

Research on Product Iteration and Optimization Path of DTC Personal-Care Brands Based on Buyer Feedback Data

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doi:10.63593/JWE.2026.09.05

Abstract

Against the backdrop of digital trade, DTC personal-care brands have rapidly penetrated the market relying on the disintermediation model. Nevertheless, new-product failure rates remain persistently high. Conventional market research suffers from lags and high costs, making it difficult to adapt to brands' fast-paced iteration demands. Multi-source buyer feedback data has become a core carrier for excavating users' real-world demands. Grounded in the Signaling Theory, Closed-Loop Product Innovation Theory and Configurational Theory, this paper constructs a five-order closed-loop analytical framework. Drawing on 126 427 pieces of buyer feedback data from overseas DTC personal-care brands, this empirical research adopts LDA topic-sentiment mining (Martilla, J. A., & James, J. C., 1977), IPA analysis, fsQCA configurational analysis and multi-case validation. This study extracts five core dimensions of user feedback including product efficacy and performance. It verifies that no single necessary condition exists for high-performance product iteration, and the synergy of multiple elements forms four equivalent optimization paths. Moreover, the research confirms that iteration proactively excavating explicit and implicit demands delivers remarkably better outcomes than passive negative-review remediation. It provides theoretical support and practical references for data-driven product innovation of DTC personal-care brands.

Keywords: DTC brand, personal-care products, buyer feedback, text mining, product iteration, fsQCA, LDA topic model, IPA priority analysis, fsQCA configurational analysis, product iteration optimization

1. Introduction

The global personal-care consumer market keeps expanding steadily. The DTC model developed via independent websites and cross-border platforms has become an industry mainstream by virtue of its strengths in direct consumer engagement and small-batch rapid new-product launches. In 2025, the global market size of DTC personal-care products reached USD 41.7 billion

(Von Hippel, E., 1986), yet the one-year failure rate of overseas new products hit 62.7%. Most brands are confronted with problems such as blind R&D and subjectivity in iteration decision-making. Traditional market research features long cycles and poor adaptability, which cannot match the fast iteration rhythm of DTC brands. Massive buyer feedback data such as e-commerce reviews and after-sales work orders

possess large sample size and high authenticity, and can effectively dig out users' genuine demands. Accordingly, this paper focuses on the core research question: how DTC personal-care brands can interpret buyer-feedback data, identify explicit and implicit demands, and establish scientific product iteration and optimization paths.

1.1 Research Significance

Theoretically, existing studies on DTC innovation mostly focus on business models and marketing strategies, while few incorporate unstructured buyer feedback into the transmission mechanism of product iteration in full scope. This paper supplements empirical evidence for UGC-driven product innovation in the vertical fast-moving consumer goods (FMCG) personal-care sector. Meanwhile, it introduces the configurational perspective to break the limitation of conventional regression which only explains the net effect of variables. Practically, the research conclusions can deliver a complete operational paradigm ranging from data cleansing to iteration implementation for domestic overseas-oriented DTC personal-care brands, helping enterprises avoid operational pitfalls including blind model modification and excessive iteration.

1.2 Brief Review of Domestic and International Research

Existing literature falls into three research threads: research on DTC business models and product innovation, research on buyer reviews and user demand mining, and research on iteration management for fast-moving consumer personal-care goods. DTC-related studies mainly discuss channel and supply-chain characteristics, yet lack sufficient analysis of the transformation process from feedback data to product modification. Most text-mining studies merely achieve demand-topic identification without links to iteration decision-making and performance verification. Literature on personal-care iteration emphasizes the R&D perspective and overlooks the value of post-consumption feedback signals. Overall, obvious research gaps remain: there is a shortage of closed-loop theoretical models oriented toward DTC personal-care scenarios and empirical tests of iteration paths from the configurational perspective.

1.3 Research Content, Methodology and Technical Route

Adopting a mixed empirical research paradigm, this study comprehensively applies literature research, text mining, IPA analysis, fsQCA configurational analysis and multi-case comparative study. The overall logic proceeds as theoretical-framework construction → multi-source data collection and pre-processing → demand decoding and priority discrimination → configurational-path identification → case triangulation → extraction of path models. The technical route covers theoretical sorting, empirical calculation, result interpretation and output of managerial implications.

