International Journal of Current Sciences and Engineering Intelligence
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
website: *https://ijcsi.com*
Volume 01, Issue 01, September 2026
OPEN ACCESS
E-ISSN :

Incremental Profit Based Budget Allocation Across Digital Marketing Channels

Ritika More[1], Shubham Yadav[2], Aditi Tiwari[3]
[1,2] Students, Nanasaheb Yashwantrao Narayanrao Chavan Arts Science Commerce College, Chalisgaon Dist. Jalgaon, Maharashtra (India)
[3] Assistant Professor, Nanasaheb Yashwantrao Narayanrao Chavan Arts Science Commerce College, Chalisgaon Dist. Jalgaon, Maharashtra (India)

Article Info

Article History:
Published: 14 Nov 2026

Publication Issue:
Volume 01, Issue 01
September 2026

Page Number:
20-26

Corresponding Author:
Ritika More

Abstract:
Digital marketing budgets are often allocated using recorded conversions even when those conversions include purchases that would have occurred without advertising. This paper develops a transparent allocation framework based on incremental orders, contribution margin, diminishing response, and channel constraints. A deterministic scenario compares a last touch motivated heuristic, an equal allocation adjusted for an email cap, and exhaustive optimization over permitted spending increments. With a budget of INR 60,000, the optimized allocation assigns INR 18,000 to search, INR 30,500 to social advertising, and INR 11,500 to email. It produces 353.72 expected incremental orders and INR 187,600.74 in modeled contribution after advertising spend. This is 10.14 percent above the heuristic and 2.66 percent above the balanced allocation. Sensitivity tests examine a weaker social response, a tighter email limit, and different total budgets. All response curves are constructed assumptions, not estimates from a merchant or advertising platform. The analysis demonstrates how causal measurement and constrained optimization answer different questions, and why an optimal allocation can be misleading when its response inputs are wrong. It provides a reproducible decision framework and an empirical validation plan rather than a promise of campaign returns.

Keywords: Marketing analytics; incremental advertising; causal inference; budget allocation; diminishing returns; contribution margin.

1 Introduction

Digital marketing dashboards provide detailed counts of impressions, clicks, attributed orders, and revenue. Their precision can create an impression that budget allocation is a straightforward ranking exercise. However, a customer who searches for a familiar brand and completes a purchase may have bought even if the advertisement had not appeared. Assigning the purchase to the last observed touchpoint answers an accounting question about the recorded path. It does not necessarily answer the managerial question of how many additional orders another unit of advertising will cause.

The causal distinction can be expressed through potential outcomes. Rubin's framework defines a treatment effect through the difference between outcomes under alternative treatment conditions [1]. In marketing, one condition may involve a campaign and another a suitable holdout. Only one condition is observed for a particular person at a particular time. A high conversion probability among exposed customers therefore cannot, by itself, establish a large advertising effect. Selection into exposure, prior purchase intention, and platform delivery rules all complicate interpretation.

Budget allocation adds another layer. Even a channel with a genuinely positive effect can exhibit diminishing returns as its most responsive audience is reached. A channel that appears weak at its present scale may deserve additional budget if its next spending increment has a larger marginal contribution. Managers must also respect inventory, delivery, audience permission, and operational limits. The relevant objective is consequently an incremental profit function subject to feasible spending constraints, not simply a maximization of total attributed conversions.

Copyright © 2026 The Author(s) : This is an open access article under the CC BY license (http://creativecommons.org/licenses/by-nc/4.0/)

This study constructs a small scenario that separates causal inputs from optimization logic. Three channel response curves are assumed, and three allocation policies are evaluated under the same budget and margin. The central question is whether explicitly accounting for diminishing incremental response changes the allocation and the resulting modeled contribution. The paper provides a reproducible numerical demonstration, sensitivity analysis, and a practical framework for collecting the missing empirical evidence. It does not use real customer records, estimate a platform's effectiveness, or claim that its numerical allocation should be adopted by an actual business.

2 Detailed Literature Review

Rosenbaum and Rubin show how propensity scores can support adjustment for observed covariates under identification assumptions [2]. This is relevant to advertising data, where exposed and unexposed users can differ systematically. However, balancing observed variables does not automatically remove unobserved purchase intention. Lewis and Rao explain why measuring advertising returns can remain statistically difficult even with large experiments [3]. Their analysis supports separating uncertainty in effect estimation from the apparent precision of a dashboard or an optimization output.

