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Combining Analytics and Business Insights for Optimizing Marketing Campaigns

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Abstract :Campaign optimization involves turning analytics into decisions considering customer requirements, logistical constraints, and business goals. This study proposes a framework connecting customer analytics with business insights of managers and evaluates its implications with a simulation-based campaign experiment. Numerical outcomes reported are simulated values meant to be replaced with observed ones; they don't constitute the complete field study. Three campaign strategies are compared among cohorts of 10,000 customers each: traditional targeting, analytics-based targeting, and integrated targeting combining both. Campaign budget is set to ₹120,000 per cohort. Observed conversion rates are 4.00%, 4.70%, and 5.20% respectively. Integrated targeting produces 1.20 percentage point improvement relative to traditional targeting, with a 95% confidence interval 0.62-1.78 percentage points. However, 0.50 percentage point superiority of integrated targeting over analytics-based targeting is not statistically significant. The framework shows how consistency in measurement, commercial limitations, and inherent uncertainty can contribute to accountable campaign decisions without equating predictive and causal success.

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Keywords : Marketing analytics; business insights; campaign optimization; customer targeting; conversion measurement; marketing profitability

Introduction

Marketing campaigns produce a lot of information regarding customer interaction, purchasing patterns, exposure to communications, and spend. Still, having more information doesn't guarantee better decisions. A campaign can create a lot of engagement and produce little contribution after discounts, costs of fulfilling orders, and spend on media are accounted for. Likewise, a targeting system can detect likely buyers but fail to prove that marketing affects their behavior.

Marketing analytics provides tools for organizing customer information, pattern detection, predictions, and resource allocation. Wedel and Kannan (2016) define analytics as a critical part of marketing expenditure optimization and personalization. Their framework acknowledges that privacy and information security issues affect the responsible use of customer information.

On top of analytics, there are business insights – interpretation of results in terms of organizational context. Commercial considerations include availability

of products, contribution margins, capability of deliveries, customer complaints, and fatigue from communications. These factors determine whether a statistically appealing recommendation is suitable from an operational perspective.

The main issue addressed in this paper is integration of analytical targeting with explicit business rules in an accountable way. This paper outlines three questions: (i) whether a campaign strategy increases conversion; (ii) whether sales generated by the campaign pay off its expenses; (iii) whether changes introduced by managers increase the value of the campaign over analytics-based recommendations.

An integrated decision-making framework is constructed in order to answer these questions. Its contribution lies in methodological aspect: it defines comparable campaign strategies, consistent financial definitions, and statistical tests necessary for interpreting positive and negative findings.

Literature Review

Marketing Analytics and Digital Strategy

Analytical challenges associated with increasing granularity of marketing data are considered in works of Wedel and Kannan (2016). This literature supports customer-level analysis and resource allocation as the purpose of the analysis rather than reporting.

Kannan and Li (2017) organize digital marketing into touchpoints, marketing actions, outcomes, and strategy. Their framework argues for inclusion of interactions into campaign decisions. Excessive focus on platform metrics can make campaign designers miss the impact of previous communications.

Lemon and Verhoef (2016) emphasize similar multi-stage and multi-touchpoint nature of customer experience. This perspective advocates for inclusion of service conditions and history of relationships into campaign designs. Customers are exposed to marketing messages together with delivery, servicing, and products; these aspects of experience can provide context for interpreting patterns.

Prediction and Strategic Decision-Making

Davenport et al. (2020) consider application of artificial intelligence for marketing strategy and customer behavior management. They discuss the relation of analytical applications and organizational implementation; privacy, bias, and ethical concerns are acknowledged as research topics.

Huang and Rust (2021) provide a strategic framework for connecting analytical capabilities and marketing research, segmentation, targeting, positioning, and actions. Overall, the above literature suggests that analytical systems should be evaluated according to decisions they allow in addition to their technical performance.

Verhoef et al. (2121) position digital transformation against the background of broader changes in organizational capabilities and business models. The framework implies that adoption of analytical technologies requires coordination of functions. In case of campaign optimization, it implies that marketing, finance, operations, and customer service functions need to operate on aligned definitions and goals.