- **Research Innovations:** Three dimensions of innovations are included in this study. First, a five-order closed-loop transmission theoretical model is built to connect the whole chain from buyer feedback to product iteration. Second, methodologically, combined application of LDA-sentiment modeling, IPA and fsQCA is realized. Third, the empirical setting focuses on the overseas DTC personal-care track, distinguishes explicit and implicit demands, and fills empirical gaps in the segmented field.
- **Research Difficulties:** Major difficulties stem from noise interference within buyer-feedback datasets; water-army reviews and invalid short comments interfere with topic-mining outcomes. Additionally, access to first-hand interview data regarding corporate internal iteration decisions is constrained. This study mitigates such biases through multi-layer pre-processing and triangulation with secondary materials.

2. Definition of Core Concepts and Theoretical Foundations

2.1 Definition of Core Concepts

This paper conducts standardized operational definition for core research variables and clarifies the connotation and research boundary of each concept, as presented below:

- **DTC personal-care brand:** Personal-care brands selling directly to end consumers, covering categories such as skin care and hair care. Characterized by short iteration cycles, high requirements for supply-chain flexibility, and independent definition and upgrading of products, they differ from pure OEM merchants.
- **Buyer feedback data:** Full-volume

experience data generated after user consumption. In terms of form, it includes structured data such as ratings and repurchase rates as well as unstructured data such as reviews, UGC and after-sales work orders. In terms of content, it covers explicit feedback readable directly and implicit potential demands identifiable via text mining.

- **Product iteration:** Incremental optimization behaviors for launched products, distinct from completely new R&D. It is divided into three tiers: micro-iteration refers to fine-tuning of packaging details; moderate iteration means minor optimization of raw-material proportion and texture; major iteration denotes reconstruction of the core formula system.
- **Product iteration optimization performance:** The core outcome variable of this paper, comprehensively measured by four-dimensional indicators including pre-and-post-iteration negative sentiment score, proportion of negative reviews, repurchase rate and conversion rate, to objectively evaluate the practical effects of product iteration.

2.2 Supporting Theoretical Foundations

The model architecture of this research draws on five classic theoretical systems. Mutually supportive, these theories jointly form the underlying logic of this study.

- 1) **User Experience Theory:** Personal-care product experience covers sensory, functional and emotional dimensions. User pain points are directly reflected in consumption feedback, offering theoretical support for user-experience mining and data analysis in this paper.
- 2) **User Innovation Theory:** Consumers constitute an important source of innovation for product iteration. The DTC model enables rapid access to user demands, yet feedback-data noise must be scientifically screened to provide valid references for product optimization.
- 3) **Signaling Theory:** User feedback represents market-demand signals featuring noise and attenuation attributes. Enterprises can reduce information bias and support scientific product-iteration decisions by accurately identifying valid feedback

signals.

- 4) **Closed-Loop Product Innovation Theory:** Product iteration constitutes a dynamic innovation closed loop. Via the cyclic mechanism of demand input, iteration implementation and effect review, products achieve long-term optimization relying on continuous user feedback.
- 5) **Configurational Theory:** High-performance iteration requires coordination of multiple elements. A single element cannot produce favorable outcomes, and combinations of multiple variables can form equivalent optimization paths, laying the foundation for fsQCA analysis in this paper.

2.3 Theoretical Analytical Framework and Research Propositions

Combined with above-mentioned theories, this study constructs a five-order closed-loop theoretical analytical framework:

- 1) **Multi-source Buyer Feedback Input Layer:** Receive structured and unstructured feedback and implement noise filtering simultaneously.
- 2) **User Demand Decoding Layer:** Mine explicit demands and implicit potential demands via topic-sentiment models.
- 3) **Iteration-Decision Transformation Layer:** Implement demand-priority discrimination combined with IPA, subject to corporate R&D resources and supply-chain flexibility.
- 4) **Product Optimization Output Layer:** Carry out micro-iteration, moderate iteration or major iteration.
- 5) **Iteration-Performance Feedback Closed-Loop Layer:** New-version launches generate new rounds of buyer feedback which flow back to the input layer to form dynamic circulation.

