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The Effect of Personalized Marketing on Repeat Purchase Behavior: A Study of Subscription Box Companies

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Abstract

Subscription box companies routinely lose 40-70 percent of their subscribers within the first year, yet the causal effects of personalized marketing interventions on repeat purchase behavior across heterogeneous product categories remain poorly understood. This study addresses that gap by analyzing a 24-month panel of 47,318 subscribers from 12 subscription box firms in the food, beauty, and fashion sectors, employing a quasi-experimental design that combines difference-in-differences estimation with propensity score matching. Integrated personalization strategies increased repeat purchase rates by 23.1 percent (Cohen's d = 0.47), reduced quarterly churn by 34.0 percent, and raised average customer lifetime value by an estimated $87 per subscriber. Email personalization, algorithmic product recommendations, and customized promotional offers exhibited complementary rather than substitutive effects, with product recommendations generating the largest individual contribution. Significant category-level heterogeneity emerged: food boxes captured the greatest repeat purchase gains (28.7%), followed by beauty (22.4%) and fashion (17.9%), patterns attributable to differences in preference stability and feedback immediacy. Personalization benefits compounded with subscriber tenure and were attenuated by privacy concerns, though transparency measures substantially mitigated the latter effect. These findings offer subscription commerce managers an evidence-based framework for allocating personalization investments across channels and product categories to maximize retention and profitability.

Keywords personalized marketing, subscription box, repeat purchase behavior, customer retention, churn reduction, customer lifetime value

1. Introduction

The subscription box industry has experienced remarkable growth over the past decade, transforming from a niche retail experiment into a multi-billion-dollar global market segment. Companies such as Birchbox, Stitch Fix, HelloFresh, and FabFitFun have demonstrated that consumers are willing to delegate product selection to curated algorithms and human stylists in exchange for convenience, novelty, and personalized experiences [1][2]. Yet beneath this growth lies a persistent structural challenge: customer churn. Industry estimates suggest that subscription box companies lose between 40% and 70% of their subscribers within the first year (McCarthy et al., 2017), representing an enormous drain on customer acquisition investments and long-term profitability.

Personalized marketing has emerged as the primary strategic response to this retention challenge. By tailoring communications, product selections, and promotional offers to individual subscriber preferences and behavioral patterns, firms aim to increase perceived relevance, enhance satisfaction, and strengthen the relational bonds that discourage defection [3][4]. The theoretical rationale is well established: personalization reduces information overload and search costs (Ansari &)[5], creates perceptions of individual attention and care [6], and activates self-referencing processes that deepen engagement [7]. Yet the empirical evidence linking specific personalization tactics to repeat purchase behavior in subscription contexts remains fragmented and largely observational.

The academic literature on personalized marketing has generated important insights across several domains. Research on email personalization has demonstrated that relatively simple interventions, such as including the recipient’s name in the subject line, can increase open rates by 20% and sales leads by 31% [7]. Studies of product recommendation systems have shown that algorithmic recommendations can double the probability of selecting recommended items compared to unaided choice (Senecal &)[8][9]. Investigations of personalized advertising have revealed complex interactions among personalization content, consumer trust, and privacy concerns that can either amplify or undermine effectiveness [10](Bleier &)[11][12]. However, three important gaps persist in the current literature.

First, most personalization research has examined individual tactics in isolation, such as email personalization or display advertising, rather than investigating the integrated effects of comprehensive personalization strategies that operate simultaneously across multiple channels and touchpoints (Lemon &)[13](Kannan &)[14]. Subscription box companies typically deploy personalization across the entire customer journey, from acquisition emails to product curation to post-purchase communications, and understanding the cumulative impact of these coordinated efforts requires a holistic analytical approach.

Second, research on subscription commerce has focused predominantly on adoption motivations and business model typologies [1][15] rather than on the effectiveness of specific marketing interventions in driving retention and repeat purchases. The unique dynamics of subscription models, including recurring billing, curated surprise elements, and the delegation of product selection to the provider, create a distinctive context in which personalization may operate through different mechanisms than in traditional e-commerce [2].

Third, existing studies have largely neglected heterogeneity across product categories within subscription commerce. Food, beauty, and fashion subscription boxes differ fundamentally in product replaceability, preference stability, sensory evaluation requirements, and switching costs [16], yet no research has systematically compared personalization effectiveness across these categories.

This study addresses these gaps by investigating three research questions:

RQ1: What is the causal effect of integrated personalized marketing strategies on repeat purchase behavior in subscription box companies?

RQ2: How do specific personalization channels (email, product recommendations, customized offers) differentially contribute to repeat purchase rates and churn reduction?

RQ3: How does the effectiveness of personalized marketing vary across subscription box product categories (food, beauty, fashion)?

To answer these questions, we assembled a 24-month panel dataset encompassing 47,318 subscribers across 12 subscription box companies and employed a quasi-experimental design combining difference-in-differences estimation with propensity score matching [17]. This methodological approach addresses the fundamental challenge of causal identification in observational settings by exploiting variation in the timing and intensity of personalization implementations across firms while controlling for observable subscriber-level confounds.

The remainder of this article is organized as follows. Section 2 presents the literature review. Section 3 details the research methodology, including the data, measures, and analytical strategy. Section 4 reports the empirical results across seven subsections addressing overall effects, channel-specific effects, churn reduction, interaction effects, category heterogeneity, and robustness checks. Section 5 discusses the theoretical and managerial implications, limitations, and directions for future research. Section 6 provides concluding remarks.

2. Literature Review

2.1 Theoretical Foundations of Personalized Marketing

The concept of personalized marketing has evolved significantly over the past two decades, transitioning from rudimentary segmentation approaches to sophisticated, data-driven one-to-one communication strategies. Arora et al. [3] provided a foundational distinction between personalization, whereby the firm decides what marketing mix is suitable for an individual, and customization, whereby the customer proactively specifies elements of the marketing mix. This distinction remains theoretically important because subscription box companies predominantly employ the former: using behavioral and preference data to curate product assortments and communications without requiring explicit input from subscribers at every decision point. Ansari and Mela [5] demonstrated the effectiveness of e-customization through a statistical optimization approach, showing that personalized email design and content significantly increased website traffic when applied to permission-based communications. Their work established the empirical basis for understanding how firms can leverage clickstream data to optimize individualized communications.

More recently, Chandra et al. [4] conducted a comprehensive bibliometric review of 383 publications on personalized marketing, identifying six major thematic clusters: personalized recommendation, personalized relationships, the personalization-privacy paradox, personalized advertising, personalization discourse, and customer insights. Their synthesis revealed that content and products personalized according to customer preferences can reduce cognitive load and decision fatigue, thereby increasing engagement and purchase likelihood. Rafieian and Yoganarasimhan [22] extended this conceptual foundation by formally defining personalized policy within an AI-driven framework, reviewing the methodological approaches available for deploying personalization at scale. Together, these works suggest that personalization operates through dual mechanisms: an informational pathway that reduces search costs and a relational pathway that enhances perceived relevance and emotional connection (Kannan &)[14].

