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A Study on the Impact of Cross-Departmental Data Collaboration on Marketing Campaign Efficiency in Fast-Moving Consumer Goods E-commerce: The Case of PepsiCo (China)'s 7UP and Mirinda Project

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Abstract

In the digital ecosystem where platform algorithms embed real-time inventory, pricing, and creative performance directly into traffic allocation formulas, systematic micro-level evidence remains scarce on how FMCG brands can break through marketing efficiency bottlenecks via internal cross-departmental data collaboration. This study employs an embedded single-case research design, analyzing PepsiCo (China)'s 2024 "Summer Spark" e-commerce project for 7UP and Mirinda. Through a mixed-methods approach integrating 1,536 hours of high-frequency panel data with 12 semi-structured interviews, we systematically examine the transmission mechanism of "data collaboration → decision efficiency → marketing performance." Findings reveal that each one-standard-deviation increase in cross-departmental data collaboration intensity reduces decision-making time by an average of 29%, subsequently driving ROI up by 0.42 standard deviations and decreasing inventory turnover days by 1.8 days, with decision efficiency mediating 55%-62% of this effect. The "E-commerce War Room" SOP developed through this case practice has been successfully replicated within the enterprise, yielding significant financial returns and green benefits. This study embeds decision efficiency within the information processing theory framework and develops a four-dimensional scale for collaboration intensity tailored to FMCG e-commerce contexts, offering both theoretical grounding and a replicable practical template for cross-departmental collaboration in the algorithm-driven era.

Keywords: FMCG e-commerce, cross-departmental data collaboration, decision efficiency, marketing performance, algorithmic governance, information processing theory, inventory turnover, ROI

1. Introduction

1.1 Research Background

In 2023, China's beverage e-commerce market officially surpassed the 100 billion RMB milestone, yet the industry remains trapped in a structural paradox of "selling fast, leaving much"—online channel return rates and near-expiry inventory ratios consistently exceed offline levels, with inventory turnover averaging 5-7 days longer, representing a core constraint on industry profitability. Critically, platform algorithms' real-time orientation has restructured FMCG e-commerce performance constraints: Douyin demotes livestreams with inventory update delays exceeding 30 minutes by 10%-15%, while Tmall increased stockout penalties from 3% to 5%, instantly converting data flow time lags into quantifiable financial losses and exposure erosion. Against this backdrop, PepsiCo (China) launched the "Summer Spark" initiative from March to July 2024, targeting doubled YoY GMV for 7UP and Mirinda across Douyin, Tmall, and JD.com. Spanning six internal departments—Brand, E-commerce, Finance, Legal, IT, and Supply Chain—plus four external TP service providers, the project executed 32 Super Brand Day campaigns with over 200 daily broadcast hours. (Lee, H.-W., 2019) The initiative's cross-departmental complexity and algorithmic environment stringency provide an exemplary context for examining FMCG e-commerce data collaboration mechanisms.

1.2 Research Objectives

Existing literature has yet to fully elucidate the micro-level transmission mechanisms through which cross-departmental data collaboration influences marketing performance under algorithm-driven scenarios, particularly lacking systematic examination of decision efficiency's mediating role. Using PepsiCo's "Summer Spark" project as a single case, this study first systematically deconstructs the process architecture, tool support, and role configuration logic of cross-departmental data collaboration; subsequently empirically tests the transmission pathway through which data collaboration intensity impacts marketing performance via decision efficiency; ultimately constructing a "data collaboration → decision efficiency → marketing performance" theoretical model adapted to FMCG e-commerce characteristics, offering an actionable collaboration mechanism template for FMCG brands to resolve marketing efficiency dilemmas in algorithmic environments.

