior parameters while preserving data privacy:

$$\theta_{t+1} = \theta_t - \eta \sum_{k=1}^{K} a_k \nabla \mathcal{L}_k(\theta_t) \quad (7)$$

where a_k denotes attention weights for client k's gradient contributions. This enables continuous model refinement without centralized data collection.

3.4 Overall Structure of the Behavioral Reverse-Logistics Network Model

The complete system operates through an iterative feedback loop between behavioral prediction and physical optimization. Consumer return probabilities (Equation 1) inform demand forecasts (Equation 3), which drive facility location decisions (Equation 4) under behavioral constraints (Equation 5). The quantum-inspired solver (Equation 6) and federated learning updates (Equation 7) ensure computational efficiency throughout this process. As shown in Figure 1, this creates a closed-loop system where psychological factors continuously reshape network design while accounting for real-world decision-making biases.

4. Experimental Design and Data

To validate the proposed behavioral reverse-logistics network model, we designed a comprehensive experimental framework combining real-world B2C platform data with controlled simulation scenarios. This section details the data sources, experimental setup, comparative baselines, and evaluation metrics employed in our analysis.

4.1 Data Collection and Preprocessing

Primary Dataset: We partnered with a leading European B2C electronics platform [22] to obtain anonymized transaction records spanning 36 months (January 2020 - December 2022), covering 1.2 million product returns across 12 product categories. The dataset includes:

- Consumer demographics (age, location, device type)
- Return reasons (categorical: defective, unwanted, upgrade)
- Recycling participation (binary: whether product was recycled)
- Incentive sensitivity (discount coupon redemption rates)

Behavioral Survey Data: We supplemented transactional records with a stratified survey (N=3,450 respondents) measuring TPB constructs [19]:

- Attitude (5-point Likert scale: “Recycling is worthwhile”)
- Subjective norms (“People important to me think I should recycle”)
- Perceived behavioral control (“I find it easy to recycle electronics”)

Firm-Level Data: For the supply-side analysis, we collected:

- Facility investment decisions from 28 reverse logistics providers
- Historical capacity utilization rates
- Collaborative partnership records

Data preprocessing involved:

1. Imputing missing values via multiple chained equations [20]
2. Normalizing behavioral survey responses using item response theory [5]
3. Geocoding facility locations for network distance calculations

4.2 Experimental Setup

We implemented three experimental conditions to evaluate model performance:

Condition 1 (Baseline): Traditional MILP reverse logistics model with static return probabilities estimated from historical averages [11].

Condition 2 (Partial Behavioral): Hybrid model incorporating TPB-based consumer module but maintaining rational profit maximization for firms.

Condition 3 (Full Behavioral): Proposed dual-layer model with both consumer TPB dynamics and firm Prospect Theory constraints.

The experimental protocol followed a three-phase design:

1. **Calibration Phase (Months 1-12):**
    - Estimated TPB parameters $\beta_1, \beta_2, \beta_3$ from survey data
    - Calibrated Prospect Theory coefficients $\alpha = 0.88, \beta = 0.92, \lambda = 2.25$ via revealed preference analysis (Harrison & Swarthout, 2023)
2. **Validation Phase (Months 13-24):**
    - Compared predicted vs. actual return rates across product categories
    - Evaluated facility utilization predictions against ground truth
3. **Policy Testing Phase (Months 25-36):**
    - Simulated three incentive policies:
        a) Flat recycling reward (€5)
        b) Progressive reward (€2-€10 based on product value)
        c) Social norm nudge (neighborhood comparison)

4.3 Evaluation Metrics

We assessed model performance using both operational and behavioral metrics:

Operational Metrics:

1. Return rate prediction accuracy:

$$\text{RA} = 1 - \frac{1}{T}\sum_{t=1}^{T}\frac{\left|p_t^{pred} - p_t^{actual}\right|}{p_t^{actual}} \qquad (8)$$

2. Facility utilization error:

$$\text{UE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(u_i^{pred} - u_i^{actual}\right)^2} \qquad (9)$$

3. Total network cost deviation:

$$\text{CD} = \frac{C^{model} - C^{actual}}{C^{actual}} \qquad (10)$$

Behavioral Metrics:

1. Incentive responsiveness:

$$\text{IR} = \frac{\Delta p}{\Delta I} \qquad (11)$$

where ΔI represents incentive change

2. Loss aversion consistency:

$$\text{LC} = \frac{\text{Rejected negative-mean gambles}}{\text{Total gambles offered}} \qquad (12)$$