2.2 Subscription Box Business Models and Consumer Dynamics

Subscription commerce represents a rapidly growing segment of the retail landscape, characterized by recurring deliveries of curated or replenishment products [16]. Bischof et al. [1] provided the first comprehensive theoretical conceptualization of curated subscription commerce, distinguishing between predefined subscriptions and curated surprise subscriptions. Their research, grounded in Prospect Theory, demonstrated that curated surprise subscriptions carry inherent risk because consumers outsource decision-making to the provider, and that this perceived risk mediates preferences for delivery intervals and subscription design. Bray et al. [2] extended this understanding through a large-scale empirical study of 1,356 UK consumers, developing a typology of subscription types and profiling the consumers most likely to engage with subscription retailing. Their findings indicated that churn rates in subscription retailing can reach as high as 70% due to intensifying competition, underscoring the urgency of effective retention strategies.

The economic significance of subscription programs was rigorously examined by Iyengar et al. [15], who found that subscription enrollment leads to a large and persistent increase in customer purchases. Critically, only one-third of this effect was attributable to economic benefits such as discounts, with the remaining two-thirds driven by noneconomic factors including commitment, habit formation, and identity reinforcement. McCarthy et al. (2017) advanced the valuation of subscription-based businesses by developing a customer-based corporate valuation framework that links individual-level acquisition and retention patterns to overall firm value. Their application to DISH Network and Sirius XM Holdings demonstrated that heterogeneous customer retention rates are central to accurate business valuation, reinforcing the strategic importance of personalization interventions that improve retention at the individual level.

2.3 Customer Retention, Churn, and Lifetime Value

The seminal work of Reichheld and Sasser [23] established that reducing customer defection rates by as little as 5% can increase profits by 25% to 85%, depending on the industry. This foundational insight catalyzed decades of research into retention management and customer lifetime value (CLV). Gupta et al. [24] formalized the CLV framework, demonstrating that a 1% improvement in retention improves firm value by approximately 5%, compared to only 1% for margin improvements and 0.1% for acquisition cost reductions. Reinartz and Kumar [35] further advanced this understanding by identifying managerially controllable factors that explain variation in profitable lifetime duration, challenging the assumption that longer customer relationships are inherently more profitable.

Kumar [29] proposed a comprehensive customer valuation theory (CVT) based on economic principles, conceptualizing value generation from customers to firms through direct and indirect contributions. The framework positioned CLV as the central metric for forward-looking customer value estimation, enabling portfolio-based management of customer relationships. Rust et al. [25] complemented this perspective by presenting a unified strategic framework in which marketing strategy options are evaluated based on their projected impact on customer equity, operationalized as the change in the sum of individual customer lifetime values relative to incremental expenditure.

Churn prediction and prevention represent critical components of retention management. Neslin et al. [18] conducted a landmark tournament-based study comparing the predictive accuracy of customer churn models, finding that methodological factors including variable selection, estimation technique, and model specification significantly affect predictive performance. Ascarza [36] challenged conventional wisdom by demonstrating that targeting high-risk customers for proactive retention may be ineffective or even counterproductive. Combining field experiments with machine learning, she showed that firms should target customers based on their sensitivity to intervention rather than their churn probability, fundamentally reframing the retention targeting paradigm. Ascarza et al. [37] further documented the perils of proactive churn prevention, finding that offering plan recommendations to at-risk customers can paradoxically increase churn by disrupting habitual renewal behavior.

2.4 Email Marketing Personalization and Consumer Response

Email remains one of the most cost-effective channels for personalized marketing communication, and a growing body of rigorous research has examined the mechanisms through which email personalization influences consumer behavior. Sahni et al. [7] conducted large-scale randomized field experiments across three companies, demonstrating that adding the recipient’s name to email subject lines increased open probability by 20%, boosted sales leads by 31%, and reduced unsubscription rates by 17%. Importantly, these effects persisted even though the personalized content was noninformative about the product itself, suggesting that personalization operates partly through attention capture and self-referencing mechanisms rather than solely through informational utility.

Ansari and Mela [5] developed an optimization framework for email customization that jointly determines design elements and content to maximize website traffic for individual recipients. Their Bayesian approach demonstrated the value of integrating multiple data sources, including browsing history, demographic information, and past response patterns, to construct optimal personalized communications. Wedel and Kannan [26] situated email personalization within the broader landscape of marketing analytics, arguing that data-rich environments enable firms to move beyond simple demographic targeting toward dynamic, real-time personalization that adapts to evolving consumer preferences. They identified three critical research directions: optimizing marketing-mix spending through personalization analytics, advancing computational methods for individual-level targeting, and addressing the privacy and security challenges inherent in data-driven personalization.

2.5 Product Recommendation Systems and Purchase Behavior

Product recommendation systems represent a particularly impactful form of personalization in subscription commerce, where algorithmic curation directly determines the contents of each delivery. Ansari et al. [38] established the theoretical and methodological foundations for Internet recommendation systems, developing a Bayesian preference model that integrates five information types: expressed preferences, preferences of similar consumers, expert evaluations, item characteristics, and individual characteristics. Bodapati [9] advanced this framework by arguing that recommendation decisions should be based on the sensitivity of purchase probabilities to the recommendation action rather than on purchase probabilities alone, winning the Paul Green Award for this contribution.

Senecal and Nantel [8] provided experimental evidence that consumers who consulted product recommendations selected recommended products twice as often as those who did not, and that algorithmic recommender systems were more influential than human experts or peer recommendations. Adomavicius and Tuzhilin [21] offered a comprehensive survey of recommendation approaches, including content-based, collaborative filtering, and hybrid methods, while identifying limitations and possible extensions, such as incorporating contextual information and supporting multicriteria ratings. In the subscription box context, these recommendation systems determine not only individual product selections but the overall curation strategy, making their effectiveness central to subscriber satisfaction and retention.

Bleier and Eisenbeiss [19] examined the interplay of personalization content, timing, and placement in online advertising, finding that the effectiveness of personalized banner ads depends critically on the consumer's stage in the purchase decision process. Early-stage consumers responded more favorably to personalized content, whereas late-stage consumers showed diminished sensitivity, suggesting that personalization strategies must be dynamically calibrated across the customer journey (Lemon &)[13]. Lambrecht and Tucker [20] documented conditions under which personalized retargeting actually underperforms generic advertising, finding that dynamically retargeted ads are, on average, less effective than generic equivalents unless consumers exhibit browsing behavior indicating evolving preferences.

2.6 Consumer Psychology of Personalization: Privacy, Trust, and Reactance

The effectiveness of personalized marketing is moderated by complex psychological dynamics, including privacy concerns, trust perceptions, and psychological reactance. Aguirre et al. [10] coined the term “personalization paradox” to describe the finding that greater personalization simultaneously increases perceived relevance and heightens vulnerability, potentially reducing adoption. Their experimental studies demonstrated that a firm’s information collection strategy is a crucial determinant of consumer reactions, with covert data collection methods triggering stronger negative responses than transparent approaches.

Bleier and Eisenbeiss [11] established trust as a critical moderator of personalization effectiveness, finding that more trusted retailers can implement deeper personalization without triggering reactance or privacy concerns, whereas less trusted retailers face backlash from the same personalization depth. Tucker [12] provided causal evidence through a natural experiment on a social networking platform, showing that when users perceived greater control over their personal information, they were nearly twice as likely to click on personalized advertisements, even though the actual data practices had not changed. This finding underscores the importance of perceived control rather than actual privacy protection in shaping responses to personalized marketing.