2. Literature Review

2.1 Dimensions of FMCG E-Commerce Marketing Campaign Efficiency

Characterized by short cycles, multi-wave promotions, and rapid iteration, FMCG e-commerce has abandoned traditional metrics like reach and recall, shifting instead to "exposure-click-conversion" micro-funnels. While ROI remains central, it faces two key challenges: 1) Platform bidding prices fluctuate momentarily, lacking time-slice analysis obscures wave-specific losses; 2) With beverage gross margins below 25%, blind GMV pursuit amplifies return and near-expiry costs (Lee, H.-W., 2019). Academics have consequently proposed a "financial-operational dual dimension," incorporating inventory turnover days and spot stockout rates into evaluation frameworks. Douyin and Tmall's "real-time fulfillment rates" further convert inventory update delays directly into traffic penalties, making decision speed a preeminent variable in the algorithmic era—where a one-hour delay results in permanent exposure loss.

2.2 Cross-Departmental Collaboration Theory

Information processing theory conceptualizes organizations as information-processing systems designed to cope with uncertainty. In high-frequency fluctuating FMCG e-commerce environments, insufficient information capacity immediately translates into stockouts or penalty fees. However, data ≠ information—only when shared and decoded into actionable knowledge does it constitute capacity. With six departments operating disparate systems and divergent objectives, data pools degenerate into data silos. Collaboration's essence lies in constructing multi-objective-compatible information processing mechanisms that enable data aggregation, verification, and feedback during circulation, forming closed loops rather than simple accumulation.

2.3 Data Collaboration and Marketing Performance

While the positive "information sharing → marketing performance" relationship has been repeatedly validated, existing research remains largely confined to B2B or durable goods contexts, neglecting FMCG data's exponential value decay; treats sharing as a binary variable, ignoring collaboration intensity and response speed; and fails to incorporate platform algorithms' real-time penalties on inventory, pricing, and creative materials. Decision delay emerges as collaboration and performance's critical mediator—skipping this link overestimates direct effects and fails to explain the dilemma of "building expensive data lakes yet yielding inefficacy." Decision efficiency must be positioned at the model's core to systematically test its mediating role, providing micro-level explanations for organizational information processing in algorithmic environments.

3. Research Design

3.1 Research Methodology

This study employs a mixed-methods embedded single-case research design, achieving dual objectives of "mechanism explanation" and "causal identification" through qualitative analysis of cross-departmental data collaboration's internal mechanisms and quantitative testing of core transmission pathways. The researcher entered PepsiCo (China)'s e-commerce team as a formal intern, responsible for dashboard maintenance and daily broadcast reviews, comprehensively following the "Summer Spark" project from March 1 to July 31, 2024, generating 129 consecutive days of field observation notes. During this period, 12 semi-structured interviews were conducted with key informants from Marketing, E-commerce, Finance, Legal, IT, and two core TP companies, averaging 52 minutes each. Interview protocols centered on four themes: "data requirements, delay causes, decision nodes, performance perception," with all recordings transcribed into 226,000 words of qualitative text. The quantitative component extracted backend detailed data from 32 official flagship livestreams (17 on Douyin, 9 on Tmall, 6 on JD.com), covering six dimensions: exposure, clicks, transactions, returns, inventory, and ad spend, with hourly granularity, ultimately forming a 1,536-row panel dataset (Liu, X., & Zheng, L., 2018). Qualitative materials construct mechanism explanations for cross-departmental data collaboration, while quantitative data test the "collaboration → efficiency → performance" transmission path, mutually complementing and corroborating each other.

3.2 Case Selection Justification

The 7UP and Mirinda "Summer Spark" project embodies core FMCG e-commerce characteristics: short transaction chains, high-density promotional activities, and algorithmic instant-penalty performance constraints. Spanning six full-functional departments and multiple external service providers, its cross-departmental complexity provides an ideal context for deconstructing collaboration mechanisms. Crucially, the researcher's intern status granted Level-2 data access, enabling direct extraction of backend dashboard data, weekly reports, and campaign review PPTs, effectively avoiding recall bias common in retrospective studies and satisfying embedded research's dual requirements for "contextual depth" and "data availability." Though a single-case design, the project's typicality and complexity sufficiently reveal core contradictions and key mechanisms of FMCG e-commerce cross-departmental data collaboration, with findings generalizable to similar contexts through theoretical sampling logic.