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Shmueli (2010) draws a distinction between explanatory and predictive models. This distinction is crucial because accurate predictions do not imply causation. Customer predicted to buy can make the purchase regardless of the campaign exposure. Therefore, quality of predictions cannot be considered a proof of campaign incrementality.

Attribution and Experimental Measurement

Conversion attribution in multichannel marketing accounting for carryover and spillover effects is investigated in Li and Kannan (2014). The findings imply that channel contributions can differ from what is shown by commonly used attribution metrics.

Attribution beyond the last touchpoint is considered by Berman (2018). The paper further supports treating attribution as a modeling problem rather than allocation of credits to the last interaction.

Comparison of observational advertising measurements and large randomized experiments is provided by Gordon et al. (2019). The findings imply that abundant observational data do not lead to estimates consistent with randomized experiments. Therefore, randomized comparison of different policies can be more solid foundation for evaluation of targeting changes than observational comparison of customers exposed to different levels of communications.

Precision of advertising return estimation in large-scale experiments is discussed by Lewis and Rao (2015). The authors argue for reporting uncertainty and refraining from definitive conclusions in case of small differences between campaigns.

Customer Selection and Intervention Value

Ascarza (2018) argues that customers with the highest predicted churn risk are not necessarily the best targets for retention intervention. The paper highlights the distinction between prediction and detection of customers whose behavior can be influenced. The distinction is also relevant to acquisition and promotion campaigns.

Research Gap

The above literature sets the importance of analytics, customer journeys, organizational capabilities, and experimental measurement. The present paper narrows the focus to the specific operational question: how to evaluate the incremental value of business-informed targeting compared with both traditional targeting and analytics-based targeting?

The proposed framework views business insights as documented decision rules so that contribution of business rules is reviewable and management decisions don't serve as unreported justification of results after the fact.

Research Objectives and Hypotheses

The main objective of the research is to test whether integration of business rules into analytical targeting increases customer conversion compared with analytics-based targeting. Secondary objectives include comparison of both approaches with traditional targeting and evaluation of their financial implications under common assumptions.

Primary null hypothesis states that integrated targeting and analytics-based targeting have the same probability of conversion. Secondary null hypotheses compare integrated targeting and traditional targeting, and analytics-based targeting and traditional targeting.

Measures of profitability are descriptive. Testing of revenue variability is not performed because of lack of customer-level transaction data

Methodology

Research Design

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Numerical analysis is performed for three synthetic campaign groups of 10,000 customers each. Counts are specified for transparency of scenario analysis; statistical quantities are computed based on these counts. No claims are made regarding actual customer records, organizational interviews, or complete field experiment.

Field design should involve random allocation of eligible customers into three policy groups prior to campaign implementation. All policies would operate during the same period with the same spending ceiling. The unit of allocation and analysis should be the customer rather than impression or click.

Common 30-day purchase window would help mitigate discrepancies arising from different attribution settings on platforms. All allocated customers stay in their original groups regardless of any communications received under suppression rule.

Campaign Strategies

Traditional targeting is based on broad eligibility criteria and common communication rules. Analytics-based targeting ranks customers according to frozen purchase propensity score based on information available before the allocation of customers.

Integrated targeting starts with the same ranking and then applies predefined business rules. Business rules suppress promotion of unavailable products, exclude customers with open complaints, adhere to contact limitations, and favor eligible products meeting contribution threshold.

Performance of integrated strategy is assessed as the whole bundle; its results don't allow to detect individual contributions of each business rule.

Table 1. Campaign Strategy Specifications

Component	Conventional	Analytics-led	Integrated
Assigned customers	10,000	10,000	10,000
Targeting basis	Broad eligibility	Propensity ranking	Propensity ranking plus business rules
Campaign spending	₹120,000	₹120,000	₹120,000
Purchase window	30 days	30 days	30 days
Offer value	Standardized	Standardized	Standardized
Financial assumptions	Common	Common	Common

Outcome Definitions

Conversion rate is defined as the number of customers with at least one purchase divided by the total number of allocated customers. In terms of financial calculation, it is assumed that each converting customer buys one purchase.