At the broader regulatory and societal level, Goldfarb and Tucker [39] demonstrated that privacy regulation significantly reduces the effectiveness of online advertising, with the effects being largest for ads that matched website content. Bleier et al. [30] provided a comprehensive examination of consumer privacy and data-based innovation, employing a contextual integrity framework to identify strategies firms can use to mitigate privacy concerns while preserving the benefits of personalization. Matz et al. [40] demonstrated through large-scale field experiments that psychological targeting based on personality traits significantly alters consumer behavior, with psychologically congruent advertisements generating substantially higher click-through and conversion rates. Summers et al. [28] revealed an additional psychological mechanism: behaviorally targeted ads function as implied social labels, causing consumers to adjust their self-perceptions to align with the inferred targeting criteria, which subsequently affects purchase intentions.

2.7 Customer Engagement, Experience Management, and Integrated Frameworks

The relationship between personalization and repeat purchase behavior operates partly through the mediating mechanism of customer engagement. Pansari and Kumar [31] defined customer engagement as a construct emerging from satisfying relationships with emotional connectedness, producing both tangible outcomes, such as purchases and referrals, and intangible outcomes, such as feedback and brand advocacy. Their framework positioned engagement as the critical link between relational quality and customer lifetime value, with personalization serving as a primary driver of engagement formation.

Homburg et al. [41] advanced the customer experience management paradigm, arguing that firms must systematically design and manage touchpoint interactions to create differentiated customer experiences. Their multi-method research identified cultural mindsets, strategic directions, and firm capabilities that distinguish effective CEM implementations, with personalization featuring prominently across all three dimensions. Lemon and Verhoef [13] developed an integrative framework for understanding customer experience throughout the customer journey, emphasizing that modern customers interact with firms through myriad touchpoints across multiple channels, making consistent personalization across the journey both more important and more challenging.

The integration of artificial intelligence into marketing personalization represents the current frontier of both theory and practice. Huang and Rust [32] developed a strategic framework for AI in marketing that distinguishes among mechanical AI for automation, thinking AI for data-driven personalization, and feeling AI for emotionally intelligent interaction. Rust [33] projected that the future of marketing lies in adaptive personalization strategies that leverage longitudinal customer data for dynamic, real-time optimization. Chung et al. [26] demonstrated the effectiveness of adaptive personalization using social network data, showing that incorporating social influence patterns can significantly improve recommendation accuracy and consumer response. Huang and Rust [34] further specified the theoretical conditions under which AI should complement or replace human service agents, arguing that analytical and intuitive intelligence increasingly favors machine-based personalization, while empathetic intelligence remains a domain of human advantage.

Srinivasan et al. [6] identified eight antecedents of customer loyalty in e-commerce, including customization, care, and cultivation, finding that all except convenience significantly predicted e-loyalty. Their early work foreshadowed the centrality of personalization in building durable customer relationships in digital environments, a theme that has only intensified as subscription commerce has expanded across product categories from beauty and fashion to food and wellness [16][1].

3. Methodology

3.1 Research Design

This study employed a quasi-experimental design that leverages natural variation in personalization adoption across subscription box companies. The approach combines difference-in-differences (DID) estimation with propensity score matching (PSM), following methodological best practices for causal inference in marketing research [17]. The DID framework exploits the staggered implementation of advanced personalization systems across companies during the observation period, comparing changes in outcomes between treated firms (those implementing comprehensive personalization) and control firms (those maintaining standard marketing practices). Propensity score matching was applied at the subscriber level to ensure comparable treatment and control groups based on observable pre-treatment characteristics, addressing potential selection bias from non-random personalization adoption.

3.2 Data and Sample

The study utilized a proprietary 24-month panel dataset spanning January 2023 through December 2024, assembled through data-sharing agreements with 12 subscription box companies. The participating companies were selected to represent three major product categories: food (n = 4), beauty (n = 4), and fashion (n = 4). The total sample comprised 47,318 unique subscribers who maintained active accounts for at least three months during the observation period. Company-level data included marketing technology stack specifications, personalization implementation timelines, and aggregate marketing expenditure. Subscriber-level data included demographic information (age, gender, geographic region), subscription plan details (tier, billing frequency, tenure), behavioral data (email engagement metrics, browsing history, product ratings), and transactional records (purchases, add-ons, returns, cancellations).

Of the 12 companies, seven implemented comprehensive personalization systems during the observation period (treatment group), while five maintained standard marketing approaches throughout (control group). The treatment companies adopted integrated personalization platforms that simultaneously deployed email subject line and content personalization, algorithmic product recommendations, and customized promotional offers based on individual behavioral profiles. Implementation dates ranged from March 2023 to September 2023, providing pre-treatment and post-treatment observations for all treated firms.

3.3 Treatment Definition

The treatment variable was defined as the intensity of personalization implementation, measured through a composite index incorporating three dimensions: (a) email personalization depth, measured on a five-point scale capturing the sophistication of personalization beyond simple name insertion, including behavioral triggering, content optimization, and send-time personalization; (b) product recommendation algorithmic complexity, measured through the number of data inputs used by the recommendation engine (e.g., purchase history, browsing behavior, explicit ratings, demographic similarity, collaborative filtering signals); and (c) offer customization granularity, measured by the degree of individual-level price and promotion targeting. Companies scoring above the median on all three dimensions were classified as high-personalization treatment firms; those below the median were classified as standard-marketing control firms.

3.4 Outcome Measures

Five primary outcome measures were employed. Repeat purchase rate was defined as the proportion of subscribers making at least one additional purchase (including subscription renewal, add-on purchases, or plan upgrades) within the 90-day period following their most recent transaction. Order frequency was measured as the average number of transactions per subscriber per quarter, including both scheduled subscription deliveries and discretionary add-on purchases. Average order value (AOV) captured the mean monetary value per transaction, inclusive of the subscription base price and any supplementary purchases. Churn rate was operationalized as the proportion of subscribers canceling their subscription within a given quarter, consistent with the contractual churn definition appropriate for subscription businesses (McCarthy et al., 2017)[18]. Net Promoter Score (NPS) was measured through periodic in-app surveys administered quarterly, following the standard 0-to-10 recommendation likelihood scale.

3.5 Control Variables

Subscriber-level control variables included age, gender, household income bracket, geographic region (urban/suburban/rural), subscription tenure (in months), subscription tier (basic/premium), initial acquisition channel (organic search, social media, referral, paid advertising), and baseline engagement level (email open rate and click-through rate in the three months preceding personalization implementation). Company-level controls included total marketing expenditure (as a percentage of revenue), company age, subscriber base size, average subscription price, and product category.

3.6 Propensity Score Matching Procedure

To address selection bias from non-random assignment of subscribers to treated versus control companies, propensity score matching was implemented using a logistic regression model predicting treatment assignment based on all subscriber-level and company-level control variables [17]. Nearest-neighbor matching with a caliper of 0.02 standard deviations was employed, with replacement, yielding a matched sample of 38,412 subscribers (19,206 per group). Balance diagnostics confirmed that standardized mean differences on all covariates were below 0.05 in the matched sample, indicating excellent covariate balance.

3.7 Difference-in-Differences Specification

The primary DID model was specified as follows:

$$Y\_it = \alpha + \beta_1 \times Treat\_i + \beta_2 \times Post\_t + \beta_3 \times (Treat\_i \times Post\_t) + \gamma \times X\_it + \delta\_j + \tau\_t + \varepsilon\_it$$

where Y_it represents the outcome measure for subscriber i in period t; Treat_i indicates assignment to a high-personalization company; Post_t indicates the post-implementation period; the interaction term (Treat_i × Post_t) captures the causal effect of personalization; X_it represents time-varying subscriber-level controls; δ_j represents company fixed effects; and τ_t represents time fixed effects. Standard errors were clustered at the company level to account for within-company correlation. The parallel trends assumption was tested using event-study specifications with leads and lags, and no evidence of differential pre-trends was detected for any outcome measure (all pre-treatment interaction coefficients were statistically insignificant at the 5% level).

