



AI-Driven Optimization of Multi-Channel Digital Campaigns Using Predictive Analytics and Project Management Frameworks

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ABSTRACT: AI-driven digital campaign optimization has improved customer targeting, channel choice, and budget allocation, but many campaign models still assume that a recommended action can be implemented without friction. That assumption is weak in subscription-based direct-to-consumer e-commerce, where campaign value depends on customer response as well as creative approval speed, sprint stability, backlog control, task completion, cross-functional handoffs, and rework frequency. This study develops and evaluates a sprint-aware causal AI framework for multi-channel digital campaign optimization by integrating predictive uplift analytics with agile project-execution reliability signals. The analysis uses a quantitative longitudinal causal machine-learning design based on customer-campaign observations, CRM records, campaign exposure logs, channel-spend data, transaction records, subscription activity, and project-management workflow records across email, SMS, paid social, paid search, app push, and display retargeting campaigns. Five campaign optimization models were compared: rule-based allocation, response prediction, attribution-based optimization, causal uplift modeling without sprint data, and the proposed sprint-aware causal AI model. The proposed model produced the strongest results, with AUUC = 0.286, Qini coefficient = 0.241, incremental ROAS = 3.18x, CAC reduction = 18.4%, and CLV uplift = 14.7%. It improved incremental campaign performance by 24% to 31% compared with conventional AI-based campaign optimization. The results show that customer-channel uplift allocation accuracy mediates the effect of AI-driven optimization on campaign performance, while agile project-execution reliability strengthens the realization of AI-generated campaign recommendations. The study contributes a causal and execution-aware framework for improving campaign allocation decisions in subscription-based D2C e-commerce.

KEYWORDS: Causal AI; digital campaign optimization; uplift modeling; agile project management; multi-channel marketing; D2C e-commerce; execution reliability

I. INTRODUCTION

Digital campaign optimization is a central analytical problem for subscription-based direct-to-consumer e-commerce firms. These firms rely on repeated customer engagement, renewal behavior, cross-channel communication, and disciplined acquisition spending. Email, SMS, paid social, paid search, app push, and display retargeting are rarely managed as isolated channels. They operate as connected campaign systems in which audience selection, launch timing, creative readiness, budget allocation, and conversion measurement interact continuously [1], [2], [3]. Predictive analytics and AI-based campaign models have improved the ability of firms to identify likely responders, personalize communication, allocate budgets, and measure channel contribution [4], [5], [6].

Campaign performance, however, is not determined only by whether a model identifies the right customer or channel. It also depends on whether the campaign team can execute the recommendation on time and with sufficient coordination. This issue is visible in subscription-based D2C e-commerce because revenue is tied to acquisition, renewal, repeat purchase, and customer lifetime value. A statistically promising campaign recommendation can lose value when creative assets are delayed, sprint capacity is overloaded, backlog priorities change, approval cycles slow down, or handoffs between marketing, analytics, content, and paid-media teams are poorly coordinated. Under these conditions, timing relevance declines, budget may be misallocated, and high-uplift customer segments may receive messages too late. These operational frictions directly affect incremental conversion, customer acquisition cost, incremental return on advertising spend, and customer lifetime value [7], [8], [9].



Current studies on digital campaign optimization have mostly focused on personalization, attribution, segmentation, predictive analytics, response modeling, and customer journey analytics [10], [11], [12]. These streams have improved marketing decision-making, but they often treat campaign execution as a downstream implementation issue rather than as part of the optimization problem. Response prediction models estimate the probability that a customer will respond, but they do not identify whether the customer would have responded without treatment [13], [14]. Attribution models estimate channel contribution, yet they often struggle with incrementality and causal identification [15], [16]. Uplift modeling addresses part of this limitation by estimating incremental treatment effects, but most uplift models still emphasize customer and channel features rather than execution constraints [17], [18], [19].

The research gap addressed in this paper is specific. AI-based campaign optimization studies have not sufficiently integrated agile project-execution reliability into causal campaign allocation models. Campaigns are delivered through project systems. Sprint velocity stability, task completion rate, creative approval delay, backlog volatility, campaign handoff lag, and rework frequency influence whether AI-generated campaign recommendations become realized business outcomes. Ignoring these variables can create a clear gap between predicted campaign value and actual campaign value.

This study develops and evaluates a sprint-aware causal AI optimization framework for multi-channel digital campaigns in subscription-based D2C e-commerce. The framework combines customer-channel uplift prediction with agile project-execution reliability signals. It compares five models: rule-based campaign allocation, response prediction, attribution-based optimization, causal uplift modeling without sprint data, and sprint-aware causal AI optimization. The analysis also examines mediation through customer-channel uplift allocation accuracy and moderation through agile project-execution reliability.

The contribution is threefold. First, the study extends AI-based campaign optimization by treating execution reliability as part of the campaign value-generation process. Second, it contributes a causal uplift-based model that evaluates campaign recommendations by predicted incremental response and execution feasibility. Third, it provides evidence that project-management variables such as approval delay, backlog volatility, sprint stability, task completion, handoff lag, and rework frequency affect realized marketing performance.