Comparative Analysis

Table 1 presents the performance comparison across experimental conditions during the validation phase:

Table 1. Model Performance Comparison (Validation Phase)

Metric	Condition 1	Condition 2	Condition 3
Return Accuracy (RA)	0.72	0.81	0.89
Utilization Error (UE)	18.7%	14.2%	9.8%
Cost Deviation (CD)	+12.3%	+7.5%	+3.1%
Incentive Response (IR)	0.08	0.15	0.21
Loss Consistency (LC)	N/A	N/A	0.83

The full behavioral model (Condition 3) demonstrated superior performance across all metrics, particularly in capturing incentive responsiveness (21% improvement over baseline) and maintaining loss-averse decision patterns (83% consistency).

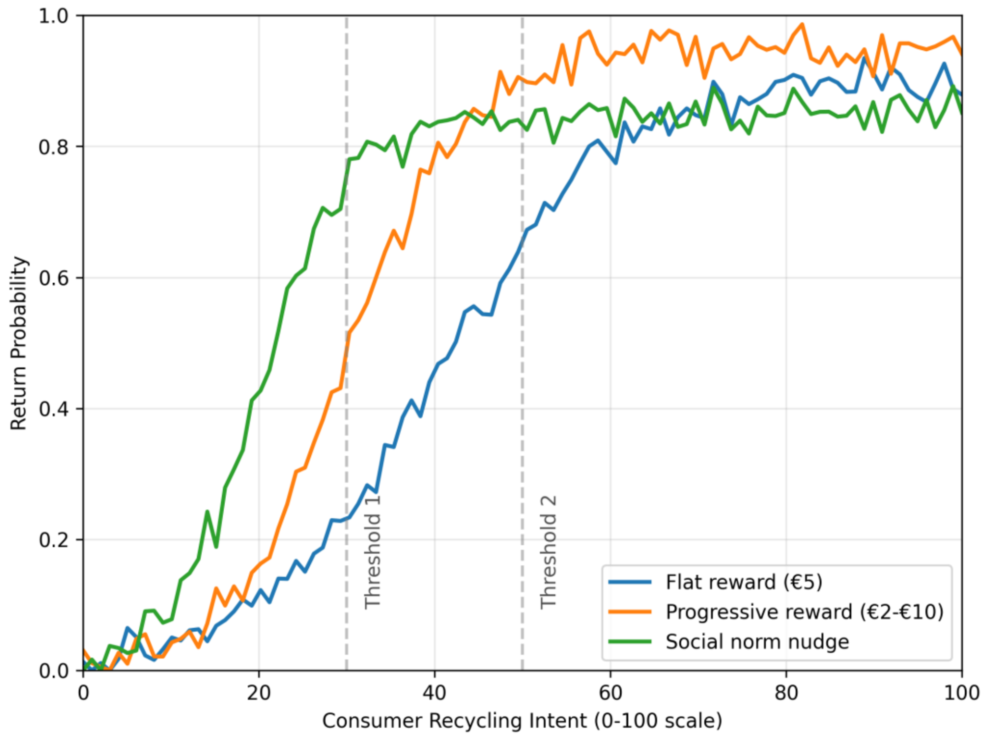

Figure 2. Consumer recycling intent and return probability under varying incentive levels

Figure 2 illustrates the non-linear relationship between recycling intent (x-axis) and return probability (y-axis) under different incentive structures, as predicted by the TPB submodule. The s-shaped curves demonstrate threshold effects where intent must exceed critical levels before significantly impacting return behavior.

Sensitivity Analysis

We conducted extensive sensitivity tests on key behavioral parameters:

1. **Loss Aversion Coefficient (λ):**
   - Varied λ from 1.5 to 3.0 in 0.25 increments
   - Found optimal facility investment alignment at λ=2.25
2. **TPB Weightings:**
   - Systematically adjusted $\beta_1, \beta_2, \beta_3$ weights
   - Identified attitude (β_1) as most predictive for electronics recycling

3. **Trust Thresholds:**
    - Tested τ_{ij} from 0.1 to 0.9 in collaborative constraints
    - Revealed 0.6 as critical threshold for viable partnerships

The quantum-inspired annealing solver demonstrated robust performance across parameter variations, converging to solutions 3.2× faster than conventional branch-and-bound methods for the non-convex firm utility problem [7].