Order value is fixed to ₹1,000, and contribution margin before campaign spending is fixed at 35%. The margin accounts for product costs, discounts, returns, and fulfillment costs.

Revenue is calculated as number of purchases times average order value. Return on advertising spend is the ratio of revenue to campaign spending. Cost per converting customer equals spending divided by the number of converting customers.

Net contribution after spending equals revenue times contribution margin minus campaign spending. This measure excludes fixed costs and therefore doesn't reflect overall organizational profit.



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Statistical Analysis

Two-sided pooled two-proportion z-test is used to compare conversion rates. Unpooled normal approximation is used to compute 95% confidence interval for difference between conversion rates. Primary comparison uses significance level of 0.05.

Secondary comparisons use Holm's adjustment to account for multiple testing in the secondary family. Financial ratios are computed using common assumptions.

These tests describe what the specified counts would imply under independent Bernoulli sampling. They don't provide real-world evidence or account for the absence of observed data.

Results

Conversion Performance

Traditional targeting makes 400 customers convert, analytics-based targeting makes 470 customers convert, and integrated targeting makes 520 customers convert. The conversion rates are 4.00%, 4.70%, and 5.20% respectively.

Integrated targeting exceeds traditional targeting in the number of conversions by 120, and analytics-based targeting by 50. Corresponding relative increases in conversion rates are 30.00% and 10.64% respectively.

Table 2. Simulated Campaign and Financial Outcomes

Measure	Conventional	Analytics-led	Integrated
Assigned customers	10,000	10,000	10,000
Converting customers	400	470	520
Conversion rate	4.00%	4.70%	5.20%
Revenue	₹400,000	₹470,000	₹520,000
Campaign expenditure	₹120,000	₹120,000	₹120,000
Cost per converting customer	₹300.00	₹255.32	₹230.77
Return on advertising spend	3.33	3.92	4.33
Contribution before campaign expenditure	₹140,000	₹164,500	₹182,000
Net contribution after campaign expenditure	₹20,000	₹44,500	₹62,000

Integrated targeting decreases cost per converting customer by 23.08% compared with traditional targeting. Its net contribution exceeds the contribution of the traditional policy by ₹42,000 and the contribution of the analytics-based policy by ₹17,500.

These comparisons concern different campaign strategies. As all groups receive some marketing policy, the calculations do not prove the absolute increment of advertising compared with no campaign.

Statistical Comparisons

Primary comparison produces 0.50 percentage point difference between integrated and analytics-based targeting. The confidence interval contains zero, and p-value is greater than 0.05; therefore, the primary null hypothesis is not rejected.

Table 3. Conversion Rate Comparisons

Comparison	Difference, percentage points	95% confidence interval	z-statistic	Unadjusted p-value

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Integrated versus analytics-led	0.50	−0.10 to 1.10	1.630	0.1031
Integrated versus conventional	1.20	0.62 to 1.78	4.051	<0.0001
Analytics-led versus conventional	0.70	0.13 to 1.27	2.427	0.0152

Both secondary comparisons remain significant after Holm adjustment. The adjusted p-values are approximately 0.00010 for integrated vs. conventional and 0.0152 for analytics-based vs. conventional comparisons.

The confidence intervals reported are individual rather than simultaneous familywise intervals. The results show the clear distinction: both analytical strategies outperform traditional targeting under the specified counts, and contribution of business rules to incremental conversion rate is indeterminate.

Financial Sensitivity

Assumptions about contribution margin materially affect the commercial interpretation. The break-even contribution margins for traditional, analytics-based, and integrated targeting are 30.00%, 25.53%, and 23.08% respectively.