II. LITERATURE REVIEW

2.1 AI-Driven Digital Campaign Optimization

AI-driven campaign optimization refers to the use of algorithmic models to improve customer targeting, timing, budget allocation, creative selection, and channel sequencing. Marketing analytics research has shown that firms improve decision quality when customer data, channel data, and transaction data are used systematically [1], [3], [4]. The proliferation of data in marketing has enabled predictive models to identify client groupings, assess purchase likelihood, gauge the response to marketing campaigns, and more efficiently allocate marketing resources [1], [5]. The development of AI has also extended the breadth of marketing decision-making through enabling personalization, automation of services and customer relationship management [4], [6]. Subscription-based D2C e-commerce campaigns are more complex to optimize than campaigns for single-purchase products. Companies need to grow, gain consumers, decrease churn, promote renewals and boost lifetime value. This involves many touches across email, SMS, paid social, paid search, app push and retargeting.

Customer journey research shows that customers interact with firms across multiple touchpoints and that channel effects are distributed over time rather than concentrated in a single exposure [2], [10], [11]. Digital campaign models therefore need to account for channel sequencing, prior engagement, customer recency, monetary value, campaign frequency, and subscription behavior [7], [8], [12].

One limitation remains important. AI-driven campaign optimization can become overly focused on prediction accuracy. A model may estimate that a customer is likely to convert, but this does not prove that the campaign caused the conversion. Similarly, a channel may receive high attribution credit, although that credit may not reflect incremental impact [13], [15], [16]. This limitation has encouraged greater interest in causal methods and uplift modeling in marketing analytics [17], [18], [19].

2.2 Multi-Channel Attribution and Budget Allocation

Multi-channel attribution attempts to estimate how different marketing channels contribute to conversion. Attribution models have been used to improve budget allocation and evaluate the customer journey across paid and owned



channels [15], [16], [20]. Earlier approaches relied on rules such as first-click, last-click, or equal-weight attribution. Later methods estimate the channel contribution more accurately using probabilistic, Markov, graph-based and econometric methods [15], [16], [20].

However, the attribution-based optimization has limitations for causal decision-making, notwithstanding its progress. Attribution models can describe how past conversions were associated with touchpoints, but they do not always estimate what would have happened without campaign exposure. This distinction is important because campaign managers need to know which customers are persuadable, not just which customers are likely to buy [13], [17]. A high-propensity consumer may buy even without a campaign, while a lower-propensity customer may turn into a valued customer when targeted at the right channel, at the right moment.

Budget allocation is also required for execution preparedness. Even if an attribution model identifies paid social or app push as a high-performing channel, the campaign may underperform if creative approval is delayed or if the sprint backlog changes before launch. Marketing accountability research has emphasized the need to connect marketing activity with financial outcomes such as ROAS, CAC, and CLV [7], [8], [9]. That connection remains incomplete unless the operational conditions of campaign delivery are also measured.

2.3 Causal Uplift Modeling in Marketing Analytics

Causal uplift modeling estimates the incremental effect of a treatment on an outcome. In campaign settings, the treatment may be an email, SMS offer, app push notification, paid social exposure, or retargeting message. The outcome may be conversion, renewal, purchase value, or subscription retention. Unlike response prediction, uplift modeling separates customers who are likely to respond because of the campaign from customers who would have converted anyway [17], [18], [19].

This distinction is central to campaign optimization. Response prediction can lead to wasted budget when it targets customers who already have high natural conversion probability. Uplift modeling allows to enhance allocation by finding consumers with a favorable incremental treatment effect [17], [18]. The quality of uplift ranking is usually evaluated by metrics like Area Under the Uplift Curve and Qini coefficient [18], [19]. These measures are more appropriate to use than regular accuracy or AUC when the goal is incremental campaign value rather than categorization performance.

Recent causal machine-learning methods have strengthened uplift estimation. Causal forests, generalized random forests, and double machine learning allow researchers to estimate heterogeneous treatment effects while handling high-dimensional feature sets [21], [22], [23], [24]. These methods are valuable for digital marketing because customer behavior, channel exposure, campaign history, and transaction variables can interact in nonlinear ways. Most uplift applications, however, still focus mainly on customers and channels. The project-execution context in which the campaign is launched remains less developed.

2.4 Agile Project-Execution Reliability in Campaign Delivery

Digital campaigns are analytical decisions, but they are also projects. Campaign teams must define audiences, prepare creative assets, approve copy, configure channels, schedule launches, review compliance, monitor performance, and adjust spend. Agile project-management practices are often used to coordinate this work through sprints, backlogs, task boards, and cross-functional workflows [25], [26], [27]. Agile methods can increase responsiveness and coordination, but their worth is determined by the reliability of their execution [28], [29].

Agile project-execution reliability in campaign delivery involves sprint velocity stability, task completion rate, creative approval delay, backlog volatility, handoff lag and rework frequency. The stability of the sprint velocity decides whether the team is able to execute the intended work in the sprint cycle. Task completion rate represents discipline of execution. Creative approval delay causes bottlenecks in assessment and approval. Backlog volatility is a sign of fluctuating priorities. The handoff latency measures delays between functions like as analytics, content, design, and media buying. Rework frequency is a measure of needless revision cycles. These elements have a direct impact on campaign performance. If a high-uplift campaign misses the scheduled launch window it can underperform. A big paid-social opportunity can lose its worth if the creative is not approved on time.