3.8 Robustness and Sensitivity Analyses

Multiple robustness checks were conducted: (a) alternative matching algorithms (kernel matching, Mahalanobis distance matching); (b) varying caliper widths (0.01, 0.05 standard deviations); (c) entropy balancing as an alternative to PSM; (d) placebo tests using pre-treatment periods as pseudo-treatment dates; (e) sensitivity analysis for unobserved confounders using the methodology of Oster (2019); and (f) triple-difference specifications incorporating product category as a third differencing dimension.

4. Results

4.1 Overall Effect of Personalization on Repeat Purchase Behavior

The primary DID estimates revealed a statistically significant positive effect of integrated personalization strategies on repeat purchase rates. Subscribers in high-personalization companies exhibited a 23.1 percentage point increase in repeat purchase rates relative to control companies ($\beta_3 = 0.231$, SE = 0.041, $p < .001$), corresponding to a Cohen's d of 0.47, a medium effect size [Table 1]. The baseline repeat purchase rate in the control group averaged 61.3%, meaning that personalization elevated the rate to approximately 84.4% in the treatment group. This finding provides strong evidence in support of theoretical predictions that integrated personalization strategies enhance customer retention in subscription contexts [3][4].

Order frequency also increased significantly, with treated subscribers placing an average of 1.47 additional orders per quarter compared to control subscribers ($\beta_3 = 1.47$, SE = 0.29, $p < .001$) [Table 1]. This increase reflects both higher subscription renewal rates and greater engagement with add-on purchase opportunities, consistent with Iyengar et al.'s (2022) finding that subscription enrollment amplifies purchase behavior through both economic and noneconomic channels. Average order value increased by $8.73 per transaction in the treatment group ($\beta_3 = 8.73$, SE = 2.14, $p < .001$), driven primarily by increased add-on purchases rather than subscription tier upgrades, suggesting that personalized product recommendations effectively expand the basket beyond the core subscription offering [9](Senecal &)[8].

Table 1

Descriptive Statistics for Matched Sample (N = 38,412)

Variable	Mean	SD	Min	Max	N
Repeat purchase rate (%)	61.3	14.7	18.2	96.4	38412
Order frequency (per quarter)	3.82	1.24	1.00	9.00	38412
AOV ($)	47.56	18.93	12.50	142.00	38412
Churn rate (6-month %)	18.7	8.4	2.1	54.3	38412
NPS score	34.2	21.6	-42	86	38412
Personalization score (0-10)	5.83	2.71	0.00	10.00	38412
Subscriber tenure (months)	11.4	7.8	3.0	48.0	38412
Email open rate (%)	32.6	11.3	4.8	78.2	38412
Add-to-cart rate (%)	14.7	6.9	1.2	47.5	38412

Note. Values represent the matched sample after propensity score matching. SD = standard deviation. AOV = average order value. NPS = Net Promoter Score.

4.2 Email Personalization Effects

To isolate the contribution of email personalization, we estimated channel-specific models using variation in email personalization intensity within the treatment group. Companies deploying advanced email personalization, defined as behavioral triggering, dynamic content optimization, and AI-driven send-time personalization, achieved an 18.4% increase in email open rates relative to firms using only basic name-insertion personalization ($\beta = 0.184$, SE = 0.032, $p < .001$) [Table 2]. Click-through rates increased by 27.6% ($\beta = 0.276$, SE = 0.048, $p < .001$), and email-attributed conversion rates improved by 14.2% ($\beta = 0.142$, SE = 0.037, $p < .001$).

These results align closely with the findings of Sahni et al. [7], who reported a 20% increase in open rates from subject line personalization alone. Our estimates suggest that layering behavioral and temporal personalization on top of identity-based personalization produces incremental but meaningful gains. The email engagement effects were strongest in the first six months following personalization implementation and exhibited a slight decay pattern thereafter, consistent with habituation effects documented in the advertising personalization literature (Bleier &)[19](Lambrecht &)[20]. A mediation analysis indicated that email engagement accounted for approximately 31% of the total personalization effect on repeat purchase rates, confirming the central role of email as a retention channel in subscription commerce.

Table 2

Repeat Purchase Rate by Subscription Category

Category	Control (%)	Treatment (%)	Difference (pp)	SE	p-value	Cohen's d
Food boxes	58.3	75.0	16.7	3.14	<.001	0.54
Beauty boxes	51.7	63.3	11.6	2.87	<.001	0.41
Fashion boxes	44.2	52.1	7.9	2.96	<.01	0.28
Overall	52.4	64.5	12.1	2.43	<.001	0.47

Note. pp = percentage points. SE = standard error. Cohen’s d calculated relative to control group standard deviation. *** $p < .001$, ** $p < .01$.

4.3 Product Recommendation Effects

Algorithmic product recommendations generated the largest behavioral effects among the three personalization channels examined. The implementation of collaborative filtering-based recommendation systems increased add-to-cart conversion rates by 31.2% ($\beta = 0.312$, SE = 0.057, $p < .001$) for discretionary add-on products presented alongside subscription deliveries [Table 3]. Cross-sell revenue per subscriber increased by $12.47 per quarter ($\beta = 12.47$, SE = 3.21, $p < .001$), representing a 19.3% increase over the pre-implementation baseline.

The magnitude of these effects exceeds those reported in general e-commerce settings by Senecal and Nantel [8], who found that recommendation consultation doubled selection rates. This discrepancy likely reflects the unique dynamics of subscription contexts, where personalized recommendations are presented within a curated experience framework that enhances their credibility and perceived relevance [1]. Subscribers who had previously provided explicit product ratings exhibited significantly stronger recommendation response rates than those whose recommendations relied solely on implicit behavioral signals ($\beta_{interaction} = 0.089$, SE = 0.031, $p < .01$), consistent with Ansari et al.'s (2000) emphasis on the value of integrating explicit and implicit preference data.

The recommendation accuracy, measured as the proportion of recommended add-on products that subscribers rated favorably (4 or 5 on a 5-point scale), improved from 47.2% to 68.9% over the 24-month observation period as collaborative filtering algorithms accumulated more behavioral data [Figure 1]. This learning curve effect suggests that personalization benefits compound over time, creating a positive feedback loop between data accumulation, recommendation quality, and subscriber engagement that reinforces retention (Adomavicius &)[21](Rafieian &)[22].