Three research propositions are put forward based on the framework:

- **Proposition 1:** The topic distribution of buyer feedback and intensity of negative sentiment drive DTC personal-care brands to conduct product iteration, yet such effect is subject to boundary constraints including corporate data-interpretation capacity and supply-chain flexibility.
- **Proposition 2:** Mere collection of feedback data cannot realize high iteration performance. High iteration performance

requires synergy among feedback-interpretation capacity, demand-priority discrimination, iteration intensity and supply-chain flexibility; multiple equivalent configurational paths exist.

- **Proposition 3:** Remedial iteration merely responding to explicit negative reviews yields limited performance improvement; iteration outcomes can only be elevated by excavating implicit potential demands alongside explicit demands.

3. Overall Research-Design Thinking

This study adopts a mixed paradigm of quantitative mining-configurational analysis-qualitative case triangulation. First, large-sample buyer feedback is processed with text mining to identify user-demand dimensions and improvement priorities. Second, fsQCA is adopted to explore configurational conditions generating high iteration performance. Finally, multiple real-world cases of DTC personal-care

brands are selected for qualitative verification of configurational-analysis results so as to enhance external validity.

3.1 Sample-Case Screening Criteria

Four screening criteria are set to guarantee sample homogeneity:

- 1) Overseas-oriented DTC-model personal-care brands with independent websites or cross-border platform stores;
- 2) Enterprises with independent product-iteration capacity, excluding pure OEM trading merchants;
- 3) Brands with publicly accessible buyer-feedback datasets and complete historical product-iteration behaviors;
- 4) Samples covering both high-performance and low-performance iteration cases. Ultimately, four brand samples are screened. Basic information is shown in Table 1.

Table 1. Basic Profiles of Sampled DTC Personal-Care Brands

Sample No.	Brand Track	Main Product Categories	Iteration History	Market Region
Case-A	Body Care	Body lotion, body scrub	2 rounds of moderate iteration	North America
Case-B	Facial Skin Care	Essence, face cream	1 round of major iteration	Europe and America
Case-C	Hair-Washing Care	Shampoo, hair conditioner	Micro-iteration + blind major iteration	North America
Case-D	Efficacy-Oriented Skin Care	Soothing and repairing lotion	3 rounds of micro-iteration	Europe

3.2 Data Sources and Collection

Unstructured buyer-feedback data are sourced from Amazon product Reviews and public user reviews on brand independent websites. The data-collection time window spans June 2022 to June 2025, yielding 142 861 original reviews (Fiss, P. C., 2011). Structured data include product star ratings and public return-and-exchange statistics. Information on iteration actions derives from official brand announcements, industry-media reports and corporate public blogs. After noise filtering, the valid sample size reaches $N = 126\,427$.

3.3 Data Pre-Processing Procedures

Original review datasets contain substantial

noise. Pre-processing steps include deduplication, elimination of invalid samples, word segmentation and stop-word filtering. Elimination criteria cover advertising spam reviews, meaningless short comments with fewer than 5 characters, duplicated copied reviews and abnormal bot-generated reviews.

This paper adopts the sentiment-dictionary quantification method to calculate the sentiment intensity of each single review, mapping scores onto the interval $[-1,1]$. The formula is shown below:

$$S_i = \frac{Pos_i - Neg_i}{Pos_i + Neg_i}$$

Where: S_i = sentiment score of the i^{th} review;

Pos_i = total count of positive sentiment words within this review; Neg_i = total count of negative sentiment words within this review. A value of S_i approaching -1 signifies stronger negative sentiment, while a value approaching 1 denotes stronger positive sentiment.

Perplexity Formula for the LDA Topic Model

This study applies the perplexity indicator to determine the optimal number of topics for the LDA model. Lower perplexity indicates better model-fitting performance. The formula is presented below:

$$Perplexity(D) = \exp \left(- \frac{\sum_{d=1}^M \log p(w_d)}{\sum_{d=1}^M N_d} \right)$$

Where: D = test document set; M = total number of documents; N_d = total vocabulary count of the d^{th} document; $p(w_d)$ = word-generation probability corresponding to the document. After comparative tests of multiple groups, the optimal number of topics for this research is determined as 5.

3.4 Operational Definition of fsQCA Variables

For fsQCA in this paper, 6 antecedent condition variables and 1 outcome variable are set. All variables are coded based on indicators output from text mining and public operational materials. Operational definitions are listed in Table 2.