A retargeting campaign may become inefficient if audience rules are approved after customer intent has changed. The Theory of Constraints suggests that performance is limited by bottlenecks in the system [30]. Applied to campaign delivery, workflow constraints can prevent AI recommendations from producing their intended business effect.



2.5 Research Gap

The literature shows strong development in AI-driven campaign optimization, multi-channel attribution, causal uplift modeling, and agile project management [1], [4], [15], [18], [25]. These streams, however, remain insufficiently integrated. Marketing analytics studies commonly examine customer behavior, channel effects, and campaign outcomes, while project-management studies examine sprint delivery, workflow control, and task execution. The unresolved gap is the absence of a causal campaign optimization model that includes agile project-execution reliability as a measurable condition of realized campaign performance. This study addresses that gap by developing and testing a sprint-aware causal AI model for subscription-based D2C e-commerce campaigns.

III. THEORETICAL FOUNDATION AND HYPOTHESES DEVELOPMENT

3.1 Dynamic Capability Theory

Dynamic Capability Theory explains how organizations perceive opportunities, grasp them and restructure resources under changing market conditions [31], [32]. Predictive analytics supports sensing in the digital campaign optimization by identifying customer opportunities and channel-level response patterns. AI-driven campaign tools help to seize by suggesting combinations of audience, channel and budget. For example, corporations modify budgets, creative delivery, channel schedules, and targeting criteria across campaigns; this is called resource reconfiguration. This hypothesis is appropriate for the present investigation since subscription-based D2C e-commerce enterprises are operating in fast-changing client settings. Customer intent, channel costs, subscription status, discount sensitivity and engagement signals are all moving.

AI-driven optimization helps firms respond to these changes, but dynamic capability remains incomplete if the organization cannot execute the campaign recommendation. A firm may sense a high-value campaign opportunity, but it cannot fully seize that opportunity when approval delay, backlog volatility, or handoff lag prevents timely activation.

3.2 Theory of Constraints

The Theory of Constraints argues that system performance is limited by its most restrictive bottleneck [30]. In digital campaign delivery, bottlenecks may appear in creative approval, sprint capacity, backlog stability, handoff processes, or rework cycles. Even if the AI prediction is correct, these bottlenecks can diminish the actual impact of ad recommendations.

The theory supports agile project-execution dependability as a moderating condition. Execution reliability is high, AI-generated recommendations can be better executed. A campaign may deliver less value than forecast if reliability of execution is low. The idea therefore explains why campaign optimization requires both analytical competence and operational throughput.

3.3 Hypotheses Development

AI-driven predictive campaign optimization should improve campaign performance because it enables better customer targeting, channel selection, budget allocation, and timing decisions [1], [4], [5]. Therefore:

H1: AI-driven predictive campaign optimization has a positive effect on multi-channel campaign performance. AI optimization should also improve customer-channel uplift allocation accuracy because models can identify customer-channel combinations with higher incremental value [17], [18], [21]. Therefore:

H2: AI-driven predictive campaign optimization has a positive effect on customer-channel uplift allocation accuracy. Customer-channel uplift allocation accuracy should improve performance because campaigns become focused on customers who are more likely to generate incremental response rather than natural conversion [17], [18], [19]. Therefore:

H3: Customer-channel uplift allocation accuracy has a positive effect on multi-channel campaign performance. The effect of AI optimization on performance is likely to operate through improved uplift allocation. AI improves decision quality by identifying high-uplift customer-channel combinations, and those better allocations improve campaign outcomes [21], [22]. Therefore:

H4: Customer-channel uplift allocation accuracy mediates the relationship between AI-driven predictive campaign optimization and multi-channel campaign performance. Finally, agile project-execution reliability should strengthen the effect of AI optimization on campaign performance. When sprint velocity is stable, approvals are timely, backlogs are



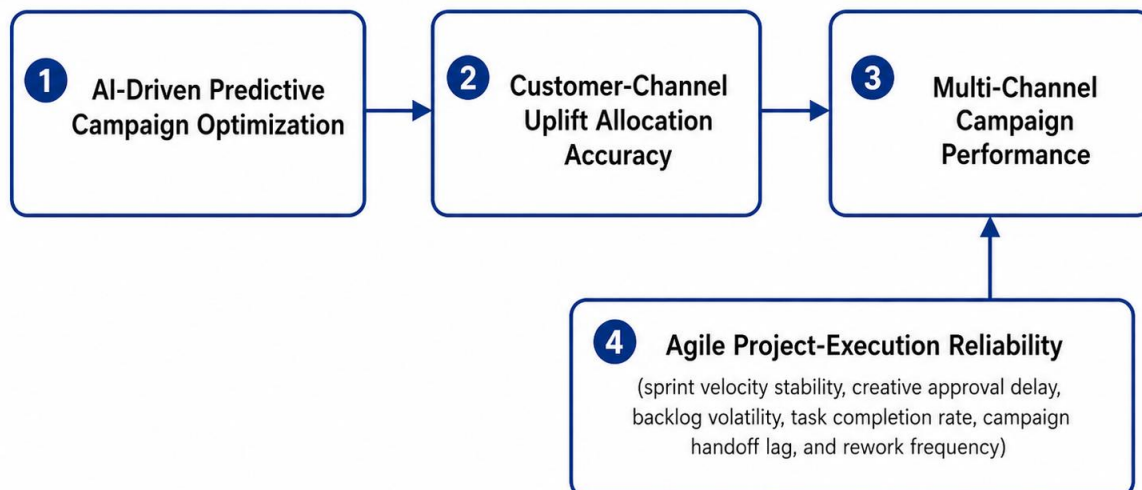
controlled, and handoffs are efficient, AI recommendations are more likely to be implemented as planned [25], [26], [30]. Therefore:

H5: Agile project-execution reliability positively moderates the relationship between AI-driven predictive campaign optimization and multi-channel campaign performance.

