Research Horizon

ISSN: 2808-0696 (p), 2807-9531 (e)

Research Horizon
Volume: 06
Issue: 03
Year: 2026
Page: 1303-1318

Citation:
Ayuningrum, B., Fudholi, D. H., & Wijayanto, F. (2026). The impact of Instagram expansion in meta ads campaigns on lead generation: A hybrid tabtransformer and causal impact analysis. *Research Horizon*, *6*(3), 1303-1318.

Article History:
Received: May 12, 2026
Revised: May 30, 2026
Accepted: June 17, 2026
Online since: June 25, 2026

The Impact of Instagram Expansion in Meta Ads Campaigns on Lead Generation: A Hybrid TabTransformer and Causal Impact Analysis

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Abstract

The growth of digital advertising spending demands more accurate measurement of the effectiveness of multi-platform strategies to optimize the distribution of advertising budgets across various advertising platforms. This study analyzes the impact of the addition of Instagram on the performance of herbal product advertising campaigns previously run solely through Facebook on the Meta Ads platform. The research approach consists of two stages, namely building a TabTransformer-based prediction model using Facebook pre-intervention data and a Bayesian Structural Time Series (BSTS)-based Causal Impact analysis, utilizing TabTransformer prediction results and advertising budget variables as covariates in the construction of counterfactuals. The evaluation results showed the best TabTransformer model was obtained in the second scenario with an MSE value of 1.84, an MAE of 0.95, and an R^2 of 80%, indicating good predictive performance on the test data. Furthermore, the results of the causal impact analysis showed that the addition of Instagram had a statistically significant positive impact, with an average increase in the number of leads of approximately 58.6%, or the equivalent of 93.21 leads per day in the post-intervention period.

Keywords

Causal Impact Analysis, Digital Advertising, Meta Ads, TabTransformer.

1. Introduction

The information technology revolution has transformed the digital market into a major trading activity, driving the rapid development of e-commerce platforms and shifting the structure of conventional trading centers (Mergel et al., 2019; Badaro et al., 2023). The rapid growth of internet penetration, social media platforms, and data-driven technologies has encouraged businesses to increasingly rely on digital channels as the primary medium for marketing communication and customer engagement (Camilleri, 2020). In the increasingly complex era of digital marketing, advertisers are not only required to allocate budgets to various promotional platforms but also to channel the objectives of each platform's contribution to campaign performance to support more efficient and diverse budget allocation decisions (Andhyka et al., 2025; Setiawan et al., 2025).

Digital campaigns are now implemented simultaneously across multiple channels, including search engines, social media, video platforms, and e-commerce ecosystems, creating interconnected patterns of consumer interaction and response. These developments have resulted in large-scale, heterogeneous digital campaign data across audiences, platforms, and time with complex and nonlinear relationships between variables, posing fundamental challenges in evaluating the effectiveness of digital campaigns (Vdovichena et al., 2024; Aulia, 2024; Reklitis et al., 2025). Furthermore, the increasing volume and diversity of campaign data require analytical approaches that are capable of capturing dynamic behavioral patterns and measuring the actual contribution of marketing interventions more accurately (Liu et al., 2025).

Digital campaign evaluation is still dominated by descriptive performance metrics, such as impressions, clicks, and engagement rates, which primarily measure the level of exposure and interaction, rather than the causal impact of an intervention (Gordon et al., 2019; Gordon et al., 2026). Rahardja and Aini (2025) point out that conventional statistical approaches, including analysis of variance and linear regression, are still commonly used in digital campaign evaluation despite their inherent limitations in identifying causal relationships. Traditional causal inference approaches are often unable to capture the complexity and nonlinearity of large-scale digital campaign data (Gui et al., 2021).

Previous studies indicate that the evaluation of digital campaign effectiveness still faces major methodological limitations (Wang et al., 2024). Xie (2025) explains that digital advertising evaluation is still dominated by correlation-based approaches that are unable to isolate the true causal effects of campaigns across multiple platforms. Similarly, Rahardja and Aini (2025) emphasize that conventional statistical methods such as ANOVA and regression remain widely used despite their limitations in identifying causal effects in a dynamic digital environment. Furthermore, Athey and Imbens (2017) argue that traditional causal inference approaches rely heavily on linearity and stability assumptions that are often incompatible with large-scale and nonlinear digital campaign data characteristics. Chalasani et al. (2017) also highlight that counterfactual-based incrementality measurement remains challenging in digital advertising environments with heterogeneous user behavior and multi-platform interactions.

