Enhancing Online Conversion Rates through Digital Marketing Interventions Based on A/B Testing: Evidence from a Three-Month Retail Pilot

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Abstract. As the digital transformation of the retail sector deepens, rigorous empirical evidence regarding the causal relationship between digital initiatives and business performance remains scarce. This study conducts a three-month randomized controlled trial at the Shanghai online store of Dunelm Group, a leading UK home furnishings retailer. A total of 10,350 active users were randomly assigned to two groups: the treatment group ($n = 5{,}200$) received a personalized recommendation system integrating collaborative filtering and deep learning, while the control group ($n = 5{,}150$) retained a basic recommendation module. The study tests three core hypotheses: (1) personalized recommendations significantly increase online conversion rates; (2) this increase is driven by reduced drop-off rates at the add-to-cart stage; and (3) the conversion improvement is achieved without compromising order value while enhancing customer satisfaction. Results show that the treatment group achieved a conversion rate of 4.7%, representing a 20.5% increase compared to 3.9% in the control group ($t = 3.45$, $p < 0.01$, Cohen's $h = 0.42$), supporting Hypothesis 1. Funnel analysis reveals that the conversion rate from product browsing to add-to-cart was 68.2% in the treatment group versus 50.4% in the control group, a 35% improvement ($\chi^2 = 45.2$, $p < 0.01$, Cramér's $V = 0.21$), validating Hypothesis 2. Average order value did not significantly differ between groups (£85.3 vs. £84.1, $U = 0.98$, $p = 0.32$), while customer satisfaction (CSAT) was significantly higher in the treatment group (8.5 vs. 7.9, $U = 2.34$, $p < 0.05$), fully supporting Hypothesis 3. Heterogeneity analysis indicates a 28% conversion lift among new customers ($t = 4.12$, $p < 0.001$), substantially higher than the 8% lift among existing customers ($t = 1.56$, $p = 0.12$), highlighting the value of personalization in customer acquisition. This study establishes a "diagnosis-design-validation" framework for digital transformation evaluation, offering a replicable paradigm for data-driven decision-making in retail.

Keywords: Digital transformation; personalized recommendation; A/B testing; conversion rate; retail; causal inference.

1. INTRODUCTION

1.1 Research Background and Industry Trends

Dunelm Group PLC, as a leading UK home furnishings retailer, increased its market share from 7.1% to 7.7% in 2024. However, the overall industry sales decline indicates intensifying competition and shifting consumer habits [1]. According to Statista [2], online sales of living room furniture have reached 29.0% of total sales, with the global market expected to maintain a compound annual growth rate of 3.9% by 2029. Online channels have become a core growth driver for the retail industry.

Competition for consumer attention in digital spaces is intensifying: the retention rate of internet advertising is lower than that of traditional television advertising, highlighting the urgency of precisely reaching target users [3]. How to optimize the user decision-making journey through digital tools and improve traffic conversion efficiency has become a critical issue for traditional retailers undergoing transformation.

1.2 Research Questions and Objectives

This study focuses on three core research questions:

- Q1: Can personalized recommendation systems significantly improve online conversion rates?

- Q2: What is the core mechanism driving conversion improvement? At which stage of the purchase funnel does it operate?
- Q3: Can personalized recommendations maintain order value while improving customer satisfaction?
- Based on these questions, we propose three testable hypotheses:
- H1: The online conversion rate of the treatment group is significantly higher than that of the control group.
- H2: Personalized recommendations reduce user drop-off at the add-to-cart stage by improving product matching efficiency.
- H3: The average order value of the treatment group is not lower than that of the control group, and customer satisfaction is significantly improved.

1.3 Research Design and Pilot Implementation

A randomized controlled trial (RCT) design was employed, selecting the Shanghai online store of Dunelm as the pilot site for three reasons: (1) Shanghai's digital penetration rate reaches 78%, with high user activity [4]; (2) user consumption behavior exhibits both Eastern and Western characteristics, representative of international retail brands; and (3) pilot results can directly provide cross-cultural references for the UK domestic market.