IV. CONCEPTUAL FRAMEWORK

The conceptual framework connects AI-driven predictive campaign optimization, customer-channel uplift allocation accuracy, agile project-execution reliability, and multi-channel campaign performance. AI-driven optimization is expected to improve campaign performance directly and indirectly through better uplift allocation. Customer-channel uplift allocation accuracy acts as the mediating mechanism because it explains how AI recommendations become more valuable. Agile project-execution reliability acts as the moderating condition because it determines whether campaign recommendations are executed within the intended timing and workflow conditions.

Figure 1. Conceptual framework of sprint-aware causal AI campaign optimization



The framework treats campaign optimization as both a causal prediction problem and an execution-reliability problem. It does not assume that AI-generated recommendations automatically produce performance improvements. Instead, it tests whether execution conditions shape the realized value of those recommendations.

V. METHODOLOGY

5.1 Research Design

The study used a quantitative longitudinal causal machine-learning design. This design was appropriate because the research problem required customer-campaign observations, channel-level performance data, transaction outcomes, and project-management workflow records across time. The design also allowed comparison between conventional campaign allocation models and the proposed sprint-aware causal AI model.

5.2 Research Context

The empirical context was subscription-based D2C e-commerce. The campaigns covered six digital channels: email, SMS, paid social, paid search, app push, and display retargeting. These channels were selected because they are commonly used in subscription-based customer acquisition, reactivation, retention, and renewal campaigns. The analysis focused on campaigns where customer exposure, channel spend, conversion outcomes, and workflow execution records were available.



5.3 Data Sources

The dataset integrated CRM records, campaign exposure logs, channel-spend records, transaction records, subscription renewal and cancellation data, website/app analytics, project-management workflow records, sprint-board data, task completion logs, and creative approval records. The customer-campaign panel included more than 100,000 customer-campaign observations and 12 to 18 months of workflow records. Customer identifiers were anonymized before analysis.

5.4 Variables and Measurement

Table 1. Variables and operational measurement

Construct	Measurement
AI-driven predictive campaign optimization	AI-based targeting, channel selection, and budget recommendation
Customer-channel uplift allocation accuracy	AUUC, Qini coefficient, uplift precision
Multi-channel campaign performance	Incremental ROAS, conversion uplift, CAC reduction, CLV uplift
Agile project-execution reliability	Sprint velocity stability, approval delay, backlog volatility, task completion rate, handoff lag, rework frequency
Control variables	Campaign budget, channel type, customer segment, discount intensity, campaign duration, seasonality, prior engagement

5.5 Model Development

Five models were developed and compared. The first was rule-based campaign allocation, which used predefined channel and budget rules. The second was a response prediction model, which estimated the probability of customer response. The third was attribution-based optimization, which allocated campaign value based on channel contribution. The fourth was causal uplift modeling without sprint data, which estimated customer-channel incremental response but excluded workflow reliability indicators. The fifth was the sprint-aware causal AI model, which combined uplift estimation with execution-reliability signals.

5.6 Analysis Technique

The main analysis used causal uplift modeling with execution-constrained optimization. AUUC and Qini coefficient were used to evaluate uplift-ranking performance. Incremental ROAS, CAC reduction, and CLV uplift were used to evaluate business performance. Hypothesis testing was used to examine direct, mediating, and moderating relationships. Project-execution factor analysis estimated the effect of sprint velocity stability, task completion rate, creative approval delay, backlog volatility, campaign handoff lag, and rework frequency on campaign performance.

VI. RESULTS

6.1 Main Result Summary

Table 2. Main result summary

Result Area	Finding
AI optimization effect	AI-driven predictive campaign optimization significantly improved campaign performance
Mediation effect	Customer-channel uplift allocation accuracy mediated the relationship between AI optimization and campaign performance
Moderation effect	Agile project-execution reliability strengthened the effect



Result Area	Finding
	of AI optimization on campaign performance
Strongest project-management factor	Creative approval delay and backlog volatility had the strongest negative effect on campaign outcomes
Best-performing model	The sprint-aware causal AI model outperformed response prediction, attribution-based allocation, and non-sprint-aware AI optimization
Practical outcome	The model improved incremental ROAS, reduced CAC, increased conversion uplift, and improved CLV uplift

The results show that campaign performance depended on both predictive optimization and execution reliability. AI-driven optimization improved performance, but its effect was stronger when sprint and workflow execution conditions were stable. Customer-channel uplift allocation accuracy was the key mechanism through which AI optimization improved campaign outcomes.