On the other hand, machine learning approaches have shown strong predictive capabilities in digital marketing. Harahap and Muhammad (2025) apply machine learning primarily for conversion prediction and advertising performance forecasting without explicitly addressing causal inference. Likewise, Vdovichena et al. (2024) focus on predictive optimization through artificial intelligence and deep learning techniques rather than causal evaluation. Belinda and Nofitasari (2025) further explain that artificial intelligence increasingly plays an important role in digital marketing strategies and consumer behavior analysis. Recent studies also demonstrate the growing use of Bayesian deep learning approaches for advertising performance prediction in e-commerce environments (Ford et al., 2023; Jha et al., 2026). Based on these gaps, the novelty of this research lies in integrating machine learning–based tabular representation with causal inference to construct counterfactual baselines for estimating the causal impact of cross-platform digital campaigns, thereby extending the role of machine learning from prediction-oriented analysis toward causal impact evaluation.

Bayesian Structural Time Series (BSTS) models have been used to estimate causal effects but are primarily designed to model time series dynamics and linear regression relationships between response variables and covariates. In the context of tabular digital advertising data with high dimensions, diverse categorical features, and complex nonlinear interactions, linear regression models have limitations in adequately representing the data structure. Therefore, this study proposes the integration of a deep learning model for tabular data, namely TabTransformer, with a Bayesian structural time series-based causal impact analysis framework to improve data representation and the accuracy of causal impact estimation of digital interventions.

2. Literature Review

2.1. Digital Marketing and Cross-Platform Performance Evaluation

The rapid proliferation of digital channels encompassing search engine marketing, social media, e-commerce platforms, and video advertising has fundamentally transformed how brands design and execute marketing campaigns. Modern campaigns are rarely confined to a single channel; instead, they operate simultaneously across multiple touchpoints, each governed by distinct algorithms, audience behaviors, and bidding mechanisms. This multi-channel nature generates rich but fragmented data, making it difficult to construct a unified view of campaign performance. da Silva Wegner et al. (2023) highlight that selecting the most appropriate platform and evaluating digital marketing performance requires multi-criteria approaches, as each channel contributes differently to brand exposure, audience targeting, and conversion outcomes across an organization's marketing mix.

Despite the availability of granular data, evaluation frameworks in digital marketing have traditionally relied on descriptive metrics such as click-through rate (CTR), impressions, and engagement rate. While these indicators offer surface-level insights into user interaction, they fall short of capturing the dynamic interplay between channels and the compounding effects of multi-platform exposure on consumer decision-making. As noted across industry literature, cross-channel metrics must account for the non-linear, often unpredictable consumer journey where users shift between platforms, devices, and touchpoints before converting. The dependence on siloed, platform-specific metrics, therefore, constitutes a fundamental limitation, underscoring the need for more integrative and analytically rigorous evaluation approaches (Verhoef et al., 2021).

2.2. Causal Inference Approaches in Digital Advertising Effectiveness

Causal inference has emerged as a critical methodological frontier in digital advertising research, moving beyond correlation-based evaluation toward understanding the true incremental impact of marketing interventions. Classical approaches such as regression analysis, ANOVA, and randomized experimental designs have long served as the backbone of advertising effectiveness measurement. Within this tradition, counterfactual reasoning, estimating what would have occurred in the absence of a campaign, provides the conceptual basis for incrementality measurement. Bayesian Structural Time Series (BSTS) models operationalize this reasoning by decomposing time-series data into trend, seasonality, and regression components to generate a synthetic counterfactual, from which the causal lift of an advertising intervention can be inferred with probabilistic uncertainty quantification (Brodersen et al., 2015).

However, classical causal methods face significant limitations when applied to modern digital advertising data, which are characterized by nonlinearity, high dimensionality, and complex cross-platform dependencies. Randomized controlled trials, while theoretically robust, are often costly or infeasible to implement at scale across multiple digital channels simultaneously. As Hair and Sarstedt (2021) argue, marketing researchers must critically evaluate the assumptions underlying causal inference methods, particularly when digital data from disparate sources are combined, a process that introduces measurement error, confounding, and distributional shifts that conventional models are ill-equipped to handle. This methodological gap motivates the integration of more flexible, data-driven causal frameworks capable of accommodating the complexity of multi-platform campaign data.