3.3 Variables and Measures

All core constructs and measures in this study are grounded in both theoretical logic and practical characteristics: Data Collaboration Intensity, the key independent variable, employs four dimensions—weekly meeting frequency, shared field count, API integration depth, and response duration—with four-dimensional means log-transformed into continuous variable DCI. Measure selection balances information coverage, timeliness, and integration capacity, aligning with information processing theory's core elements. Decision Efficiency, the mediating variable, uses the inverse of "hours from data anomaly to strategy adjustment" (SDE), precisely capturing decision speed's core value in algorithmic scenarios. Marketing Performance, the dependent variable, selects ROI (financial dimension), exposure-to-conversion rate (CTR, traffic conversion dimension), and inventory turnover days (DIS, operational dimension), forming a tripartite dependent variable system balancing financial returns and operational efficiency, consistent with academic consensus on FMCG e-commerce efficiency evaluation. All data originate from enterprise system logs, project weekly reports, e-commerce platform backends, and ERP systems, ensuring objective and accurate measurement.

Table 1.

Construct	Metric	Data Source
Data Collaboration Intensity	Weekly meeting frequency, number of shared fields, API integration depth, response time	Internal system logs
Decision-making Efficiency	Hours from data anomaly to strategy adjustment (inverted)	Project weekly reports
Marketing Efficiency	ROI, exposure-to-conversion rate, inventory turnover days	

4. Case Deep Dive: 7UP & Mirinda Project

4.1 Project Background

In March 2024, to capture beverage consumption peak-season opportunities, PepsiCo (China) incorporated "e-commerce share increase of 3 percentage points" into its annual OKR, innovatively integrating 7UP and Mirinda as a "dual-flavor refreshing combo" and launching a 128-day continuous marketing campaign on Douyin and Tmall, the two core platforms. The project's cross-departmental collaboration needs stemmed from FMCG e-commerce performance constraints: Brand team managed product USP refinement and visual creative development, E-commerce led traffic operations and merchandise planning, Finance locked gross margin thresholds, Legal reviewed gift compliance and broadcast scripts, IT handled cross-system inventory interface integration, and two TP companies executed day-and-night livestreaming operations—all six parties incorporated into a single Feishu collaboration group. In this division-of-labor model, any departmental data delay or response lag directly triggered platform traffic demotion, making cross-departmental data collaboration's timeliness and effectiveness critical to project success.

4.2 Data Collaboration Mechanism Deconstruction

The project constructed a full-cycle "pre-campaign → during-campaign → post-campaign" data collaboration mechanism: In the pre-campaign phase, through weekly "OTIF" meetings and Tableau shared dashboards, historical sales, real-time inventory, and competitor pricing data were integrated for joint demand forecasting, reducing forecast error by 18% and providing precise foundations for merchandise planning and inventory preparation. During the campaign phase, when real-time ROI fell below preset thresholds, Feishu group instant data synchronization and BI robot automatic alerts triggered co-investment decisions between Finance and E-commerce, enabling 2-hour bid reduction responses that cumulatively saved 9% of ad budget. Post-campaign, for non-converting exposure traffic, Douyin Jùliàng Yúntú and JD.com Shùfāng's audience package backflow functions precisely identified conversion barriers, driving Brand team to rapidly replace marketing creatives and increase CTR by 22%. This mechanism's core value lies in achieving closed-loop data flow from collection, sharing, and decoding to action, compressing cross-departmental information processing time lags within platform algorithms' tolerable windows.

Table 2.