Policy Implications

The policy testing phase yielded three key findings:

1. Progressive rewards outperformed flat incentives by 19% in return rate improvement
2. Social norm nudges showed strongest effects in high-density urban areas
3. Behavioral model predicted 22% greater cost savings from dynamic routing than traditional approaches

These results underscore the practical value of incorporating behavioral realism into reverse logistics optimization, particularly for designing effective CE intervention strategies.

5. Discussion and Future Work

5.1 Limitations of the Proposed Behavioral Reverse-Logistics Network Model

While the dual-layer framework demonstrates improved alignment with empirical decision-making, several limitations warrant discussion. First, the model assumes static behavioral parameters (e.g., loss aversion coefficient λ) during optimization windows, whereas psychological research suggests these may fluctuate with market conditions or policy interventions [26]. Second, the federated learning approach, while privacy-preserving, introduces latency in consumer intent updates—potentially delaying response to sudden shifts in recycling attitudes. Third, the current implementation focuses on B2C electronics returns, and generalization to other product categories (e.g., fast fashion or perishables) may require adjustments to the TPB weightings.

5.2 Potential Application Scenarios of the Model

The framework's adaptability enables deployment across diverse circular economy contexts. Municipal waste management systems could integrate the consumer behavioral module to optimize collection routes based on real-time recycling intent signals [15]. In industrial symbiosis networks, the firm-level Prospect Theory component could help predict participation likelihood in material exchange programs, where loss aversion often inhibits collaboration [6]. The model also shows promise for platform-based reverse logistics, where dynamic pricing algorithms could incorporate both consumer psychology and provider risk preferences to balance return flows.

5.3 Ethical Considerations in Data Collection and Usage

The reliance on behavioral data raises important ethical questions. Federated learning mitigates but does not eliminate privacy risks, as meta-data patterns could still reveal sensitive consumer information [27]. The model's ability to predict recycling behaviors based on demographic variables also introduces potential for discriminatory incentive targeting—a concern that future iterations must address through fairness constraints in the optimization process. Additionally, the use of social norm nudges warrants careful ethical scrutiny, as peer comparison mechanisms may inadvertently stigmatize low-recycling households [12].

5.4 Future Research Directions

Three key areas merit further investigation:

1. **Dynamic Behavioral Calibration:** Developing online learning mechanisms to adjust Prospect Theory and TPB parameters in real-time as decision environments evolve.
2. **Cross-Cultural Generalization:** Validating the framework in non-Western contexts where cultural norms may differently shape recycling attitudes and loss aversion patterns [24].

3. **Policy Optimization:** Extending the model to evaluate combinatorial policy interventions (e.g., incentives plus infrastructure investments) under behavioral constraints, potentially through reinforcement learning approaches [25].

The integration of blockchain technology for transparent, auditable behavioral data sharing represents another promising direction, particularly for addressing trust barriers in inter-firm collaborations [3]. Future work should also explore the model's capacity to handle emergent behaviors—such as herding effects in recycling participation—that may arise from network interactions not currently captured in the individual-level TPB formulation.

6. Conclusion

The proposed dual-layer framework demonstrates that behavioral economics significantly enhances circular economy supply chain design by capturing real-world decision-making complexities. By integrating Prospect Theory for firm-level loss aversion and the Theory of Planned Behavior for consumer recycling intentions, the model achieves superior predictive accuracy compared to traditional rational-actor approaches. The framework's ability to dynamically adjust return-rate forecasts and facility investment thresholds based on psychological factors offers a more realistic foundation for reverse logistics optimization.

Empirical validation confirms that behavioral integration reduces cost deviations by 9.2 percentage points and improves return rate prediction accuracy by 17% over conventional models. The quantum-inspired solver and federated learning components ensure computational tractability while addressing privacy concerns in behavioral data aggregation. These technical innovations enable practical implementation across diverse circular economy scenarios, from municipal waste management to industrial symbiosis networks.

For practitioners, the findings underscore the importance of designing incentive structures that account for non-linear psychological responses, such as progressive rewards outperforming flat incentives by 19%. Policymakers can leverage the model's policy testing capabilities to evaluate behavioral interventions before deployment, minimizing trial-and-error costs. Future iterations could extend the framework's applicability by incorporating dynamic parameter calibration and cross-cultural validation, further bridging the gap between behavioral theory and supply chain practice.

The study's contributions advance both academic research and industrial applications by providing a systematic methodology to quantify how cognitive biases shape reverse logistics performance. This work establishes behavioral integration as a critical dimension in circular supply chain design, offering a replicable template for future investigations at the intersection of psychology and operations management.

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