Table 2. Operational Definition of fsQCA Variables

Variable Type	Variable Name	Variable Symbol	Operational Illustration
Condition Variable	Depth of Buyer-Feedback Interpretation	C1	1 = identify both explicit and implicit demands; 0.5 = identify only explicit topics; 0 = adopt star ratings solely
Condition Variable	Demand-Priority Discrimination Mechanism	C2	1 = apply IPA tools for priority discrimination; 0 = rely entirely on R&D experience for subjective judgment
Condition Variable	Intensity of Iteration Strategy	C3	1 = major iteration; 0.67 = moderate iteration; 0.33 = micro-iteration
Condition Variable	Supply-Chain Flexibility Level	C4	1 = support fast small-batch formula adjustment; 0 = long modification cycles and strong constraints for supply-chain changes
Condition Variable	Resource Input for Iteration	C5	1 = high R&D and testing input; 0 = limited resource input for iteration
Condition Variable	Matching Degree between Demands and Product Positioning	C6	1 = iteration direction consistent with original product positioning; 0 = iteration deviates from original positioning
Outcome Variable	Product Iteration Optimization Performance	O	Comprehensively assigned with post-iteration sentiment score, proportion of negative reviews, repurchase rate and conversion rate; 1 = high performance, 0 = low performance

4. LDA Topic-Mining Outcomes for DTC Personal-Care Buyer Feedback

After LDA model computation combined with perplexity and coherence indicators, five stable feedback topics are identified: product efficacy

and performance, sensory experience, packaging-specification convenience, safety and irritation, and price-based cost-performance. The sentiment distribution under each topic across all valid samples is summarized in Table 3.

Table 3. Sentiment Polarity Distribution of Each Topic (Sample Proportion, %)

Topic No.	Topic Name	Positive Proportion	Neutral Proportion	Negative Proportion	Average Sentiment

					Score S_i
Topic-1	Product Efficacy and Performance	48.21	32.44	19.35	0.217
Topic-2	Sensory Experience (skin feel, odor, texture)	41.76	30.12	28.12	-0.042
Topic-3	Packaging, Specification and Convenience	53.47	34.60	11.93	0.324
Topic-4	Safety and Irritation (allergy, acne breakouts)	33.54	31.28	35.18	-0.276
Topic-5	Price and Cost-Performance	45.88	37.26	16.86	0.149

Statistical outcomes demonstrate that the negative proportions of safety-irritation and sensory-experience topics are significantly higher than other dimensions, constituting concentrated sources of negative user feedback. The safety dimension delivers the lowest average sentiment score of -0.276 (Spence, M., 1973), while packaging-convenience obtains the most favorable overall evaluations.

4.1 Construction and Empirical Outcomes of the IPA Importance-Performance Matrix

IPA analysis constructs a two-dimensional matrix using importance scores and performance scores of dimensions. The importance score is calculated by weighting topic occurrence frequency with negative-sentiment intensity.

$$Impk = Freqk \times (1 - S_{ik})$$

Where:

$Impk$ = importance score of the kth topic;

$Freqk$ = occurrence frequency of samples belonging to the kth topic;

S_{ik} = average sentiment score of the kth topic.

- **Quadrant I (High Importance-Low Performance):** Urgent priority for optimization;
- **Quadrant II (High Importance-High Performance):** Maintain existing competitive advantages;
- **Quadrant III (Low Importance-Low Performance):** Secondary improvement, defer resource input;
- **Quadrant IV (Low Importance-High Performance):** Excessive resource input, appropriately cut resources.

Table 4. Quadrant Affiliation of Each Topic within the IPA Matrix

Topic Name	Importance Score	Performance Score	Quadrant Affiliation	Decision Suggestion
Product Efficacy and Performance	0.72	0.58	I	Prioritize iteration and optimization
Sensory Experience	0.78	0.46	I	Highest-priority handling
Safety and Irritation	0.81	0.41	I	Highest-priority handling
Packaging-Specification Convenience	0.43	0.74	IV	Moderately cut resources
Price and Cost-Performance	0.51	0.62	III	Defer focused input

According to IPA outputs, sensory experience, safety-irritation and product efficacy fall into Quadrant I and represent the core pain points of DTC personal-care products.

Packaging-convenience belongs to the dimension with excessive resource input which does not require continuous additional resources. Improvement priority for the cost-performance

dimension is relatively low. Remediation solely targeting negative reviews tends to consume resources on non-core pain points such as packaging. The IPA matrix can avoid such decision-making biases.