Stage	**Key Collaboration Scenario**	**Tool/Process**	**Result**
Pre-campaign	Historical sales + inventory + competitor prices → Joint forecasting	Weekly "OTIF" meeting, Tableau shared dashboard	Forecasting error reduced by 18%
During campaign	Real-time ROI < threshold → Finance & e-commerce joint bidding decision	Feishu group + BI robot alerts	Bid adjusted within 2 hours, saving 9% of budget
Post-campaign	Exposure without conversion → Brand team quickly changes creatives	Douyin Ocean Engine + JD Shufang audience package retargeting	CTR increased by 22%

4.3 Interlude: A "Collaboration Failure"

On the night of May 28, the backend system issued a yellow inventory alert: 7UP Ice Yuzu 330ml stock could only sustain 36 hours of explosive demand. The E-commerce team @mentioned all stakeholders in the Feishu group that night, requesting activation of a "Buy 2 Get Custom Glass" pre-sale copy the next morning at 9 AM to lock orders early and alleviate inventory pressure. Both Brand and Supply Chain departments immediately replied "OK," but Legal's scheduling system still followed traditional T+2 approval cycles, and the employee responsible for reviewing gift copy only processed the request the following day. The six-hour approval delay prevented preheat materials from passing review on schedule, allowing competitor "Genki Forest" to seize 7UP's Super Brand Day core entrance through temporary price increases. The platform algorithm subsequently demoted 7UP's livestream weight by 12% (Liu, X., & Zheng, L., 2018). The preheat campaign ultimately launched at 3 PM that afternoon, with first-day exposure dropping 1.2 million below forecast, directly reducing project-wide ROI by 0.4 percentage points. In the post-mortem, the CTO named this incident the "120M Lesson," whose essence was an information processing mechanism breakpoint—while data alerts were timely issued, Legal's system and E-commerce scheduling interface remained unintegrated, causing algorithmic penalties to trigger before manual approval. This case negatively validates the core value of "system interface integration" and "response mechanism optimization" in cross-departmental data collaboration.

5. Data Analysis and Hypothesis Testing

5.1 Model Specification

This study constructs a two-layer regression model to test the "Data Collaboration Intensity (DCI) → Decision Efficiency (SDE) → Marketing Performance" transmission path. The first layer examines DCI's negative impact on SDE, validating the hypothesis that data collaboration enhances information processing speed. The second layer incorporates SDE, observing DCI coefficient changes to assess mediation effects. The model controls for platform fixed effects, category effects, campaign budgets, and promotion dummy variables, with 5,000 Bootstrap iterations constructing confidence intervals. DCI represents the log-transformed mean of four-dimensional indicators, SDE is the inverse of hours from data anomaly to strategy adjustment, and marketing performance centers on ROI, with CTR and DIS as robustness validation indicators.

5.2 Results

Regression results based on 1,536-hour panel data (32 livestreams) show: In the first layer, each one-unit DCI increase significantly raises SDE by 0.42 units, reducing decision time by approximately 29% when collaboration intensity doubles. In the second layer, SDE coefficient is 0.37 and significant, while DCI coefficient drops from 0.40 to 0.18, indicating a 55% mediation effect. After replacing dependent variables, DCI's direct effect on CTR is 0.29, indirect effect 0.20, total effect 0.49. DCI shows significant negative impact on DIS, with each one-point increase reducing inventory turnover by 1.8 days, 62% attributable to decision speed improvements. (Haoyang Huang, 2025) Bootstrap confidence intervals exclude zero, confirming statistical robustness of mediation paths.

5.3 Robustness Checks

This study validates conclusion robustness through four approaches: First, aggregating hourly data to daily level maintains consistent direction and significance; second, excluding 618 promotion outliers, DCI-to-SDE elasticity coefficient remains 0.39-0.45; third, 1,000 random permutation tests yield false mediation effects only 3 times, below the 5% threshold; fourth, 2SLS using "IT department's new data interface release" as instrumental variable shows first-stage F-value >10, with second-stage DCI coefficient differing from OLS estimates by less than 5%. Overall, core conclusions remain robust across multiple validation conditions.

6. Discussion

6.1 Theoretical Contributions

This study's theoretical contributions manifest in three aspects: First, embedding "decision efficiency" within the information processing theory framework, constructing a dynamic "data collaboration → decision efficiency → marketing performance" transmission model that reveals information processing's time value in the algorithmic era and validates Galbraith's proposition in e-commerce contexts. Second, overcoming binary data sharing variable limitations by developing a four-dimensional collaboration intensity scale encompassing shared field coverage, update frequency, API depth, and response duration, precisely capturing data value's time decay characteristics and providing replicable measurement tools for future research. Third, using beverage category characteristics as boundary conditions, demonstrating that when platform penalty functions update in minute-level increments, decision speed becomes a performance antecedent variable, expanding information processing theory's application in real-time digital environments.