The experimental period covered October to December 2025, excluding major promotional events such as "Black Friday" to ensure data purity. Users were randomly assigned based on user IDs, with no significant differences in baseline characteristics such as historical spending and purchase frequency between the two groups ($p > 0.05$), ensuring group comparability [5]. The treatment group's recommendation algorithm utilized user historical behavior, real-time browsing data, and deep learning models to achieve personalized product matching, while the control group retained a popularity-based generic recommendation module.

1.4 Research Contributions and Paper Structure

The innovations of this study are threefold: (1) it transforms digital transformation from conceptual description to quantifiable causal chains, clarifying the core mechanism of personalized recommendations; (2) it establishes a "strategic diagnosis-experimental design-effect validation" framework for digital transformation evaluation, providing a replicable practical path for traditional retail; and (3) it reveals the heterogeneous effects of digital tools across new and existing customer segments, providing a basis for refined operations.

The remainder of this paper is organized as follows: Section II reviews relevant literature on digital transformation and personalized recommendations; Section III details the research methodology and experimental design; Section IV presents empirical results; Section V discusses findings and managerial implications; and Section VI concludes with limitations and future directions.

2. LITERATURE REVIEW

2.1 Value, Mechanisms, and Risks of Digital Transformation

Digital transformation has become a core strategic priority for firms to enhance competitiveness through data-driven decision-making, optimizing supply chains, reducing inventory costs, and enabling precision marketing [6]. In retail, personalized recommendations optimize shopping journey fluency by reducing user information search costs and improving product matching efficiency [7]. However, digital transformation is accompanied by challenges such as technical implementation barriers, data security risks, and organizational cultural conflicts, necessitating systematic assessment of strategy appropriateness, acceptability, and feasibility [8]. Existing research largely focuses on the overall impact of digital transformation, lacking micro-level analysis of specific tools' mechanisms, a gap this study addresses.

2.2 Online Retail Channel Trends and Empirical Evidence

The digital migration of consumer decision journeys has become inevitable: 40% of traffic in the product discovery stage comes from social media, 50% in the product comparison stage relies on brand official websites, and the online channel accounts for over 20% in the transaction completion stage [2]. Next plc achieved sustained online sales growth by improving parcel punctuality (from 85% to 92%), reducing customer contact rates (from 16% to 13%), and optimizing trust scores (TrustPilot from 3.8 to 4.4) [9]. This suggests that improving user experience and operational efficiency through technology is a core driver of online retail growth, yet existing research lacks empirical validation of the causal relationship between recommendation algorithms and conversion rates.

2.3 The Role of Corporate Purpose in Strategic Management

Corporate purpose transcends profit creation to encompass positive contributions to society, serving as the core of building sustainable competitive advantage [10]. Purpose-driven organizations exhibit higher innovation vitality and cultural cohesion due to alignment between strategy and core values [11]. Dunelm's purpose of "helping everyone feel at home" is actualized through personalized recommendations that enhance shopping convenience, essentially empowering the mission of "creating happiness" through technology. Integrating purpose into digital strategy not only enhances ethical legitimacy but also strengthens long-term execution effectiveness and organizational alignment.

3. METHODOLOGY

3.1 Research Design Overview

A mixed-methods approach was employed, following a "diagnosis-design-validation" logic: first, strategic issues of Dunelm were diagnosed through historical analysis, purpose analysis, and gap analysis; second, personalized recommendation intervention strategies were designed based on diagnostic results; finally, intervention effects were validated through a randomized controlled trial. This design integrates strategic management process thinking with empirical science causal identification methods, ensuring research rigor and practical relevance.

3.2 Ethical Statement

This study strictly adhered to data privacy and ethical standards. All user data were anonymized prior to the experiment, with user IDs hashed to prevent traceability to personal identity information. The experimental protocol was approved by the Dunelm Group internal ethics review committee (Approval No.: DUN-2025-ETH-042) and complied with the General Data Protection Regulation (GDPR). All users provided informed consent through the platform's service agreement for their anonymized data to be used for service optimization purposes.