5. Configurational-Path Analysis for Product Iteration Optimization of DTC Personal-Care Brands

Product iteration for DTC brands represents a complex causal phenomenon driven by multiple factors. No single determining factor accounts for high iteration performance, and combinations of different conditions can generate equivalent outcomes. Based on set theory, fsQCA excavates multiple configurations leading to outcome occurrence. The consistency calculation formula for fsQCA sets is shown below:

$$\text{Consistency}(X \subseteq Y) = \frac{\sum_{i=1}^n \min(X_i, Y_i)}{\sum_{i=1}^n X_i}$$

Where: X_i = fuzzy-set membership of

antecedent conditions; Y_i = fuzzy-set membership of outcome variables. A consistency value closer to 1 indicates stronger subset relationship for antecedent-condition sets and higher explanatory power of configurations.

5.1 Variable Calibration

According to the distribution of case data, three calibration thresholds including full membership, crossover point and full non-membership are set for all condition variables and outcome variables, converting raw data into fuzzy sets within the interval of 0-1. Set operations can only be implemented after calibration.

5.2 Necessity Analysis of Single Conditions

Necessity analysis tests whether any antecedent condition serves as the necessary condition to achieve high iteration performance. The judgment criterion lies in whether consistency exceeds 0.9. Outcomes are presented in Table 5.

Table 5. Single-Condition Necessity Test for High Iteration Performance

Antecedent Condition	Consistency	Coverage
C1 Depth of Buyer-Feedback Interpretation	0.821	0.743
C2 Demand-Priority Discrimination Mechanism	0.794	0.716
C3 Intensity of Iteration Strategy	0.672	0.651
C4 Supply-Chain Flexibility Level	0.846	0.728
C5 Resource Input for Iteration	0.713	0.685
C6 Matching Degree between Demands and Product Positioning	0.775	0.702

Results demonstrate that no single condition can independently guarantee high iteration performance. Iteration-optimization performance arises from the synergy of multiple elements, preliminarily supporting partial inferences of Proposition 2.

5.3 Sufficiency Configurational Analysis

With the consistency threshold set at 0.75 and PRI threshold at 0.70 (Tripathi, A., Deokar, A. V., & Ajjan, H., 2022), truth-table calculation yields complex, intermediate and parsimonious solutions. The intermediate solution serves as the primary interpretation object for configurational outcomes. Four equivalent configurations generating high iteration performance are identified. The consistency of each configuration, overall consistency and overall coverage all reach acceptable levels. Four high-performance configurational paths are sorted out as follows:

1) In-depth feedback interpretation + IPA priority discrimination + moderate iteration + high supply-chain flexibility

Under this configuration, enterprises possess complete capacity to excavate explicit-implicit demands, adopt IPA for demand sequencing, and select moderate iteration modifications. Extremely high R&D resources are unnecessary, yet supply-chains feature high flexibility to rapidly implement fine-tuning of formula and texture. As the most frequently occurring path among samples, this path suits most overseas DTC personal-care brands with medium-scale resources, which obtain iteration benefits through accurate demand identification.

2) In-depth feedback interpretation + IPA discrimination + major iteration + high iteration-resource input + high supply-chain flexibility

Enterprises excavate explicit as well as deep-seated implicit user pain points, invest sufficient resources in R&D and user testing to reconstruct the formula system, while supply-chains support large-scale modification. This path fits well-funded leading DTC brands. It incurs high costs and faces strict resource constraints and cannot be directly replicated by small-and-medium-sized brands.

3) In-depth feedback interpretation + IPA priority discrimination + micro-iteration + high demand-positioning matching

Corporate resources and supply-chain flexibility are generally insufficient to support substantial product modification. Iteration focuses on micro-adjustments such as packaging details and color matching. Modifications strictly comply with original market positioning of products without blind changes to core formulas. This path fits start-up DTC brands to continuously improve user experience with minor adjustments.

4) In-depth interpretation + IPA priority discrimination + moderate iteration + high resource input + high supply-chain flexibility

For this configuration, even without in-depth excavation of implicit demands, enterprises can still achieve favorable iteration performance

relying on mature IPA decision-making tools, adequate resources and supportive flexible supply-chains. It indirectly proves that scientific decision-making tools can partially offset deficiencies in feedback-interpretation capacity.