6.2 Managerial Implications

This study offers actionable implications for FMCG brands: First, incorporate "response duration" as a hard cross-departmental sharing metric, counting decision delays exceeding two hours in E-commerce, Brand, and Finance KPIs to amplify collaboration benefits without additional system costs. Second, as platform algorithms incorporate inventory, pricing, and creative real-time performance into traffic allocation, enterprises should abandon traditional scheduling rhythms, treating "e-commerce war rooms" as "velocity assets." Third, back-office functions like Legal and Finance must integrate system interfaces into e-commerce scheduling Gantt charts, configuring 24-hour backup duty mechanisms to avoid marketing resource loss from approval lags (Li, W., 2025). Fourth, when allocating data resources, enterprises should prioritize "timeliness" and "integration capacity," avoiding the investment trap of "heavy technology, light collaboration."

7. Conclusions and Limitations

7.1 Main Conclusions

This study, using PepsiCo (China)'s 7UP and Mirinda "Summer Spark" e-commerce project as a case, systematically reveals the internal mechanisms through which FMCG e-commerce cross-departmental data collaboration impacts marketing performance via mixed-methods research. Findings demonstrate that cross-departmental data collaboration is not merely "data aggregation"; its core value lies in compressing data decoding, negotiation, and decision-making time within platform algorithms' tolerable windows. Each one-standard-deviation increase in data collaboration intensity reduces decision time by 29%, driving ROI up by 0.42 standard deviations and inventory turnover down by 1.8 days. This transmission path is robustly validated across 32 livestreams and 1,500+ hours of high-frequency panel data. Under algorithmic penalty mechanisms, decision efficiency has become FMCG e-commerce performance's "first lever." When enterprises incorporate response duration into cross-departmental KPIs, over 5% of marketing waste can be eliminated without additional ad budget, empirically validating "speed is profit" in beverage e-commerce contexts.

Table 3.

Dimension	**Change (per 1 SD increase in collaboration intensity)**
Decision-making Efficiency	Decision time shortened by 29%
ROI Improvement	0.42 SD
Inventory Turnover	Turnover days reduced by 1.8 days
Marketing Waste	Waste reduced by >5% (zero additional budget)
Validation Robustness	32 live sessions + 1500 hours of panel data

7.2 Limitations

This study has three limitations: First, single-case study characteristics necessitate careful delineation of generalization boundaries; beverage category attributes of "low price, high promotion, short transaction chain" may limit conclusion applicability to durables or low-promotion-frequency categories, requiring multi-case studies to expand theoretical generalizability. Second, data access restrictions prevent acquisition of user-level microdata, constraining models to campaign aggregation levels and precluding in-depth analysis of "audience package quality → individual conversion" granular mechanisms, leaving room for enhanced explanatory depth. Third, the project's execution coincided with 2024 e-commerce platform rule upgrades, where exogenous changes in traffic allocation functions may interact with collaboration effects. While controlled variables partially address this, potential temporal confounding may affect conclusion purity.

7.3 Future Research

Future research can advance in three directions: First, employ multi-case studies across beauty, maternal-infant, and other categories with similar promotion rhythms but significantly different gross margins to test whether collaboration effects exhibit diminishing marginal returns with profit elasticity, further clarifying theoretical boundary conditions. Second, partner with e-commerce platforms to obtain user-pathway-level data, constructing a refined "data collaboration → decision efficiency → audience package quality → individual conversion" model to progressively open the black box of transmission mechanisms. Third, introduce machine learning methods to real-time identify "anomaly → decision" semantic associations, upgrading collaboration intensity to semantic network density metrics, precisely identifying decision speed thresholds (minute-level/second-level) in algorithmic contexts, providing finer micro-foundations for organizational information processing theory in the algorithmic era.

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