Gordon and colleagues compare advertising measurement approaches against large field experiments [4]. Their work provides a concrete reason to question whether observational adjustment consistently reproduces experimental effects. Blake, Nosko, and Tadelis investigate paid search through a large scale field experiment and show the importance of consumer heterogeneity [5]. These studies do not imply that all advertising is ineffective. They show why the incremental response of a channel cannot safely be inferred from the number of purchases credited to it.

Ghost advertising methods improve experimental measurement by constructing informative counterfactual exposure opportunities [6]. Lewis and Reiley examine the connection between online advertising and offline sales through a controlled experiment [7]. Together, these contributions emphasize that measurement design must match the outcome of interest. A campaign may affect purchases outside the tracked website or change the timing of purchases. An allocation system should state its observation window, outcome definition, and treatment assignment mechanism before interpreting a measured lift as a durable commercial return.

Privacy and audience constraints also shape feasible campaigns. Goldfarb and Tucker examine privacy regulation and online advertising [8]. Their study motivates attention to changes in the information available for targeting without establishing the current legal requirements of any particular jurisdiction. Lambrecht and Tucker investigate when retargeting works and how information specificity matters [9]. The implication for the present model is that the effective audience is not an unlimited homogeneous pool. The chosen message and the customer's stage of consideration can change the response curve.

Sahni, Wheeler, and Chintagunta use field experiments to study email personalization [10]. Sahni, Narayanan, and Kalyanam examine the frequency and timing of retargeted advertising [11]. These papers demonstrate that campaign design affects response as well as channel choice. A budget model that treats all spending within a channel as identical may therefore miss creative changes, audience fatigue, or timing effects. The present exponential curves are a deliberately restricted abstraction, used to make the allocation logic interpretable rather than to describe every campaign mechanism.

Multichannel attribution research offers richer descriptions of customer journeys. Li and Kannan develop an empirical model and field experiment for attributing conversions across channels [12]. Anderl and colleagues examine graph based attribution [13], while Berman analyzes incentives and attribution beyond the last touch [14]. Such work shows that channel interactions and the assignment of credit are substantive modeling issues. Nevertheless, path decomposition and incremental budget response remain distinct estimands. A channel's credited share of completed journeys need not equal the additional sales generated by expanding that channel next month.

Heterogeneous effect estimation provides another route toward allocation. Athey and Imbens develop recursive partitioning for treatment effect heterogeneity [15]. Wager and Athey extend causal estimation through random forests [16], and Künzel and colleagues organize flexible treatment effect estimators as meta-learners [17]. These methods can inform audience selection when their data and identification requirements are satisfied. Gutierrez and Gérardy's review connects causal inference with uplift modeling [18]. For the current study, these contributions motivate future estimation of the response curves rather than supply their numerical parameters.

Optimization then converts a response model into a feasible action. Boyd and Vandenberghe provide the mathematical foundation for reasoning about constrained objectives and concavity [19]. Athey and Wager study policy learning with observational data and application specific constraints [20]. These perspectives make clear that estimation quality and decision quality are related but separate. An optimizer can solve its stated problem exactly while recommending a poor real campaign if the response model is biased, the margin is wrong, or a relevant constraint is omitted. This focused narrative review therefore supports a workflow that validates causal inputs before relying on an optimized allocation.

3 Detailed Methodology & Framework

3.1 Constructed response model

The scenario represents a hypothetical advertiser using search, social advertising, and email. Spending is measured in thousands of Indian rupees. Each channel's expected incremental orders follow an exponential saturation curve: the channel's maximum response multiplied by one minus an exponential decay term. Equation 1 defines the response and profit objective. The parameter a represents the asymptotic incremental orders, b controls the spending scale of saturation, and s is allocated spend. These parameters describe an assumed scenario and are not estimates from any cited study.

$$F_i(s_i) = a_i(1 - e^{-\frac{s_i}{b_i}})$$

$$max\ \Pi = 0.7 \sum_i F_i(s_i) - \sum_i s_i,\ \sum_i s_i \leq B$$

Equation 1. Saturating incremental response and constrained profit. Spend, budget B and profit are measured in thousands of INR; channel caps also apply.

Search uses a maximum response of 160 orders and a saturation scale of 12, with a spending cap of 30. Social uses 240 orders and a scale of 30, with a cap of 40. Email uses 100 orders and a scale of eight, with a cap of 15. Each incremental order contributes INR 700 after nonadvertising variable costs. The contribution is constant across channels, and expected refunds or fulfillment costs are assumed already included. Organic orders are omitted because the model compares only the additional contribution caused by advertising.

The total spending ceiling is INR 60,000. Spending is permitted in INR 500 increments, including zero. The email cap is an illustrative audience and contact limit, not a legal threshold. Channel responses are assumed additive, meaning that allocating to one channel does not change another channel's response. This is a strong simplifying assumption because real customer journeys may involve overlap and spillovers. Its purpose is to isolate the distinction between average credited performance and diminishing incremental response before introducing interactions.