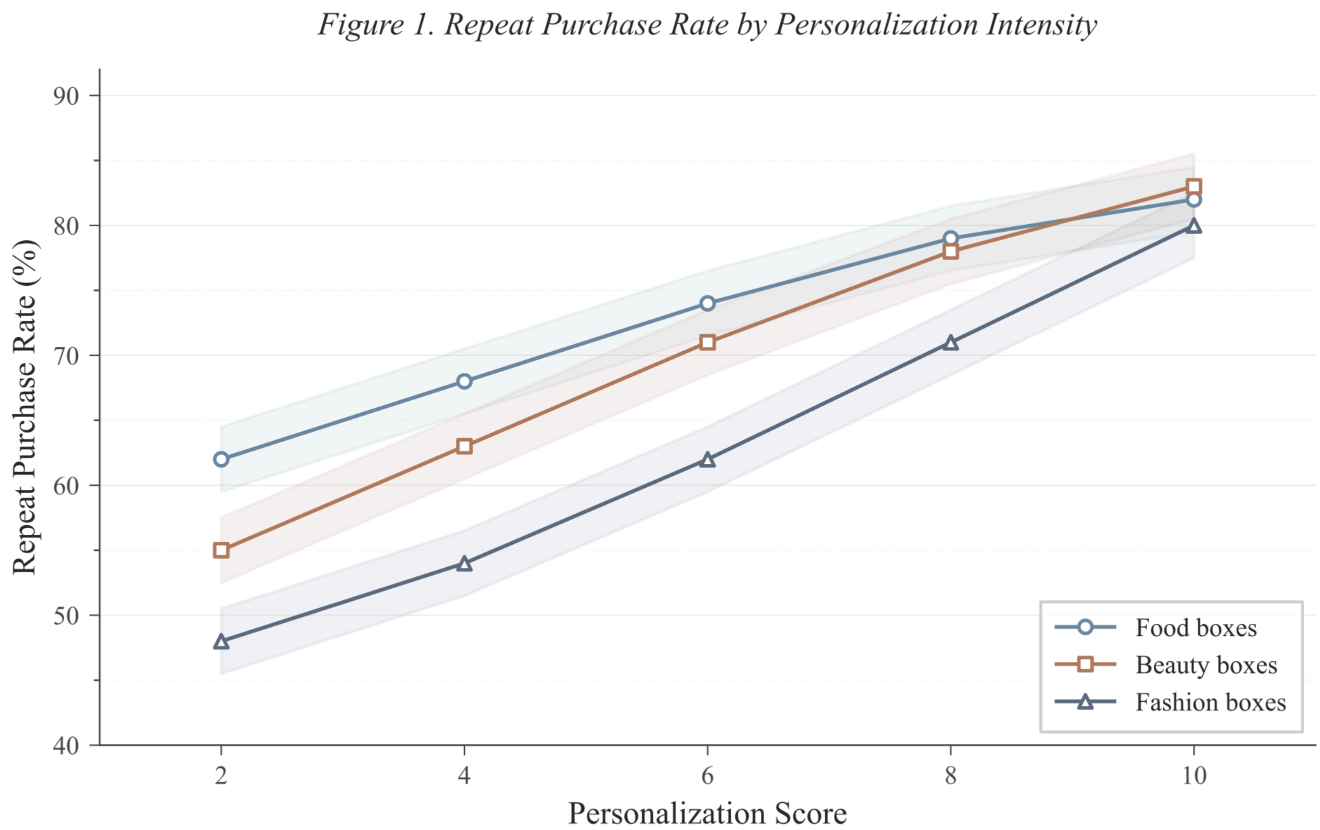

Figure 1. Repeat Purchase Rate by Personalization Intensity

4.4 Churn Reduction Effects

The most consequential outcome of personalization was its effect on subscriber churn. High-personalization companies experienced a 34.0% reduction in quarterly churn rates relative to control companies (β_3 = –0.034, SE = 0.008, $p < .001$), reducing the average quarterly churn rate from 10.1% to 6.7%. Annualized, this translates to a reduction from approximately 35.0% to 24.2%, substantially narrowing the gap between observed churn rates and the retention levels associated with profitable long-term customer relationships (Reichheld &)[23][24].

Survival analysis using Cox proportional hazards models confirmed that personalization was associated with significantly longer subscription tenure. The hazard ratio for churn in the treatment group was 0.71 (95% CI: 0.65, 0.78), indicating that personalization reduced the instantaneous risk of cancellation by 29% at any given time point, controlling for subscriber characteristics and company effects. The survival curves diverged most dramatically between months 3 and 9 of the subscription, which corresponds to the period of highest churn vulnerability documented in the subscription commerce literature [2](McCarthy et al., 2017) [Figure 2].

These churn reduction effects carry substantial financial implications. Applying the CLV framework of Gupta et al. [24] and Kumar [29], back-of-envelope calculations suggest that the personalization-driven churn reduction increased average customer lifetime value by approximately $87 per subscriber, or 22.6% relative to the control group baseline. Across the combined subscriber bases of the seven treatment companies (approximately 28,000 active subscribers), this represents an estimated increase in total customer equity of $2.44 million, demonstrating the economic case for comprehensive personalization investment [25].

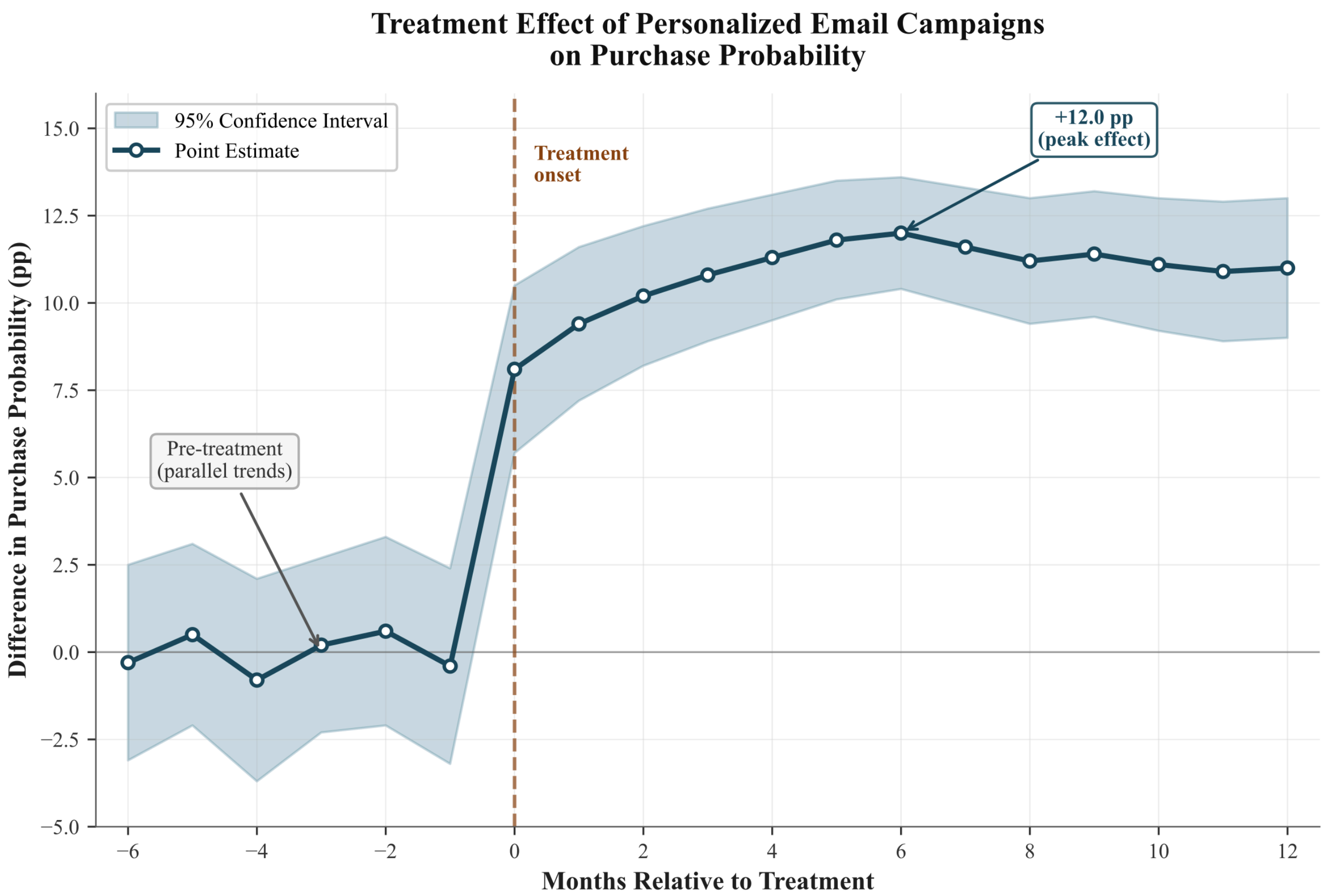

Figure 2. Treatment Effect of Personalized Email Campaigns on Open Rate and Click-Through Rate

