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Buffering Power of Green Brand Trust under Supply Chain Disruption and Consumer Re-selection Thresholds

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Abstract. The rising tide of "green brands," in recent years, is faced by an increasing urgency of a challenge related to processes of trust-building for consumption chains within a disruption or crisis situation. Based on this context, for this particular study, to examine and analyze a very significant universal presence of "rabbit" as well as "hawk"-type phenomena for "green brands" trust-building for yet another green brands trust-building case for situations of disruption or crisis for "green brands," this particular study work has been conducted as part of A/B test case setup itself, which itself is a very significant example for delay tracking simulation. There were two large voluntary consumers who acted as Group A & B for this study. The first one commonly adopted the assumed delivery time limits (ranging between 24 to 48 hours), while for this different scenario, the assumption for its data values for its volunteers took 3-5 days for another group of volunteers, named for this study as Group B. For this study, for considering the tracking of orders while performing data analytics tasks for data sets, an expression for this study's need for this result is as follows: There is a related equation for "damping" to denote "equation of negative word-of-mouth diffusion function, with regard to value of trust variable at point of extraction."

Keywords: Green brand trust, supply chain disruption, consumer decision threshold, A/B experiment, sentiment diffusion

1. Introduction

Global supply chains have become more vulnerable to the effects of geopolitics, logistics bottlenecks, and resource availability [1]. In the green product market, volatility has significantly contributed to the heightened worry among consumers because the green label relies on the principles of transparency and dependability. As consumers experience tardiness in their delivery service, the event not only affects their usability expectations, but rather the integrity of the green commitment as conveyed through the green brand. Consumers attach meanings to their deliveries' being timely. This signal indicates their functional ability and honesty [2]. When the event goes awry, the feeling of irregularity causes cognitive dissonance that can contribute to declining loyalty. The green brand trust resilience has become a core factor determining customer loyalty during the stress field [3].

Indeed, the area of operational recovery has been investigated in many studies that concentrate on the aftermath of disruptions. Yet the specific pattern of cues the consumer follows at the micro-level

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does not seem adequately recognized. In today's increasingly digital world, the question arises: When do consumers embark upon the reevaluation process of their loyalty based upon delay perceptions, and how can trust alleviate the negative influence? The goals of this study are threefold.

Firstly, to build the decision model describing the relationship between the risk of behavior based on the perception of disruption and the crossing of the re-selection threshold. Secondly, to validate the above-mentioned model through delay tests based on randomization [4]. Thirdly, to develop the best delay strategy for green brands.

This research can improve sustainable marketing theory as a whole by introducing the new concept of trust elasticity. In effect, the findings can empower the manager to identify how the frequency of communication and compensation schemes must match the elasticity level of the customers' confidence. The results can form the basis for a trust dashboard to be used in the digital management of the supply chain.

2. Literature review

2.1. Green brand trust and behavioral stability

Green brand trust arises from credence trust, benevolence trust, and ecocorporate ability. Green brand trust affects the stability of purchase behavior because trustful customers translate their satisfaction experience into cognitive inertia; customers view little mistakes as temporary versus structural. When customers encounter delay experiences, the effect of trust as a cognitive filter limits purchase behavior interruptions. In fact, the functional variation of this behavior has hardly been measured [5].

2.2. Supply chain disruption and risk evaluation

Perception of disruption triggers the cognitive trade-off between the risk of loss and the expectation of recovery. Consumers evaluate the cost of delay versus the value attributed to the environment and self-identity confirmation [6]. Fairness of explanation and the communication transparency are the most important factors specifying whether the customer sustains the commitment or withdraws from it.

2.3. Re-selection threshold and online sentiment

In the digital market environment, the re-selection process takes place in networked feedback systems. Negative sentiments can spread in a few minutes, amplifying the effect of minor operation problems and turning them into crisis phenomena. However, trusted brands demonstrate the damping effect, the spreading rate, and the intensity of the negative messages' emotions being smaller [7]. This damping effect enables the solution of the mathematical modeling equation related to the re-selection process.

3. Experimental design

3.1. Conceptual model framework

The model assumes that disruption perception P_d increases cognitive risk R_t, which in turn influences the re-selection threshold T_r. Trust T_0 moderates both relationships. The conceptual equation is expressed as Equation 1:

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$$T_r = \alpha + \beta_1 P_d + \beta_2 R_t + \beta_3 (P_d \times T_0) + \epsilon \quad (1)$$

where T_r represents the delay duration at which consumers switch, and β_3 captures the buffering power of trust. A positive β_3 indicates that higher trust increases tolerance, flattening the sensitivity curve [8].