3.2 Allocation policies and optimization

The last touch motivated comparator assigns INR 30,000 to search, INR 25,000 to social, and INR 5,000 to email. This allocation is stipulated to represent a manager favoring the channel that appears closest to purchase. No fabricated attribution dataset is used to claim that the allocation was empirically derived. The balanced comparator first divides the budget equally, then redistributes the INR 5,000 exceeding the email cap equally to the other channels. Its resulting allocation is INR 22,500, INR 22,500, and INR 15,000.

The optimization enumerates all feasible combinations on the INR 500 grid, calculates incremental orders and contribution for each combination, and selects the highest profit. The search space includes allocations that do not exhaust the budget. Full spending is therefore an output of this scenario, not a constraint that forces unprofitable expenditure. Exhaustive enumeration establishes the best solution on the specified discrete grid. It does not claim an exact continuous optimum or a universally optimal allocation outside the assumed response functions.

The economic logic is visible in marginal response. For a saturation curve, the first spending increments reach more responsive customers, while later increments generate fewer incremental orders. At an unconstrained continuous optimum, active channels have compatible marginal contribution after accounting for their constraints. If one channel's next increment is more productive, moving budget toward it can improve profit until the advantage disappears or a cap binds. Figure 1 connects this decision step with the experimental measurement and monitoring needed in a practical implementation.

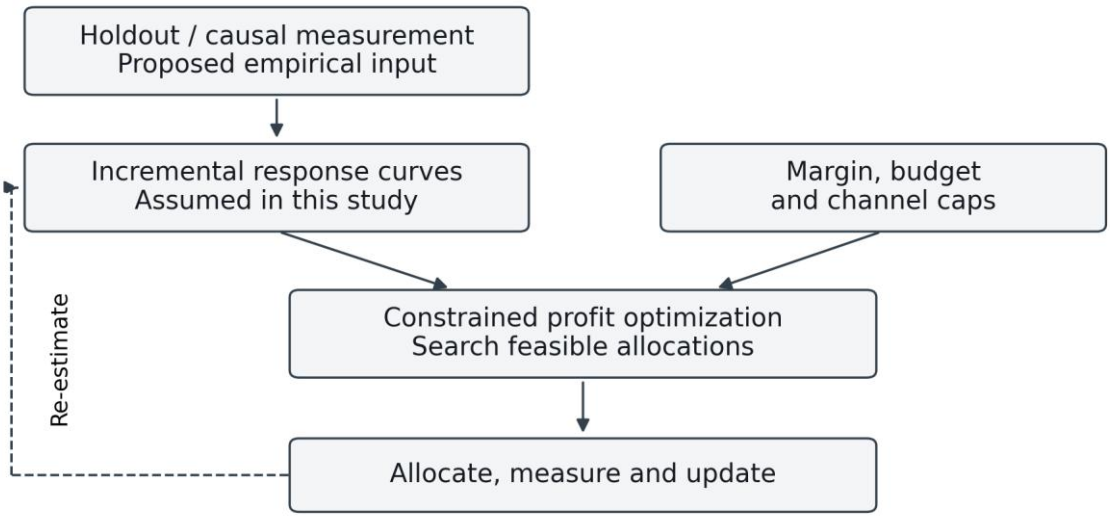


Figure 1. Allocation and measurement framework. This study supplies assumed response curves; causal measurement and feedback are proposed implementation steps.

3.3 Sensitivity and reproducibility

The first sensitivity test reduces social advertising's maximum incremental response by 20 percent, from 240 to 192, leaving its saturation scale unchanged. Both the original optimized allocation and a newly optimized allocation are evaluated under this weaker response. The second test tightens the email cap to INR 8,000. A third evaluates total budgets of INR 40,000 and INR 80,000 under the original channel parameters. These changes reveal the consequences of response uncertainty, operational restrictions, and diminishing portfolio returns.

All outputs are deterministic expectations. Fractional orders describe the response curve's expected outcome rather than literal partial purchases. The calculations do not support p-values, confidence intervals, or statements of statistical significance. An empirical application would estimate response curves from randomized spending or exposure variation, preserve holdout data, and propagate parameter uncertainty into the allocation decision. The reproduction script uses only exponential evaluation and finite enumeration, allowing every result to be checked without access to a proprietary platform or undisclosed customer dataset.