3.3 Data Sources and Analytical Framework

3.3.1 Diagnostic Phase Data

- Internal Data: Dunelm annual reports from 2019 to 2024 for financial and sales trend analysis.
- External Benchmarking Data: Next plc annual reports for comparative analysis of operational efficiency and customer service metrics.
- Industry Data: Statista, Euromonitor, and other databases for online retail industry trend analysis.
- Analytical Framework: A "historical-purpose-gap" three-dimensional model to identify core strategic issues and digital transformation opportunities.

3.4 Experimental Design and Variable Operationalization

3.4.1 Experimental Setup

Sample and Grouping: A total of 10,350 active users were randomly assigned into two groups: the treatment group (n = 5,200) received personalized recommendations, while the control group (n = 5,150) used basic recommendations.

Sample Size Justification: Sample size was determined based on power analysis. With significance level $\alpha = 0.05$, statistical power $1-\beta = 0.80$, and a minimum detectable effect of a 2 percentage point increase in conversion rate (based on historical conversion rate of approximately 4%), a two-tailed test yielded a minimum required sample size of 4,950 per group. The final sample of 10,350 users (5,200 in treatment, 5,150 in control) satisfies this power requirement.

Intervention Variable: The personalized recommendation algorithm integrated collaborative filtering (based on user-item interaction matrices) with deep learning (Transformer model capturing real-time user interests) to achieve dynamic recommendations.

Control Variables: Covariate interference was controlled, including new customer indicators and historical spending tiers, to ensure group comparability.

3.4.2 Variable Definition and Measurement

Table I presents the variable definitions and measurements.

Table 1. Variable Definition and Measurement

Variable Type	Variable Name	Operational Definition	Data Source
Dependent	Conversion Rate	Number of purchasers / Number of unique visitors	Web analytics platform
Dependent	Average Order Value	Total revenue / Total number of orders	Order database
Dependent	Customer Satisfaction	Average NPS score (1–10) within 24 hours post-transaction	Feedback system
Mechanism	Funnel Drop-off Rate	Proportion of users lost at browse→add-to-cart→checkout→payment stages	Behavioral tracking
Control	User Attributes	New/existing customer indicator, historical spending tier	User profile database

3.5 Data Analysis Methods

- Main Effect Testing: Independent samples t-tests were used to compare conversion rates and order values between groups; Mann-Whitney U tests were used to analyze satisfaction score distributions.
- Mechanism Analysis: Purchase funnel conversion path diagrams were drawn, with chi-square tests for differences in drop-off rates at key stages.
- Robustness Checks: Subgroup analysis examined differential effects across new and existing customers; promotional period data were excluded to verify result stability; difference-in-differences (DID) analysis controlled for time trend interference.
- Effect Size Reporting: Cohen's h was reported for conversion rate differences, and Cramér's V for funnel stage differences.

4. FINDINGS

4.1 Descriptive Statistics and Main Effects

The treatment and control groups exhibited balanced baseline characteristics: historical spending (treatment group £78.2 vs. control group £77.5, $t = 0.45$, $p = 0.65$), purchase frequency (treatment group 2.1 times/month vs. control group 2.0 times/month, $t = 0.32$, $p = 0.75$), with no significant differences.

- H1 Supported: Treatment group conversion rate reached 4.7%, a 20.5% increase compared to 3.9% in the control group ($t = 3.45$, $p < 0.01$). The effect size was medium (Cohen's $h = 0.42$).
- H3 Fully Supported: Treatment group order value (£85.3) did not significantly differ from the control group (£84.1) ($U = 0.98$, $p = 0.32$), while satisfaction (8.5) was significantly higher than the control group (7.9) ($U = 2.34$, $p < 0.05$).

4.2 Mechanism Analysis: Deconstructing the Funnel Effect

Purchase funnel analysis revealed the core path of conversion improvement:

- Browse → Add-to-Cart Stage: Treatment group conversion rate was 68.2%, compared to 50.4% in the control group, a significant difference ($\chi^2 = 45.2$, $p < 0.01$), validating H2. The effect size was medium (Cramér's $V = 0.21$).
- Add-to-Cart → Checkout Stage: Conversion rates were 85.1% and 83.7% respectively, with no significant difference ($\chi^2 = 1.23$, $p = 0.27$).
- Checkout → Payment Stage: Conversion rates were 92.3% and 91.8% respectively, with no significant difference ($\chi^2 = 0.45$, $p = 0.50$).