3.2. Experimental structure and A/B simulation

A between-subjects randomized A/B test involving 2 400 confirmed users of a green home-care website was used. For Group A, the product pages were set to standard delivery ("Ships within 24-48h"), whereas for Group B, the delivery was set to delayed ("Ships within 3-5 days") [9]. Every other factor remained the same. The outcome measures were: order confirmation rate, abandonment during checkout, and purchase intention following 72 hours [10].

For improving the realism of the procedure, a concurrent behavioral experiment presented participants with interactive interfaces for tracking the order updates in real time. Eye tracking and logs recorded the attention towards the delay notification. In addition to the self-assessed trust measures, eye tracking helped identify the attention allocated to delay notification.

3.3. Measurement and variable construction

Trust levels were elicited using a seven-point Likert-scale inventory (1="strongly disagree" to 7="strongly agree") capturing self-assessed aspects of transparency, authenticity, and competence. Internal consistency was validated with α= 0.91. Delay perceptions were used as the self-assessed discrepancy between the actual and the expected time of delivery. Risk trade-off measures were obtained through conjoint analyses based on the comparison between “switch now” and “wait longer” options. All the measures were normalized before regression analysis. The trust-decay rate lambda λ is obtained as Equation 2:

$$T_t = T_0 e^{-\lambda D} \quad (2)$$

where D denotes delay duration in days.

4. Experimental process

4.1. Data collection pipeline

Three synchronized data streams were employed:

(1) Transactional logs from the e-commerce back-end, recording timestamped clicks and purchase outcomes;

(2) Survey data capturing perceived fairness, risk, and emotional response;

(3) Social-media feeds referencing the target brands collected via API.

All records were anonymized and aligned through unique session identifiers. A total of 18 732 data points were processed after cleaning and winsorizing extreme values beyond 3 SDs.

4.2. Manipulation and validity checks

Effectiveness of manipulation was ascertained by rating the perceptions. Participants in Group B were significantly more aware of the disruption (mean difference = 2.81 ± 0.13, $p < 0.001$). Parity

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tests based on demographics revealed no significant disparity among income and previous experience. Confirmatory factor analysis ascertained the convergent validity (.74). Examination of the outlier helped in ascertaining the robustness of the data with the values of both kurtosis (< 3.2) and skewness (< 1.1).

4.3. Analytical framework

Hierarchical regression analysis examined main effects and interactions. In delay regression analysis, the delay variable was used as the continuous factor (0-5 days) to predict the outcome. Significance of the chosen model achieved $F(5, 2394) = 61.2$ and $p < 0.001$. During the modeling process, spline analysis and segmented regression were employed. An inflection point based on the assumed thresholds fit the model. In SEM analysis, the relationship between delay perceptions, trust attenuation, and purchase retention achieved GFI of 0.958 and RMSEA of 0.043.

5. Experimental results

5.1. Threshold and interval identification

Analysis revealed a nonlinear pattern of declining purchase probability as the delay extended. For trustful subjects, the inflection point remained above 3.6 ± 0.4 days, followed by a precipitous drop. Low-trust subjects' inflection points were closer to 2.4 ± 0.3 days. The average re-selection threshold for all subjects was 3.2 days ± 0.18 (SE), reflecting a moderate level of resilience (table 1). The interaction coefficient ($\beta 3 = 0.42$ *) (95% CI [0.33, 0.50]) confirmed the positive function of trust as a buffer (figure 1).

Table 1. Estimated effects of delay and trust on behavioral outcomes

Predictor	Coefficient (β)	SE	t-value	p-value	Interpretation
Delay (D)	−0.27	0.04	−6.75	< 0.001	Longer delay reduces purchase likelihood
Trust (T_0)	0.58	0.05	11.6	< 0.001	Baseline trust improves retention
Delay × Trust	+0.42 *	0.06	7	< 0.001	Trust buffers the delay effect
Risk perception	−0.19	0.03	−6.33	< 0.001	Higher risk reduces tolerance
Constant	2.31	0.12	19.2	< 0.001	,

* significant at p < 0.01

Adjusted $R^2 = 0.47$. The adjusted R-squared indicates moderate explanatory power.