4 Detailed Results and Analysis

4.1 Comparative allocation outcomes

The optimized allocation spends INR 18,000 on search, INR 30,500 on social, and INR 11,500 on email. Table 1 compares these amounts with both baselines. The optimized policy produces 353.72 expected incremental orders, compared with 329.04 under the heuristic and 346.76 under the balanced allocation. Because each policy spends the same total amount, the contribution differences arise entirely from the response curves' interaction with the spending distribution.

Table 1. Allocation comparison for a budget of 60 thousand INR.

Policy	Search	Social	Email	Incremental orders	Profit
Last touch heuristic	30.0	25.0	5.0	329.04	170.33
Equal allocation + email cap	22.5	22.5	15.0	346.76	182.73
Profit optimization	18.0	30.5	11.5	353.72	187.60

Search, social and email allocations and profit are in thousands of INR. Orders are expected model outputs; all response curves are assumed.

Modeled contribution after advertising is INR 187,600.74 for the optimized allocation, INR 170,325.68 for the heuristic, and INR 182,731.82 for the balanced policy. Optimization therefore improves modeled contribution by 10.14 percent relative to the heuristic and by 2.66 percent relative to the balanced policy. The smaller second improvement matters for interpretation. A simple balanced rule is already competitive in this constructed scenario; adding an optimizer creates value only if its estimation, implementation, and monitoring costs do not exceed the attainable gain.

The optimized policy does not maximize spending in the channel with the largest initial response per rupee. Search's early increments are productive, but it saturates more rapidly than social advertising. Email also has strong early response but a smaller maximum audience. Allocating some budget to each channel and then comparing marginal gains produces a different decision from ranking channels by their average performance. The exact spending amounts are scenario specific, while the logic of marginal comparison is general to separable diminishing response models.

4.2 Response uncertainty and constraints

When social response is reduced by 20 percent, the original optimized allocation yields INR 166,157.19 in contribution. Reoptimization shifts spending to INR 20,000 for search, INR 27,500 for social, and INR 12,500 for email, yielding INR 166,833.34. The approximately INR 676 recovery is small relative to the loss caused by weaker response. This distinction is important: rearranging budget cannot compensate for every deterioration in campaign effectiveness. Better creative, offer design, or measurement may matter more than repeatedly solving the same allocation problem.

Restricting email to INR 8,000 produces an optimized allocation of INR 19,000 to search and INR 33,000 to social, with contribution of INR 185,333.66. The modeled cost of this tighter constraint is approximately INR 2,267 compared with the original optimum. Such a calculation can inform operational discussions, but it does not justify violating the constraint. Audience permission, contact frequency, and service capacity remain inputs to the feasible set rather than penalties that can be ignored when an optimizer finds more revenue elsewhere.

At a budget of INR 40,000, optimized contribution is INR 157,247.22. Increasing the budget to INR 60,000 raises it by approximately INR 30,354. Increasing the budget again to INR 80,000 adds only approximately INR 13,434, producing INR 201,035.21. The decreasing increment reflects saturation and binding channel caps. A business should compare these additional contributions with the opportunity cost of funds and implementation effort, while recognizing that the figures here are constructed analytical results and not forecasts.

4.3 Interpretation limits

The largest limitation is additive channel response. Search may capture demand created by social exposure, and an email may shift the timing of an already planned order. If these interactions are ignored, independently estimated curves can double count incremental outcomes. The constant contribution assumption also excludes differences in product mix, returns, acquisition quality, and repeat purchase value. Consequently, the numerical comparison supports the internal logic of incremental allocation but does not establish that the same channel ranking would hold for any particular advertiser.

5 Future Enhancement

An empirical extension should begin with a clearly defined conversion window and a contribution measure that includes expected refunds and service costs. Randomized holdouts or controlled geographic spending changes could identify incremental response over a realistic range of budgets. The resulting curves should be checked on withheld periods, with uncertainty intervals retained rather than replaced by single optimistic estimates. Experiments should also examine cross-channel overlap so that combined effects are not counted repeatedly.

The allocation framework can then incorporate uncertain margins, inventory limits, creative fatigue, and intertemporal effects. A robust policy could avoid allocations whose apparent advantage disappears under plausible parameter changes. Exploration budgets may be justified when learning about a poorly understood channel has future value, but that value should be distinguished from immediate sales contribution. These developments would make the model

more realistic while preserving the core requirement that attribution, causal estimation, and allocation remain separately auditable stages.

6 Conclusion

Incremental profit based allocation provides a coherent alternative to distributing budgets according to recorded conversion credit. In the stated scenario, explicitly modeling diminishing returns produces a feasible allocation with greater expected contribution than either a last touch motivated heuristic or a balanced rule. The gain over the balanced rule is modest, which helps place the value of optimization in perspective.