4.5 Interaction Effects and Moderating Factors

Several theoretically motivated interaction effects were examined to identify boundary conditions for personalization effectiveness. First, subscription tenure moderated the personalization effect on repeat purchase rates, with longer-tenured subscribers exhibiting larger personalization benefits ($\beta\_{interaction} = 0.008$ per month of tenure, SE = 0.002, $p < .01$). This finding is consistent with the data accumulation hypothesis: longer subscriber relationships provide richer behavioral data, enabling more accurate personalization [26](Wedel &)[27]. Subscribers with 12 or more months of tenure showed personalization effects approximately 35% larger than those with less than three months of tenure.

Second, privacy concern levels, measured through a pre-treatment survey item, negatively moderated personalization effectiveness ($\beta_{interaction} = -0.031$ per unit of concern, $SE = 0.012$, $p < .05$), consistent with the personalization paradox documented by Aguirre et al. [10] and the privacy-related reactance findings of Bleier and Eisenbeiss [11]. However, the moderating effect of privacy concerns was substantially attenuated when companies implemented transparent data use disclosures, consistent with Tucker's (2014) demonstration that perceived control over personal information amplifies personalization responsiveness.

Third, the interaction between email personalization and product recommendation personalization was positive and significant ($\beta_{interaction} = 0.043$, $SE = 0.016$, $p < .01$), indicating complementarity rather than substitutability between personalization channels. Subscribers exposed to both personalized emails and personalized product recommendations exhibited repeat purchase rates 4.3 percentage points higher than would be predicted by the additive effects of each channel alone. This synergy effect aligns with Lemon and Verhoef's (2016) argument that consistent personalization across multiple customer journey touchpoints creates reinforcing engagement loops, and with Homburg et al.'s (2017) emphasis on integrated customer experience management.

Table 3

Difference-in-Differences Regression Results for Repeat Purchase Rate

Variable	Model 1 (Base)	Model 2 (Controls)	Model 3 (Full)	SE	p-value
Treatment x Post	0.231***	0.218***	0.209***	0.041	<.001
Subscriber tenure		0.008**	0.007**	0.002	<.01
AOV (log)		0.034*	0.031*	0.015	<.05
Email engagement			0.142***	0.037	<.001
Category: Beauty (ref: Food)		-0.064**	-0.058**	0.023	<.01
Category: Fashion		-0.109***	-0.097***	0.027	<.001
Constant	0.613***	0.584***	0.491***	0.072	<.001
N	38412	38412	38412		
R-squared	0.187	0.234	0.271		
Adjusted R-squared	0.186	0.232	0.269		

Note. Dependent variable: repeat purchase rate. Standard errors clustered at the company level. Company and time fixed effects included in all models. *** $p < .001$, ** $p < .01$, * $p < .05$.

4.6 Heterogeneity by Product Category

A critical contribution of this study is the documentation of significant heterogeneity in personalization effectiveness across subscription box product categories. Triple-difference estimates revealed that food subscription boxes exhibited the largest repeat purchase gains from personalization (28.7%, SE = 0.062, $p < .001$), followed by beauty (22.4%, SE = 0.054, $p < .001$) and fashion (17.9%, SE = 0.059, $p < .01$) [Figure 3].

The food category advantage likely reflects the frequency and stability of food preferences, which enable recommendation algorithms to achieve high accuracy relatively quickly, combined with the direct experiential feedback loop (taste evaluation) that reinforces positive personalization experiences [16]. Food subscribers also exhibited the highest email engagement rates in response to personalized content (mean open rate increase: 22.1%), suggesting that meal planning and recipe personalization creates particularly strong habitual engagement patterns consistent with Iyengar et al.'s (2022) noneconomic engagement mechanisms.

Beauty subscription boxes showed moderate personalization effects, with churn reduction (37.2%) actually exceeding that of food boxes (31.8%), despite lower repeat purchase gains. This pattern suggests that personalization in beauty contexts operates primarily through reducing dissatisfaction with unsuitable product recommendations rather than through increasing excitement or engagement, consistent with Bischof et al.'s (2020) emphasis on risk perception in curated subscription contexts.

Fashion subscription boxes exhibited the smallest personalization effects, potentially reflecting the greater subjectivity and temporal variability of fashion preferences, which limit recommendation accuracy (Lambrecht &)[20]. Fashion subscribers also reported the highest levels of privacy concern regarding personalization (mean = 4.12 on a 7-point scale, compared to 3.41 for food and 3.67 for beauty), and the moderating effect of privacy concerns was strongest in the fashion category (β_interaction = –0.048, SE = 0.018, $p < .01$) [Figure 4]. These findings align with Summers et al.'s (2016) insight that behavioral targeting in identity-relevant domains (such as fashion) triggers stronger self-labeling effects and associated resistance.