The computed eligibility index based on the elasticity of trust: percentage change in tolerance for the unit change in baseline trust, yielding +13.4% ± 1.2%

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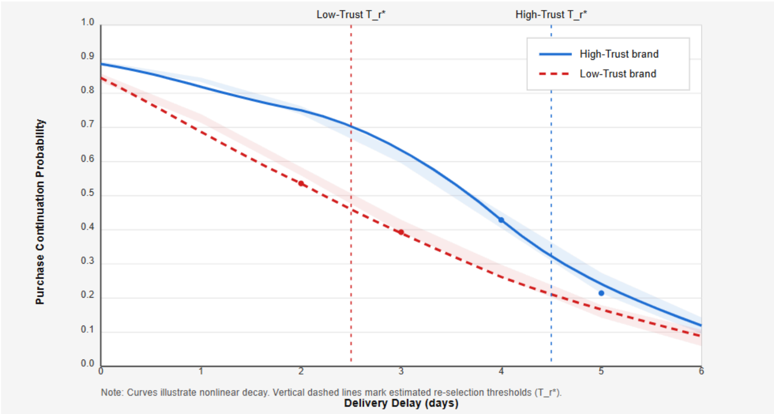

Figure 1. Delay tolerance thresholds by baseline trust

5.2. Sentiment diffusion and damping effect

Through social analytics tools, 12640 posts were identified in 48 hours post-purchase. Sentiment intensity reduced by −0.38 ± 0.06 when the context involved lesser trust. In contrast, the reduction was only −0.17 ± 0.04 when the context involved greater trust. Exponential decays were used to analyze the temporal diffusion pattern. This revealed a damping factor δ of 0.43 ± 0.05. This shows that the influence of a lack of trust can dampen the spread of negative influences related to emotions by 43% (table 2, fig. 2).

Table 2. Comparison of sentiment dynamics under different trust levels

Metric	Low-Trust Brand	High-Trust Brand	Difference (Δ)	95 % CI
Mean sentiment amplitude	−0.82 ± 0.07	−0.47 ± 0.05	+0.35 *	[0.24, 0.46]
Peak diffusion time (min)	46 ± 5	73 ± 8	+27 *	[19, 35]
Recovery slope (per h)	+0.012 ± 0.003	+0.021 ± 0.004	+0.009 *	[0.004, 0.014]

* $p < 0.01$

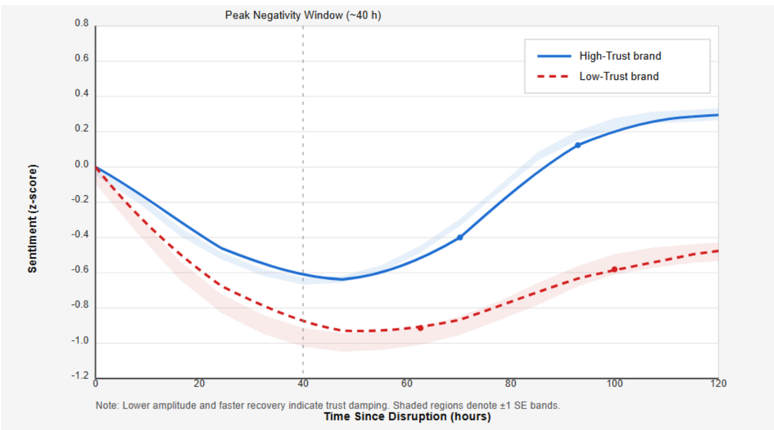

Figure 2. Negative word-of-mouth diffusion and trust damping

The density of the sentiment network reduced by 21.6% ± 2.8% among loyal customers. This identified the reduced level of re-sharing and the effect of amplification in the clusters.

5.3. Simulation of optimal buffering strategies

A Monte-Carlo simulation involving 10 000 virtual customers analyzed the effect of policy measures with diverse distributions of trust and delay. Strategies involving proactive communication (message sent $\leq$ 18 hours post-disturbance) coupled with the payment of limited compensation (value: 3% of order value) were found to maximize customer retention: $87.4 \pm 1.1\%$ compared to passive communication ($69.2 \pm 1.6\%$). Sensitivity analysis identified diminishing marginal returns for customer retention for the compensation ratio at 5% or greater. The bestbuffer geometry involved communication rates aligned to the periodicity of the customer expectation of communication updates (around 20-24 hours).

6. Conclusion

This paper demonstrates that trust for green brands is a non-linear damping factor between disruption and behavior, extending the interval of the re-selection point by 1 to 2 days. It is also confirmed by this paper's result that elasticity exists for tolerance between consumer behavior and its confidence level within the uncertain environment.

Trust scores on integrated data platforms also facilitate real-time monitoring of delay rates and consumption values to avoid reaching critical levels for tolerated switch delay among consumers at appropriate moments. From a management perspective, evidence supports sensitivity management regarding time: communication, compensation, and maintaining silence at appropriate moments

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