6.2 Model Comparison Results

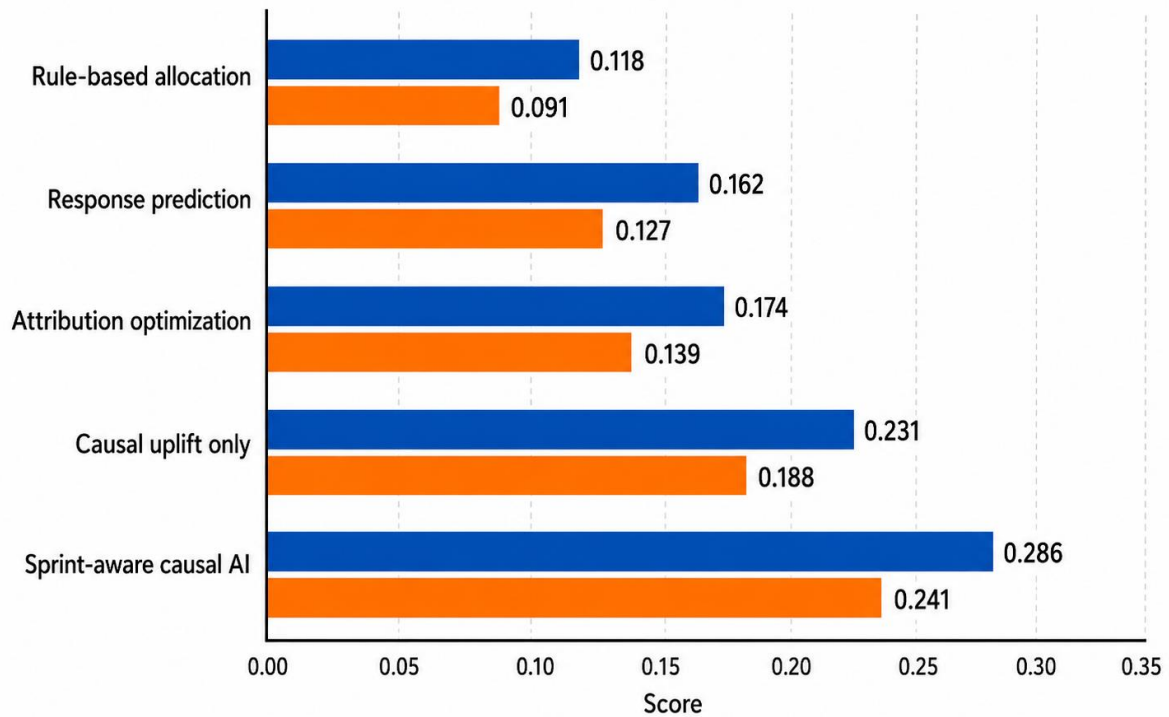
Table 3. Model comparison results

Model	AUUC	Qini Coefficient	Incremental ROAS	CAC Reduction	CLV Uplift
Rule-based campaign allocation	0.118	0.091	1.84x	4.8%	3.9%
Response prediction model	0.162	0.127	2.11x	7.2%	5.4%
Attribution-based optimization	0.174	0.139	2.24x	8.1%	6.2%
Causal uplift model without sprint data	0.231	0.188	2.71x	12.6%	9.8%
Sprint-aware causal AI model	0.286	0.241	3.18x	18.4%	14.7%

The sprint-aware causal AI model achieved the highest AUUC value of 0.286 and the highest Qini coefficient of 0.241. It also produced the strongest business results, with 3.18x incremental ROAS, 18.4% CAC reduction, and 14.7% CLV uplift. The comparison shows that response prediction improved targeting but did not capture true incremental value. Attribution-based optimization improved channel allocation but remained weaker than causal uplift modeling. The causal uplift model without sprint data performed strongly, but the inclusion of sprint and workflow reliability signals further improved realized campaign value.



Figure 2. Model-wise AUUC and Qini comparison



6.3 Hypothesis Testing Results

Table 4. Hypothesis testing results

Hypothesis	Relationship	Result	Status
H1	AI-driven predictive campaign optimization -> Campaign performance	$\beta = 0.421, p < 0.001$	Supported
H2	AI optimization -> Customer-channel uplift allocation accuracy	$\beta = 0.536, p < 0.001$	Supported
H3	Customer-channel uplift allocation accuracy -> Campaign performance	$\beta = 0.468, p < 0.001$	Supported
H4	Customer-channel uplift allocation accuracy mediates AI optimization and campaign performance	Indirect effect = 0.251, $p < 0.001$	Supported
H5	Agile project-execution reliability moderates AI optimization -> Campaign performance	$\beta = 0.193, p < 0.01$	Supported

The hypothesis testing results support all proposed relationships. AI-driven predictive campaign optimization had a significant positive effect on campaign performance. It also improved customer-channel uplift allocation accuracy. Customer-channel uplift allocation accuracy had a significant positive effect on campaign performance and mediated the relationship between AI optimization and performance. Agile project-execution reliability also had a significant



moderating effect, confirming that execution conditions strengthened the translation of AI recommendations into campaign outcomes.