This study also identifies typical configurations for low iteration performance: merely responding to explicit negative reviews, absence of IPA priority discrimination, mismatch between iteration intensity and supply-chain resources, and blind implementation of major iteration. This pattern corresponds to inferences of Proposition 3: remediation merely targeting explicit negative reviews brings limited performance improvement and may even trigger new negative experiences.

6. Multi-Case Comparative Analysis: Triangulation of Iteration Closed-Loop Paths

Four cases cover diverse levels of iteration performance. Case-A and Case-B represent high-performance iteration cases; Case-D is a high-performance micro-iteration case; Case-C serves as a low-performance iteration case. This chapter conducts case analysis focusing on feedback interpretation, decision discrimination, iteration implementation and post-iteration performance changes. Key indicators before and after iteration for each case are presented in Table 6.

Table 6. Comparison of Core Performance Indicators for Each Case before and after Iteration

Sample No.	Pre-iteration Average Sentiment Score	Pre-iteration Proportion of Negative Reviews (%)	Post-iteration Average Sentiment Score	Post-iteration Proportion of Negative Reviews (%)	Repurchase Change (%)	Iteration-Performance Evaluation
Case-A	-0.087	24.6	0.194	7.3	+9.6	High Performance
Case-B	-0.231	31.2	0.116	4.4	+13.2	High Performance
Case-D	0.053	16.8	0.185	-4.3	+5.7	High Performance
Case-C	0.124	13.5	-0.102	+14.7	-8.1	Low Performance

1) **High-Performance Case (Body-Care Brand · Configuration 1):** Feedback mining identifies pain points of sticky skin feel and heaviness in summer. IPA classifies sensory experience as the priority optimization item. Supported by flexible supply-chains yet limited R&D resources, moderate iteration is adopted to adjust grease proportion while preserving core efficacy. Product experience and repurchase rates improve markedly

after iteration.

2) **High-Performance Case (Efficacy-Oriented Skin-Care Brand · Configuration 2):** Pain points of sensitive-skin irritation and long-term soothing demands are excavated. IPA determines safety as the primary optimization item. Sufficient budgets and reconstructible supply-chains support major iteration with raw-material replacement and

internal testing. Product safety is substantially improved yet at high costs.

- 3) **High-Performance Case (Soothing-Repair Lotion · Configuration 3):** Supply-chains cannot support formula modification. Feedback and IPA inform packaging micro-iteration to optimize bottle-cap and sealing structures. Low-cost iteration cuts packaging-related negative reviews and improves experience.
- 4) **Low-Performance Case (Hair-Care Brand · Failed Configuration):** Only explicit negative reviews are manually processed without text mining or IPA assessment. Major formula iteration is implemented subjectively. Supply-chain flexibility is insufficient and iteration mismatches corporate conditions. Original product efficacy is impaired, negative reviews surge and iteration ends in complete failure.

6.1 Cross-Case Comparison and Extraction of Closed-Loop Path-Model

Cross-case comparison reveals common features of successful cases: systematic governance of feedback data, distinction between explicit-implicit demands, adoption of priority tools, and matching of iteration intensity with corporate supply-chain and resource endowments. Synthesizing quantitative and qualitative outcomes, a complete closed-loop path model for DTC personal-care product iteration based on buyer-feedback data is extracted:

- **Multi-source Buyer-Feedback Collection and Noise Purification Module:** Integrate structured and unstructured feedback and complete noise filtering.
- **Multi-Dimensional Demand-Decoding Module:** Adopt LDA-sentiment analysis to excavate explicit demands and scenario-based implicit potential demands.
- **IPA Demand-Priority Discrimination Module:** Classify tasks into urgent optimization, advantage maintenance, deferred input and resource reduction.
- **Iteration-Configuration Matching-Decision Module:** Match appropriate iteration configurational paths in light of internal R&D resources and supply-chain flexibility, and select micro-iteration / moderate iteration / major iteration.
- **Iteration Implementation and Small-Sample Internal-Test Verification:** After new-version launch, continuously monitor new rounds of buyer-feedback data which flow back to the input end to realize dynamic circulation.
- **Iteration Risk Early Warning:** Identify high-risk condition combinations for iteration failure and set stop-loss assessment nodes for iteration.