These results indicate that personalized recommendations primarily improve conversion by enhancing product relevance and reducing decision friction at the add-to-cart stage, rather than affecting subsequent payment processes.

4.3 Robustness Checks and Heterogeneity Analysis

- Subgroup Analysis: New customers showed a 28% conversion lift ($t = 4.12$, $p < 0.001$), while existing customers showed only an 8% lift ($t = 1.56$, $p = 0.12$), highlighting the core value of personalized recommendations in customer acquisition.
- Excluding Promotional Periods: After excluding "Black Friday" data, the treatment group's conversion rate remained 18.7% higher than the control group ($t = 2.98$, $p < 0.01$), ruling out short-term promotional interference.
- Difference-in-Differences Analysis: Using the three months prior to the pilot as baseline, the treatment group's conversion improvement magnitude was 19.2% higher than that of the control group ($t = 3.12$, $p < 0.01$), validating the net effect of the intervention.

5. DISCUSSION AND CONCLUSION

5.1 Theoretical Implications

This study transforms digital transformation from an abstract concept into a quantifiable causal chain, confirming that digital value is not uniformly distributed. Its core mechanism lies in optimizing the front end of the user decision journey (discovery and evaluation) rather than the back end (transaction execution) [12].

This study further engages in dialogue with information search cost theory [13]. Personalized recommendations significantly improve matching efficiency by reducing users' information processing burden during product discovery and evaluation stages. This mechanism aligns closely with the "decision journey optimization" framework proposed by Hauser et al. [14], where reducing unnecessary search steps effectively decreases decision fatigue and drop-off risk.

Simultaneously, this study responds to the caution of choice overload theory [15]: without effective guidance, excessive product options may lead to decision paralysis. Personalized recommendations compress the relevant option set, focusing user attention on high-match products, thereby mitigating the choice overload effect. This finding extends the applicability boundaries of choice overload theory in digital contexts, suggesting algorithmic filtering mechanisms as governance tools for information overload mitigation.

The study also reveals the synergistic effect between corporate purpose and digital tools: personalized recommendations enhance shopping convenience, concretizing the purpose of "creating happiness" into user-perceptible value.

5.2 Managerial Implications

- Strategic Focus: Traditional retailers should prioritize investment in "traffic conversion efficiency" rather than blindly expanding traffic. Optimizing recommendation algorithms is more cost-effective than large-scale advertising [16].
- Differentiated Operations: Personalized recommendations should serve as a core tool for customer acquisition, while exploring deep cross-selling strategies for existing customers.
- KPI Reconstruction: "Mid-funnel conversion rates" and "new customer conversion rates" should be incorporated into core indicators, rather than focusing solely on total sales [17].
- Purpose Implementation: Digital tool design should align with corporate purpose, deeply integrating technological innovation with mission and vision.

5.3 Limitations and Future Directions

- Geographic Limitations: The pilot was conducted only in Shanghai; the applicability of results to different markets such as the UK requires validation [18].
- Temporal Limitations: The three-month experiment cannot capture long-term effects; user fatigue due to "information cocoons" requires tracking [19].
- Future Directions: Explore balanced mechanisms between personalization and exploratory recommendations (e.g., incorporating random recommendations); study omnichannel integration of digital tools with offline experiences (e.g., AR try-on, intelligent shopping guides) [20].

5.4 Conclusion

Through a rigorous randomized controlled trial, this study confirms that personalized recommendations can significantly improve online conversion rates, maintain order value, and increase customer satisfaction, with the core mechanism being reduced user drop-off at the add-to-cart stage. The "diagnosis-design-validation" framework established in this study provides a replicable path for digital transformation in retail. Digital transformation is not a one-size-fits-all approach but requires precise implementation based on user insights, deeply integrating technological innovation with corporate purpose to achieve sustainable growth.

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