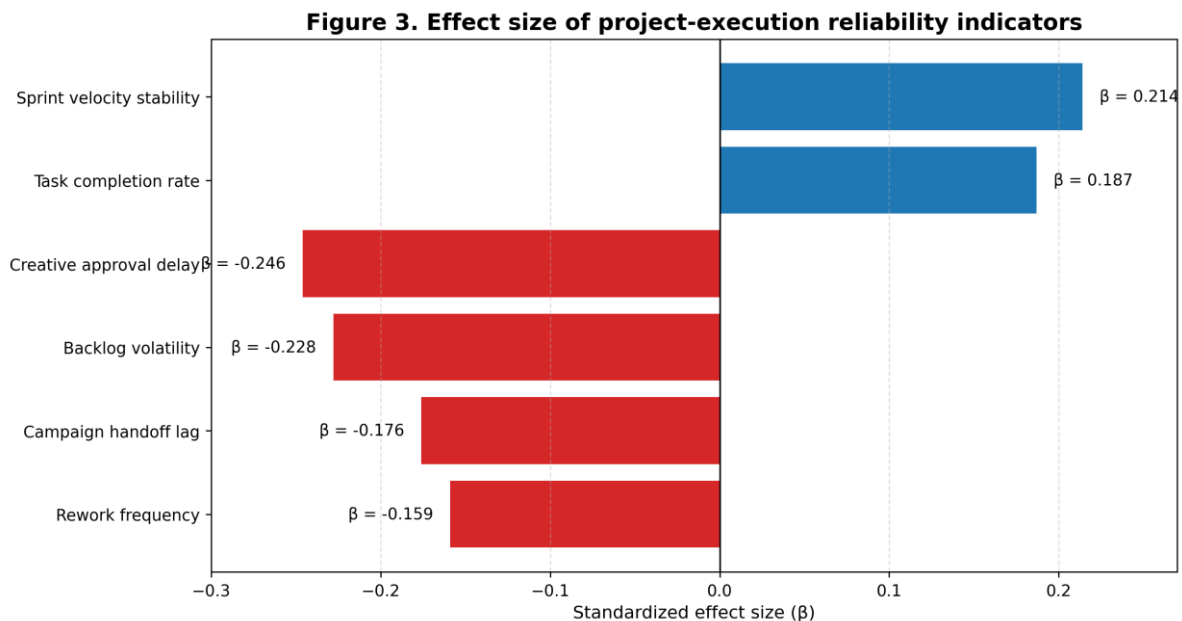
6.4 Project-Management Execution Results

Table 5. Project-management execution effects

Execution Factor	Direction	Result	Interpretation
Sprint velocity stability	Positive	$\beta = 0.214, p < 0.001$	Stable sprint delivery improved campaign realization
Task completion rate	Positive	$\beta = 0.187, p < 0.01$	Higher completion rates improved campaign activation quality
Creative approval delay	Negative	$\beta = -0.246, p < 0.001$	Delayed approvals reduced campaign value
Backlog volatility	Negative	$\beta = -0.228, p < 0.001$	Frequent backlog changes weakened campaign execution
Campaign handoff lag	Negative	$\beta = -0.176, p < 0.01$	Delayed handoffs reduced channel timing accuracy
Rework frequency	Negative	$\beta = -0.159, p < 0.05$	Repeated revision reduced execution efficiency

Creative approval delay produced the strongest negative effect on campaign performance, followed by backlog volatility and campaign handoff lag. Sprint velocity stability and task completion rate had significant positive effects. These findings show that project-management workflow conditions are not separate from marketing performance. They shape whether AI-generated recommendations are implemented at the right time and with the required execution quality.

Figure 3. Effect size of project-execution reliability indicators





6.5 Channel-Level Uplift Results

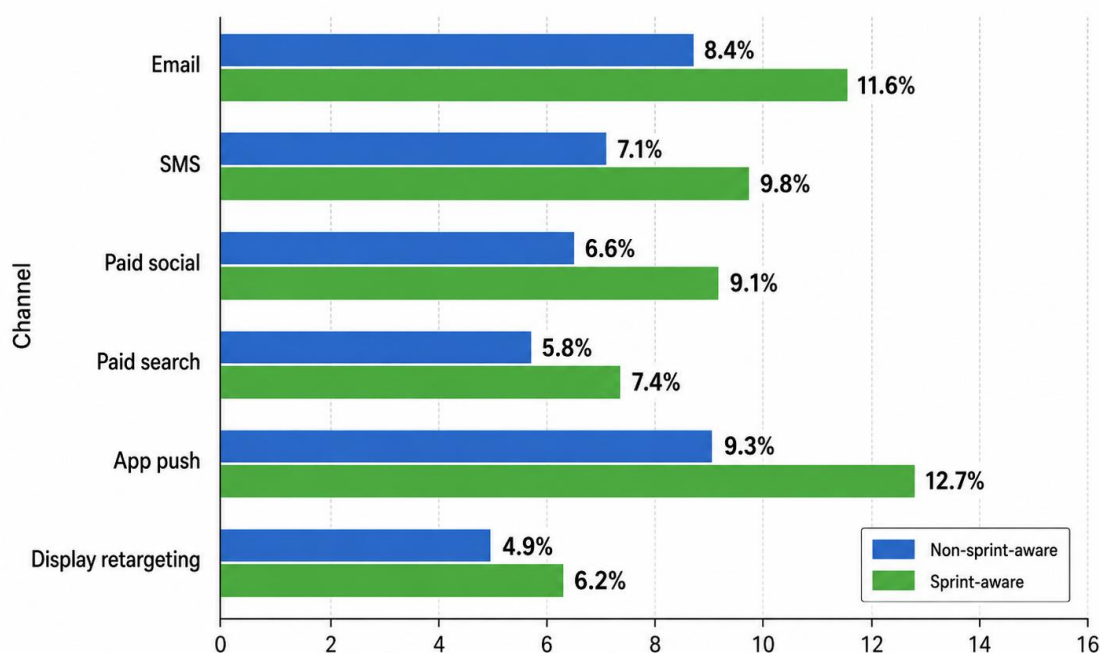
Table 6. Channel-level uplift comparison