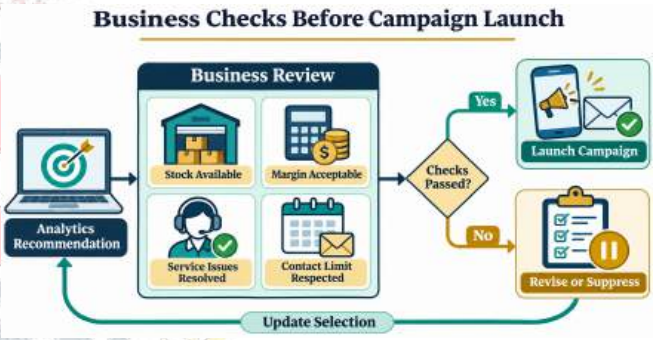
Table 4. [Missing title in original text] Net Contribution Under Alternative Margin Assumptions

Contribution margin	Conventional	Analytics-led	Integrated
25%	−₹20,000	−₹2,500	₹10,000
35%	₹20,000	₹44,500	₹62,000
45%	₹60,000	₹91,500	₹114,000

Under the central assumption, integrated targeting produces ₹17,500 higher net contribution than analytics-based targeting. Implementation costs higher than this difference would eliminate the simulated financial benefit, all other conditions being the same.

Discussion

The results show the importance of campaign assessment combining response measurement and financial interpretation. Higher conversion rate leads to higher revenue under the given order value; however, contribution is determined by the margin and campaign spending.



The most robust numerical finding is comparison with traditional targeting. Both analytical strategies outperform traditional targeting under the specified scenario. The principal research question concerns the incremental value provided by business insights; this comparison is statistically indeterminate.

This distinction prevents the descriptive ranking from being considered as evidence-based claim of superiority. Non-significance of the result does not imply equivalence; the interval is consistent with small disadvantage and with commercially important advantage.

Business rules may bring value in addition to immediate purchases. Suppression of unavailable products can reduce customer dissatisfaction; exclusion of customers with complaints can improve relationship management. These potential benefits are not covered by the current calculations and should be measured separately.

The framework also distinguishes the prediction from persuasion. Propensity model finds customers likely to make purchases; some customers will make purchase regardless of communication. Therefore, the

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prospective implementation should combine policy comparisons and holdout group or some other design for measuring campaign incrementality.

Managerial Implications

Organizations should start with common business goal and consistent outcome definition. Marketing team should have finance-approved contribution measures; operational team should provide inventory and service information timely.

Business rules should be documented prior to assessment. Documentation should state rule, its rationale, operational ownership, and the conditions when targeting changes occur. This will help in reproducing the assessment and prevent retrospective interpretation.

Campaign dashboard should include absolute differences, uncertainty intervals, spending, and contribution altogether. Reporting only relative improvements can overestimate practical significance in case of low baseline conversion rate.

Adoption decisions should also account for implementation costs. Integrated strategy leading to modest increment of revenue may not be advantageous if it requires expensive manual processing, complex integration, or high maintenance.

Limitations

The analysis is based on simulated aggregate counts and does not prove empirical effectiveness. There is no customer-level data to perform sub-group analysis, covariate adjustment, predictive model validation, or uncertainty estimation at the transaction level.

Common order values and contribution margins facilitate financial comparison. Actual campaigns can change basket composition, usage of discounts, return rates, and fulfillment costs.

It is important to point out that the framework does not separate the influence of inventory management rules, complaint suppression, and contribution thresholds as it deals with policy packages but not single mechanisms.

In addition, due to the lack of an untreated control group, it is impossible to measure the absolute value of incremental advertising contribution. A short-term study would understate delayed purchasing, repeat purchasing, and the influence on the clients.

Future Research

- The field study should be registered and pre-registered with the main comparison. The number of observations should be calculated based on the minimum effect size which can be regarded as commercially valuable. It is necessary to use an untreated control group if it is possible.
- Customer level contribution should be used instead of margin assumptions. A longer observation period is required to measure the contribution of repeat purchases, complaints, returns, and contact fatigue.
- Factorial experiment may help to separate the influence of different business rules. The comparison of uplift-based targeting with propensity ranking would allow us to learn whether targeting persuadable clients contributes to incremental contribution.

Conclusion

Combining analytics and business insight allows developing a framework for optimizing a marketing campaign when the decision rules and metrics are explicitly defined. In the simulation, integrated targeting gives the maximum contribution and conversion rate; however, the difference between analytics-driven targeting and other strategies is statistically insignificant. Therefore, the framework allows conducting disciplined experimentations and consistent measurement of financial contribution. For making empirical conclusions, it is required to substitute observed counts in the campaign for the simulated ones and to reestimate all associated metrics.

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