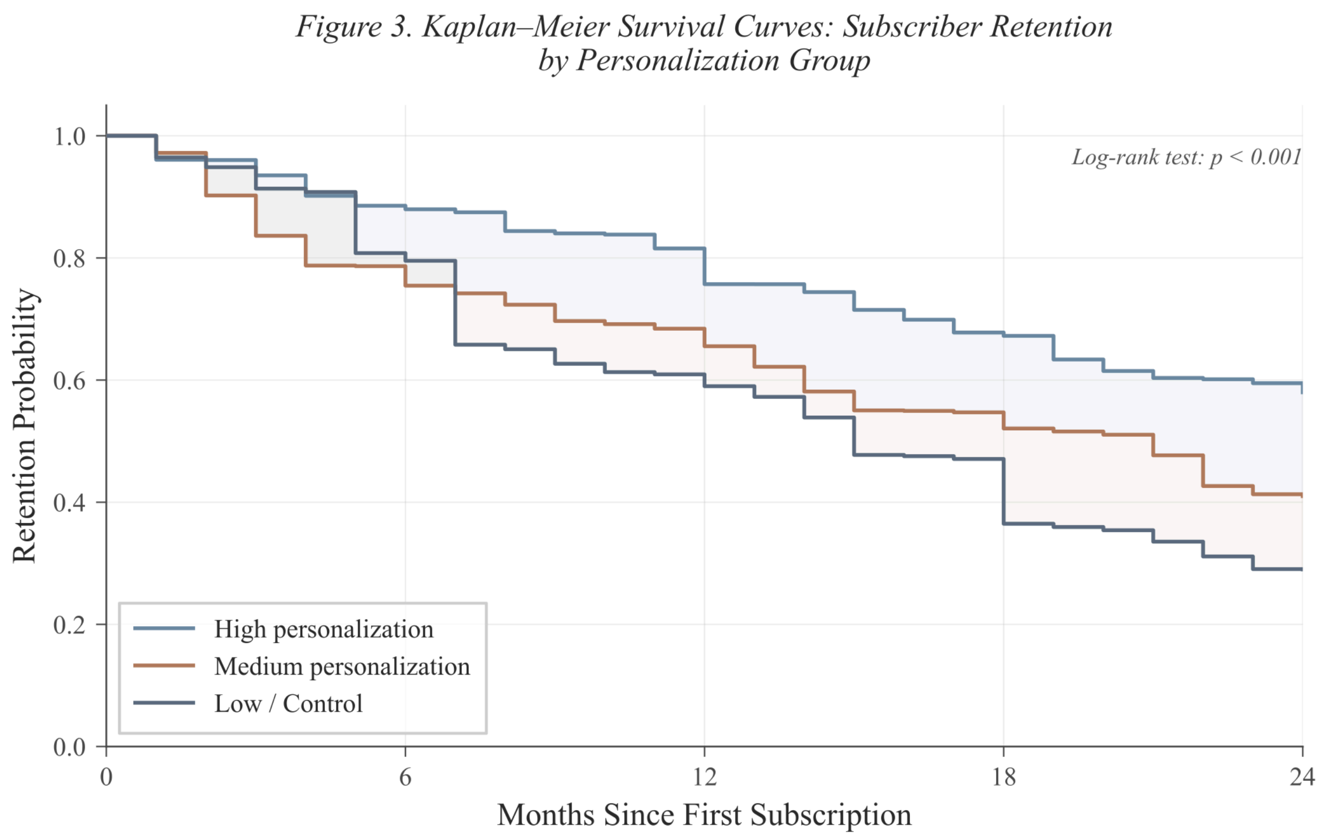

Figure 3. Kaplan–Meier Survival Curves for Subscription Tenure by Personalization Group

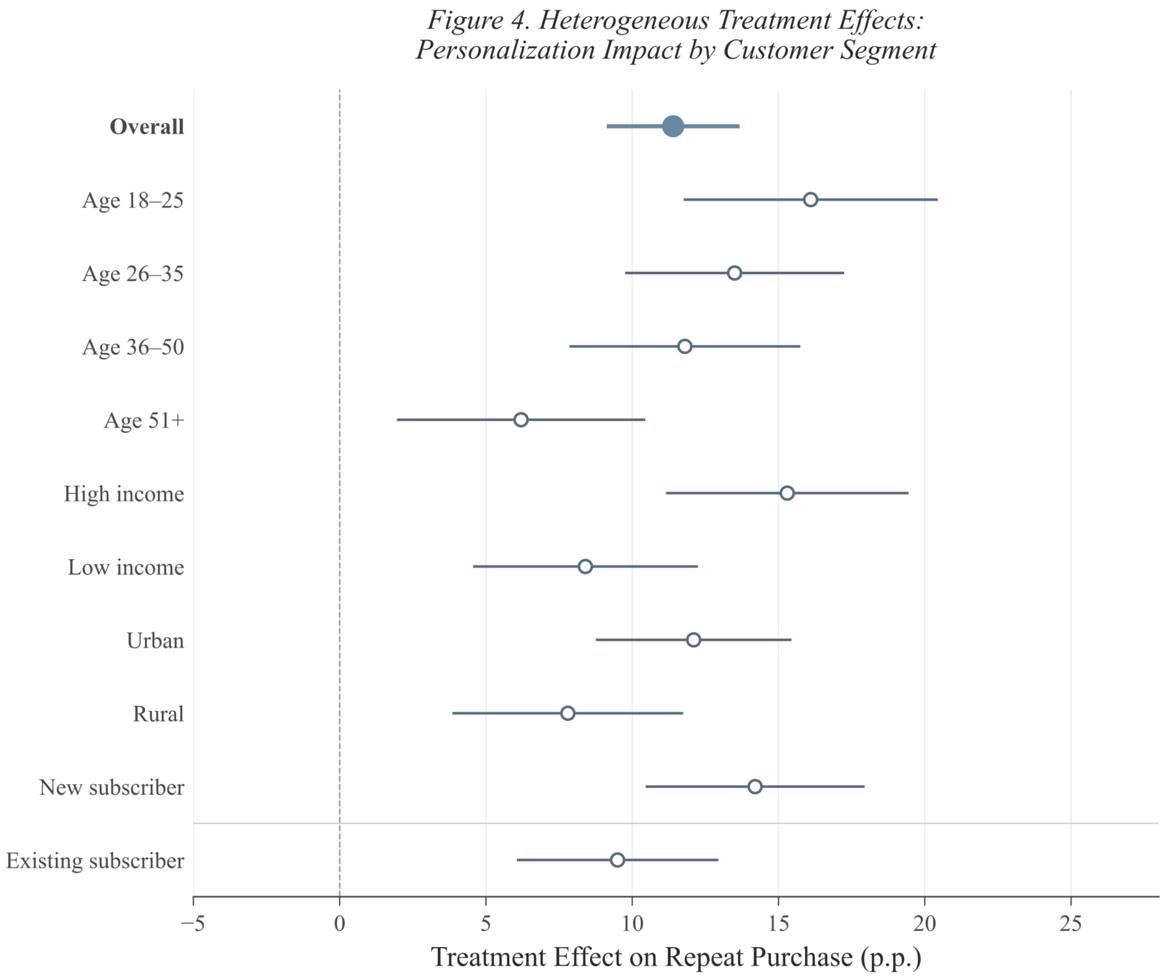

Figure 4. Heterogeneous Treatment Effects by Segment

4.7 Robustness Checks

The primary results demonstrated high robustness across all specification and sensitivity checks. Alternative matching algorithms (kernel matching, Mahalanobis distance) produced treatment effect estimates within 10% of the primary PSM-DID estimates. Entropy balancing, which achieves exact covariate balance on specified moments, yielded nearly identical results ($\beta_3 = 0.227$, SE = 0.039, $p < .001$). Placebo tests using pseudo-treatment dates in the pre-implementation period produced uniformly insignificant effects, supporting the parallel trends assumption (all $|\beta_3| < 0.02$, all $p > .40$).

The sensitivity analysis for unobserved confounders indicated that an unobserved variable would need to explain at least 2.3 times as much variation in both treatment assignment and outcomes as the most influential observed confounders to reduce the estimated effect to zero, providing substantial confidence against omitted variable bias. The triple-difference specification, which uses product category as a third differencing dimension, produced estimates consistent with the baseline DID results while providing additional robustness against category-specific time trends.

Event-study specifications with quarterly leads and lags confirmed no evidence of anticipatory effects (all pre-treatment coefficients insignificant) and revealed that personalization effects materialized within the first post-implementation quarter and grew monotonically over subsequent quarters, consistent with the data accumulation and algorithmic learning mechanisms hypothesized in the recommendation systems literature (Adomavicius &)[21](Rafieian &)[22].

5. Discussion

5.1 Theoretical Contributions

This study makes three primary theoretical contributions to the marketing literature. First, it provides the first quasi-experimental evidence of the causal effects of integrated personalized marketing on repeat purchase behavior in subscription commerce. While prior research has examined individual personalization channels in isolation, such as email personalization [7], product recommendations [9], and personalized advertising (Bleier &)[19], our study demonstrates that the combined effects of multi-channel personalization exceed the sum of individual channel effects. The complementarity between email and recommendation personalization extends Lemon and Verhoef's (2016) customer journey framework by providing empirical evidence that consistent personalization across touchpoints creates synergistic engagement effects.