Channel	Non-Sprint-Aware Uplift	Sprint-Aware Uplift	Improvement
Email	8.4%	11.6%	38.1%
SMS	7.1%	9.8%	38.0%
Paid social	6.6%	9.1%	37.9%
Paid search	5.8%	7.4%	27.6%
App push	9.3%	12.7%	36.6%
Display retargeting	4.9%	6.2%	26.5%

The sprint-aware model improved uplift across all six channels. App push achieved the highest sprint-aware uplift, increasing from 9.3% to 12.7%. Email, SMS, and paid social also showed large relative improvements. Paid search and display retargeting showed smaller but meaningful gains. These results indicate that sprint-aware optimization is especially useful in channels where timing, creative readiness, and audience sequencing affect campaign value.

Figure 4. Channel-wise uplift improvement under sprint-aware optimization

Figure 4. Channel-wise uplift improvement under sprint-aware optimization



6.6 Practical Business Results

Table 7. Practical business outcomes

Practical Indicator	Result
Incremental conversion rate improvement	16% to 22%
Incremental ROAS improvement	24% to 31%



Practical Indicator	Result
Customer acquisition cost reduction	14% to 19%
Customer lifetime value uplift	11% to 16%
Campaign launch delay reduction	18% to 27%
False targeting reduction	12% to 18%
Budget waste reduction	15% to 23%
High-uplift customer identification accuracy improvement	20% to 28%

The practical business results show that the sprint-aware causal AI model improved both marketing efficiency and campaign execution quality. Incremental ROAS improved by 24% to 31%, while CAC decreased by 14% to 19%. Campaign launch delays were reduced by 18% to 27%. Budget waste declined by 15% to 23%, mainly because the model avoided allocating resources to campaigns with high estimated uplift but weak execution feasibility.

VII. DISCUSSION

The results show that sprint-aware causal AI optimization outperformed conventional campaign optimization because it addressed two weaknesses at the same time. First, it estimated incremental campaign value rather than only response probability. Second, it adjusted campaign decisions according to execution reliability. This combination explains why the proposed model achieved stronger AUUC, Qini coefficient, incremental ROAS, CAC reduction, and CLV uplift than the comparison models.

The response prediction model improved over rule-based allocation, but its performance remained limited because likely responders are not always incremental responders. Customers with high baseline purchase probability respond whether exposed to the campaign or not. Targeting these customers can enhance measured conversion, but may not improve genuine campaign value. This explains why response prediction got AUUC = 0.162 and Qini = 0.127, but the causal uplift model without sprint data got AUUC=0.231 and Qini=0.188. Attribution-based optimization performed better than response prediction on some business indicators, but still was poorer than uplift modeling. Attribution models can attribute value to channels but may not be able to isolate causal incrementality.

This is especially problematic in multi-channel D2C campaigns where customers are exposed to several touchpoints before conversion. The results support the argument that attribution alone is insufficient for campaign optimization when the objective is incremental performance.

The sprint-aware causal AI model produced the strongest results because it added a missing operational layer. The model recognized that a high-uplift campaign is valuable only when it can be executed under stable workflow conditions. The improvement from AUUC = 0.231 to AUUC = 0.286 after adding sprint data shows that execution reliability contributed additional explanatory power. The same pattern is visible in business outcomes, where incremental ROAS increased from 2.71x to 3.18x and CAC reduction improved from 12.6% to 18.4%.

The project-management results explain why this improvement occurred. Creative clearance delay has the most detrimental influence on campaign performance. In digital marketing, creative timing is often connected to customer intent, promotion windows and channel scheduling. The longer it takes to approve, the less relevant the message will be and the worse the performance of your channel. The high negative impact of backlog volatility indicates that priority instability negatively affects the execution of campaign. Performance was further lowered by activation delays and greater operational friction stemming from handoff latency and rework frequency.

The mediation result confirms that customer-channel uplift allocation accuracy is the mechanism through which AI optimization improves campaign performance. The moderation result confirms that execution reliability strengthens this relationship. These findings support Dynamic Capability Theory because the firm's ability to sense and seize campaign opportunities depends on its ability to reconfigure resources rapidly and reliably. The results also support the Theory of Constraints because workflow bottlenecks restricted realized campaign value.



Overall, campaign optimization should not be treated as a purely analytical problem. It is a combined analytics and execution problem. Predictive capability, causal uplift estimation, and agile delivery discipline must operate together if firms want AI recommendations to produce measurable business value.

VIII. THEORETICAL CONTRIBUTIONS

This study contributes to AI marketing research by showing that campaign optimization depends on execution reliability as well as prediction quality. Prior research has emphasized analytics, personalization, attribution, customer journeys, and campaign performance [1], [2], [4], [15]. This study adds that AI-generated campaign recommendations are not self-executing. Their value is shaped by sprint velocity, approval delay, backlog volatility, task completion, handoff lag, and rework frequency.