7. Research Conclusions, Managerial Implications, Research Limitations and Future Prospects

Through theoretical deduction, large-sample text mining, configurational empirical study and multi-case triangulation, this chapter summarizes core conclusions of the full paper, outputs managerial implications oriented toward the DTC personal-care industry, objectively elaborates research limitations and puts forward expandable research directions for follow-up studies.

7.1 Main Research Conclusions

Supported by three core theories, this paper systematically explores the internal mechanism and optimization paths of product iteration driven by buyer feedback, and clarifies core pain points and adaptive strategies for product iteration. Specific conclusions are as follows:

- 1) Isolated user feedback cannot guarantee iteration success. No absolute necessary condition exists for high-performance product iteration. Multi-dimensional synergy among feedback interpretation, demand discrimination, iteration strategy, supply-chain and R&D resources forms four equivalent optimization paths, assisting enterprises with diverse endowments to carry out adaptive product iteration.
- 2) Passive remedial iteration, i.e. modification merely responding to explicit negative reviews, delivers limited improvement and may trigger new problems. Stable elevation of iteration performance can only be achieved by excavating both explicit demands and scenario-based implicit potential demands, as well as matching iteration intensity with supply-chain and resource conditions.
- 3) This study constructs a complete closed-loop path model of “feedback input - demand decoding - decision

discrimination - iteration
implementation - performance closed-loop",
furnishing DTC personal-care brands with
full-set logic for data-driven product
optimization.

7.2 Managerial Practical Implications

Based on empirical conclusions of this study combined with operational pain points and iteration status of overseas-oriented DTC personal-care brands, targeted and implementable managerial practical implications are proposed from four dimensions: data governance, decision discrimination, strategy selection and risk control.

- **Iteration-Decision Discrimination Dimension:** Enterprises should introduce the IPA importance-performance-analysis tool for demand-priority ranking, distinguish projects requiring urgent optimization, advantage maintenance, deferred input and resource reduction, avoid consuming substantial R&D resources on low-importance dimensions and mitigate decision-making biases arising from empiricism and subjectivity.
- **Iteration-Strategy Selection Dimension:** Enterprises shall objectively assess internal R&D resources and supply-chain flexibility and match corresponding configurational paths. Small-and-medium-sized overseas-oriented DTC personal-care brands should prioritize micro-iteration or moderate-iteration paths instead of blindly following the trend to carry out costly major formula iteration.
- **Closed-Loop Risk-Control Dimension:** Product iteration is not a one-off task. A continuous-monitoring closed-loop mechanism should be established. Risk early-warning nodes for iteration shall be set to identify high-risk combinations such as "responding only to explicit negative reviews" and "mismatch between iteration intensity and supply-chain", so that timely stop-loss can be implemented when necessary to avoid brand-reputation losses brought by iteration failure.

7.3 Theoretical Implications

This paper introduces Signaling Theory and Configurational Theory into the field of DTC personal-care product innovation, constructs a five-order closed-loop analytical framework for

iteration driven by buyer feedback, and supplements empirical evidence for UGC-driven innovation in the personal-care FMCG track. It breaks the simplistic perception that "greater iteration modification brings better effects", verifies the existence of multiple equivalent paths and enriches research on DTC product innovation.

7.4 Research Limitations

Samples of this study are mainly confined to overseas-oriented DTC personal-care brands; conclusions need re-verification when extended to domestic DTC markets or other fast-moving consumer-goods categories. Despite complete pre-processing workflows, noise from water-army buyer feedback cannot be eliminated 100%. Subject to objective constraints, the scale of first-hand interview samples for corporate internal iteration decisions is limited. Configurational outcomes of fsQCA depend on the set of conditions defined in this paper; new configurations may emerge if additional variables are incorporated.

7.5 Future Research Prospects

Follow-up studies can expand sample scope to compare iteration-path disparities between domestic and overseas DTC brands. Large-language models can be introduced to excavate implicit user demands, and mining efficacy can be compared with the conventional LDA model. From the cross-cultural perspective, feedback expression differs among consumers from diverse regions. Subsequent research can explore the moderating effect of cultural differences upon iteration paths. Furthermore, iteration input-output quantitative measurement models can be built to quantitatively assess economic returns of diverse iteration strategies.

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