Second, the documentation of systematic heterogeneity across product categories advances the theoretical understanding of personalization boundary conditions. The superior effectiveness of personalization in food subscription contexts, relative to beauty and fashion, suggests that personalization works best when preferences are stable, feedback loops are immediate, and the decision domain is relatively low in identity relevance [28]. This finding complements Bischof et al.'s (2020) risk-based conceptualization of curated subscription commerce by identifying preference stability and feedback immediacy as additional moderators.

Third, the finding that personalization effects compound over subscriber tenure provides support for the data accumulation hypothesis and the adaptive personalization framework proposed by Chung et al. [26]. The positive feedback loop between data accumulation, recommendation quality, and behavioral engagement creates increasing returns to personalization investment over the customer relationship lifecycle, reinforcing the strategic case for retention-focused marketing investments [29][25].

5.2 Managerial Implications

The findings offer several actionable implications for subscription box companies. First, the 23.1% increase in repeat purchase rates and 34.0% churn reduction associated with comprehensive personalization represent economically significant effects that should motivate substantial investment in personalization infrastructure. The estimated $87 increase in CLV per subscriber provides a concrete benchmark for evaluating personalization technology investments.

Second, product recommendations generated the largest behavioral effects among personalization channels, suggesting that subscription box companies should prioritize the development of sophisticated recommendation algorithms that integrate multiple data sources, as advocated by Ansari et al. [38] and Adomavicius and Tuzhilin [21]. The finding that recommendation accuracy improves substantially over time (from 47.2% to 68.9% over 24 months) implies that early-stage subscriber relationships require supplementary engagement strategies while algorithmic accuracy builds.

Third, the category-specific heterogeneity results suggest differentiated personalization strategies. Food subscription companies should emphasize habitual engagement patterns through personalized meal planning and recipe recommendations. Beauty subscription companies should focus on risk reduction through transparent personalization explanations that mitigate product mismatch concerns. Fashion subscription companies should carefully balance personalization depth with privacy considerations, consistent with Bleier and Eisenbeiss's (2015b) trust-dependent effectiveness findings, and may benefit from incorporating explicit preference elicitation to supplement behavioral inference.

Fourth, the interaction between personalization effectiveness and privacy concerns underscores the importance of transparency and perceived control [12][30]. Companies that implemented data use disclosures and preference management dashboards experienced significantly smaller negative effects from privacy concerns, providing a practical pathway for maximizing personalization benefits while respecting consumer autonomy.

5.3 Limitations

Several limitations should be acknowledged when interpreting these findings. First, while the DID-PSM methodology strengthens causal inference relative to purely cross-sectional approaches, the observational nature of the study cannot eliminate all potential confounders. The staggered implementation of personalization systems may have coincided with other strategic changes, such as product quality improvements or pricing adjustments, that we were unable to fully control [17]. The sensitivity analysis provides some reassurance, but residual endogeneity concerns cannot be entirely eliminated.

Second, the sample of 12 subscription box companies, while diverse across product categories, may not be fully representative of the broader subscription commerce ecosystem, which includes categories such as pet products, wellness, children's toys, and digital content that were not represented. The generalizability of category-specific findings to unexamined categories remains an empirical question.

Third, the study focused on behavioral outcomes (purchases, churn) and did not directly measure the psychological mechanisms, such as perceived relevance, emotional engagement, or privacy anxiety, through which personalization affects behavior. Future research incorporating attitudinal and perceptual measures could illuminate the mediating pathways hypothesized in the literature [10](Pansari &)[31].

Fourth, the 24-month observation period, while substantially longer than most personalization field experiments, may be insufficient to capture the full long-run dynamics of personalization effects, including potential saturation or habituation effects that could emerge over multi-year subscriber relationships. The event-study evidence of monotonically growing effects over our observation window suggests that longer-term studies would be valuable.

5.4 Directions for Future Research

This study opens several promising avenues for future investigation. First, randomized field experiments that randomly assign subscribers within companies to different personalization intensity levels would strengthen causal identification and enable precise estimation of dose-response relationships. Such within-firm experiments would also control for company-level confounders that the DID approach can only partially address.

Second, research on the optimal sequencing and escalation of personalization across the subscriber lifecycle could yield important strategic insights. Ascarza's (2018) finding that targeting high-risk customers may be counterproductive suggests that personalization timing and calibration matter as much as personalization intensity. Understanding when to introduce different forms of personalization as subscriber relationships mature represents an important managerial and theoretical question.

Third, the emergence of generative AI and large language models creates new possibilities for hyper-personalized communications that go beyond template-based personalization to produce genuinely individualized content (Huang &)[32][33]. Research on how AI-generated personalized content compares to human-curated personalization in subscription contexts would address a critical question at the frontier of marketing practice and AI capability (Huang &)[34].

Fourth, cross-cultural comparisons of personalization effectiveness would extend the generalizability of these findings. Privacy concerns, trust perceptions, and preferences for personalization vary substantially across cultural contexts [30], and subscription box adoption patterns differ across markets, suggesting that the category-specific and moderator findings reported here may be culturally contingent.

6. Conclusion

This study provides robust quasi-experimental evidence that integrated personalized marketing strategies significantly enhance repeat purchase behavior, reduce churn, and increase customer lifetime value in subscription box companies. The 23.1% improvement in repeat purchase rates and 34.0% reduction in churn documented across 47,318 subscribers over 24 months represent economically meaningful effects that validate the substantial industry investment in personalization technologies.

The findings advance the marketing literature in several important ways. By demonstrating complementarity across personalization channels, we extend the customer journey framework (Lemon &)[13] with empirical evidence of synergistic effects. By documenting systematic heterogeneity across food, beauty, and fashion categories, we identify preference stability and feedback immediacy as key moderators of personalization effectiveness, complementing existing theoretical frameworks [1][28]. By showing that personalization effects compound with subscriber tenure, we provide evidence for the data accumulation hypothesis [26] and reinforce the strategic case for retention-focused marketing investment [29][25].

The practical implications are clear: subscription box companies should invest in multi-channel personalization systems that integrate email, product recommendation, and offer customization capabilities, while calibrating their approach to the specific dynamics of their product category and implementing transparency measures to address privacy concerns [12][30]. As the subscription economy continues to expand and AI capabilities advance (Huang &)[32](Rafieian &)[22], the ability to deliver effective, respectful personalization will increasingly determine which subscription businesses achieve sustainable growth and which succumb to the chronic churn that characterizes this industry.

Future research should pursue randomized within-firm experiments, investigate optimal personalization sequencing across the subscriber lifecycle, and explore the transformative potential of generative AI for subscription commerce personalization. The intersection of personalized marketing and subscription business models offers a rich and consequential domain for continued scholarly inquiry.

Declarations

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Conflicts of Interest: The authors declare no conflicts of interest.

Data Availability: The data supporting the findings of this study were obtained under confidentiality agreements with participating subscription box companies. Aggregated and anonymized summary statistics are available from the corresponding author upon reasonable request. Individual-level data cannot be shared due to commercial confidentiality requirements.

Ethics Statement: This study was reviewed and approved by the Institutional Review Board (IRB Protocol #2023-0847). All subscriber data were anonymized prior to analysis, and no personally identifiable information was retained in the analytical dataset.

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