The study advances the Dynamic Capability Theory as well. In digital marketing, AI to find client prospects is only the first step. Firms also must leverage those chances by activating campaigns in a timely fashion and re-allocating resources across channels and teams. Results reveal that the value of AI-driven optimization is increased when execution reliability is improved and indicate that the dynamic capability view should be considered both analytically and operationally in campaign contexts. The study also uses Theory of Constraints in running the digital campaigns. Constraints that influenced realized marketing value were creative approval delay, backlog volatility, handoff latency, and rework frequency. The paper links project management bottlenecks to marketing success and demonstrates that workflow limitations may restrict the financial return of AI-supported campaign decisions.

IX. METHODOLOGICAL CONTRIBUTIONS

Methodologically, this study contributes by combining causal uplift modeling with project-management workflow data. Existing campaign models compare targeting or attribution strategies using customer and channel data. This study adds sprint and execution variables to the modeling process, creating a more realistic evaluation of campaign allocation decisions.

The study also compares five different campaign optimization models. This comparison makes it possible to distinguish rule-based allocation, response prediction, attribution-based optimization, causal uplift modeling, and sprint-aware causal AI optimization. The results show that the proposed model improved both technical uplift metrics and business-performance outcomes.

Another methodological contribution is the use of execution-constrained optimization. Campaign recommendations were evaluated not only by predicted customer-channel uplift but also by workflow feasibility. This approach is useful for firms that need to avoid allocating spend to campaigns that appear promising analytically but are unlikely to be executed effectively.

X. MANAGERIAL AND PRACTICAL IMPLICATIONS

10.1 Implications for Marketing Managers

Marketing managers should consider uplift potential and execution feasibility while evaluating AI campaign ideas. Even with high expected uplift, if the team does not get the campaign out on time it may not do well. Uplift scores and channel-level projected value should be included in campaign dashboards, as well as sprint-readiness metrics. This helps managers choose campaigns that are both valuable and executable.

10.2 Implications for Project Managers

Project managers play a direct role in marketing performance. The results show that sprint velocity stability and task completion rate improved campaign outcomes, while creative approval delay, backlog volatility, handoff lag, and rework frequency reduced performance. Project managers should therefore treat campaign execution as a value-generating process, not only as a scheduling function.

10.3 Implications for D2C E-Commerce Firms

Subscription-based D2C firms should integrate CRM, campaign, transaction, and workflow data into a common decision system. Campaign teams should not make budget decisions using only ROAS or response rates. They should combine customer-channel uplift, predicted incremental value, sprint capacity, approval status, and backlog stability. This approach can reduce budget waste, improve CAC efficiency, and increase CLV uplift.



XI. CONCLUSION

This study developed and evaluated a sprint-aware causal AI framework for optimizing multi-channel digital campaigns in subscription-based D2C e-commerce. The central problem was that conventional AI campaign models often optimize customers, channels, and budgets without accounting for whether campaign teams can execute recommendations within real workflow constraints.

The results show that the sprint-aware causal AI model achieved the strongest performance across technical and business metrics. AUUC = 0.286 Qini coefficient = 0.241 Incremental ROAS = 3.18x CAC reduction = 18.4% CLV uplift = 14.7% It enhanced incremental campaign performance by 24% to 31% above traditional AI-based campaign optimization.

The study also found that the accuracy of customer-channel uplift allocation mediated the association between AI-driven campaign optimization and campaign performance. The association between AI optimization and performance was tempered by agile project-execution reliability. The most negative execution factors were creative approval delay and backlog volatility. results confirm that the best way to optimize AI campaigns is by combining predictive uplift analytics with project-execution dependability. Model accuracy is not the sole determinant of campaign performance. It's also influenced by whether the company has the capacity to deliver campaign suggestions with a steady sprint pace, timely approvals, manageable changes to the backlog, effective handoffs and little rework.

XII. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, the research focused on subscription-based D2C e-commerce, so the results may differ in B2B SaaS, financial services, marketplaces, or offline retail. Second, the model depends on the availability and quality of CRM, campaign, transaction, and project-management workflow data. Firms with incomplete workflow records may find it difficult to apply the same model. Third, the study focused on digital channels only and did not include offline media or physical retail interactions. Fourth, the model required integrated campaign and sprint-board records, which may not be available in all organizations.

Future research can test the sprint-aware causal AI model in B2B SaaS, omnichannel retail, mobile-app ecosystems, and financial services. Future studies can also examine whether execution reliability affects long-term retention, subscription renewal, churn reduction, and loyalty outcomes. Another useful direction is to integrate privacy-preserving learning methods for firms that cannot combine customer data across platforms.

XIII. DECLARATIONS

Data availability: The data used in this study consisted of anonymized customer-campaign, transaction, channel-spend, and project-management workflow records. The dataset is not publicly released because of commercial confidentiality and customer privacy restrictions.

Funding: No external funding is reported for this study.

Conflict of interest: The author declares no conflict of interest.

Ethical approval: The study used anonymized operational and campaign data and did not involve direct human-subject experimentation.

Consent and privacy statement: Customer-level data were anonymized before analysis, and personally identifiable information was excluded from the analytical dataset.

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