The decisive requirement is credible response estimation. An optimizer does not turn biased attribution into causal evidence, and reallocation cannot fully recover the effects of weaker campaign response. The paper therefore offers a reproducible analytical framework and a structured route toward empirical testing. Its numerical values demonstrate conditional relationships among response, margin, budget, and constraints; they should not be presented as measured campaign results or adopted as forecasts without appropriate data and validation.

References

[1] Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of Educational Psychology, 66(5), 688-701. doi: 10.1037/h0037350

[2] Rosenbaum, P. R., and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55. doi: 10.1093/biomet/70.1.41

[3] Lewis, R. A., and Rao, J. M. (2015). The Unfavorable Economics of Measuring the Returns to Advertising. Quarterly Journal of Economics, 130(4), 1941-1973. doi: 10.1093/qje/qjv023

[4] Gordon, B. R., Zettelmeyer, F., Bhargava, N., and Chapsky, D. (2019). A Comparison of Approaches to Advertising Measurement: Evidence from Big Field Experiments at Facebook. Marketing Science, 38(2), 193-225. doi: 10.1287/mksc.2018.1135

[5] Blake, T., Nosko, C., and Tadelis, S. (2015). Consumer Heterogeneity and Paid Search Effectiveness: A Large-Scale Field Experiment. Econometrica, 83(1), 155-174. doi: 10.3982/ECTA12423

[6] Johnson, G. A., Lewis, R. A., and Nubbemeyer, E. I. (2017). Ghost Ads: Improving the Economics of Measuring Online Ad Effectiveness. Journal of Marketing Research, 54(6), 867-884. doi: 10.1509/jmr.15.0297

[7] Lewis, R. A., and Reiley, D. H. (2014). Online ads and offline sales: Measuring the effect of retail advertising via a controlled experiment on Yahoo! Quantitative Marketing and Economics, 12, 235-266. doi: 10.1007/s11129-014-9146-6

[8] Goldfarb, A., and Tucker, C. E. (2011). Privacy Regulation and Online Advertising. Management Science, 57(1), 57-71. doi: 10.1287/mnsc.1100.1246

[9] Lambrecht, A., and Tucker, C. (2013). When Does Retargeting Work? Information Specificity in Online Advertising. Journal of Marketing Research, 50(5), 561-576. doi: 10.1509/jmr.11.0503

[10] Sahni, N. S., Wheeler, S. C., and Chintagunta, P. (2018). Personalization in Email Marketing: The Role of Noninformative Advertising Content. Marketing Science, 37(2), 236-258. doi: 10.1287/mksc.2017.1066

[11] Sahni, N. S., Narayanan, S., and Kalyanam, K. (2019). An Experimental Investigation of the Effects of Retargeted Advertising: The Role of Frequency and Timing. Journal of Marketing Research, 56(3), 401-418. doi: 10.1177/0022243718813987

[12] Li, H., and Kannan, P. K. (2014). Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment. Journal of Marketing Research, 51(1), 40-56. doi: 10.1509/jmr.13.0050

[13] Anderl, E., Becker, I., von Wangenheim, F., and Schumann, J. H. (2016). Mapping the customer journey: Lessons learned from graph-based online attribution modeling. International Journal of Research in Marketing, 33(3), 457-474. doi: 10.1016/j.ijresmar.2016.03.001

[14] Berman, R. (2018). Beyond the Last Touch: Attribution in Online Advertising. Marketing Science, 37(5), 771-792. doi: 10.1287/mksc.2018.1104

[15] Athey, S., and Imbens, G. (2015). Recursive Partitioning for Heterogeneous Causal Effects. arXiv preprint, arXiv:1504.01132. Source

[16] Wager, S., and Athey, S. (2015). Estimation and Inference of Heterogeneous Treatment Effects using Random Forests. arXiv preprint, arXiv:1510.04342. Source

[17] Künzel, S. R., Sekhon, J. S., Bickel, P. J., and Yu, B. (2017). Meta-learners for Estimating Heterogeneous Treatment Effects using Machine Learning. arXiv preprint, arXiv:1706.03461. Source

[18] Gutierrez, P., and Gérardy, J.-Y. (2017). Causal Inference and Uplift Modelling: A Review of the Literature. Proceedings of Machine Learning Research, 67, 1-13. Source

[19] Boyd, S., and Vandenberghe, L. (2004). Convex Optimization. Cambridge University Press. Source

[20] Athey, S., and Wager, S. (2021). Policy Learning With Observational Data. Econometrica, 89(1), 133-161. doi: 10.3982/ECTA15732