2.3. Machine Learning and Deep Learning for Tabular Marketing Data

Machine learning has become increasingly central to digital marketing practice, with applications spanning customer segmentation, conversion prediction, ad targeting, and campaign optimization. Structured or tabular data comprising campaign metrics, user demographics, behavioral signals, and channel-specific features represents the dominant data format in marketing analytics. While gradient-boosted decision trees have historically performed well on such data, recent advances in attention-based architectures have expanded the modeling frontier. The TabTransformer, proposed by Huang et al. (2020), applies multi-head self-attention mechanisms to categorical feature embeddings within tabular datasets, enabling the model to learn rich contextual representations that capture complex, nonlinear feature interactions that traditional regression models cannot adequately represent.

Despite their predictive power, conventional machine learning models, including TabTransformer, are optimized primarily for forecasting outcomes rather than identifying causal relationships. As demonstrated by Langen and Huber (2023), predictive ML models are fundamentally limited in their ability to isolate the causal effects of specific marketing interventions, such as a campaign exposure or spend allocation decision, because they minimize prediction error on observed data without accounting for confounding bias or counterfactual scenarios. This distinction between predictive accuracy and causal validity is pivotal in the context of digital campaign evaluation: a model may accurately forecast conversions while attributing credit incorrectly across channels. This limitation motivates a hybrid approach that leverages TabTransformer's representational capacity for nonlinear feature learning while embedding causal reasoning, such as BSTS-based incrementality estimation, to achieve both accurate prediction and valid causal attribution.

3. Methods

This study employed a quantitative causal inference design integrating machine learning–based predictive modeling with Bayesian time-series analysis to evaluate the causal impact of cross-platform digital advertising interventions. The dataset consisted of advertising campaign data from a herbal product managed through Meta Ads Manager, divided into pre-intervention and post-intervention periods. The pre-intervention period covered January to July 2025, during which campaigns were conducted only on Facebook, while the post-intervention period covered August 2025, when campaigns were simultaneously implemented on Facebook and Instagram. The dataset included categorical variables, namely platform and placement, as well as numerical variables such as reach, impressions, views, link clicks, Cost-Per-Click (CPC), spends, and leads. Numerical variables were normalized before model training to reduce scale differences and improve model stability.

The analytical framework consisted of two integrated stages. The first stage involved the development of a TabTransformer predictive model using pre-intervention data. TabTransformer is an adaptation of the Transformer architecture specifically designed for tabular data with mixed categorical and numerical features. Unlike conventional Transformers that rely on positional encoding for sequential data, TabTransformer utilizes contextual embeddings and self-attention mechanisms to model interactions among tabular features more effectively (Vaswani et al., 2017; Huang et al., 2020; Badaro et al., 2023). In this study, the model used placement, reach, impressions, link clicks, and CPC as input variables, while leads served as the target variable. Hyperparameter tuning was conducted across multiple parameter combinations, including embedding dimension, number of attention heads, transformer blocks, feedforward dimensions, dropout rates, learning rates, batch sizes, and epochs to obtain the optimal predictive model.

The second stage employed Causal Impact analysis based on Bayesian Structural Time Series (BSTS) to estimate the causal effect of the intervention. BSTS, introduced by Scott and Varian (2014), applies Bayesian inference to model temporal dynamics and generate counterfactual predictions. The Causal Impact framework developed by Brodersen et al. (2015) estimates causal effects by comparing observed post-intervention outcomes with predicted counterfactual outcomes generated from pre-intervention patterns. In this study, TabTransformer predictions and spending variables were used as covariates to improve the construction of counterfactual baselines and separate the effects of budget fluctuations from intervention effects. Bayesian inference principles were further applied to update prior beliefs using observed data and estimate posterior distributions of intervention impacts (Li et al., 2023; Martin et al., 2024).

This approach is formally based on Bayes' Theorem, which is formulated as follows.

$$p(\theta|t) = \frac{p(t|\theta)\, p(\theta)}{p(t)}$$

With,

$p(\theta)$	:	Prior distribution
$p(t\|\theta)$	:	Likelihood function
$p(t)$	:	evidence
$p(\theta\|t)$	:	Posterior distribution

The results analysis focused on several aspects. First, predictive model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Second, the causal impact analysis examined three key outputs: the comparison between actual observations and counterfactual predictions, the daily intervention impact, and the cumulative impact over the post-intervention period. These analyses were used to determine whether the expansion of advertising campaigns from Facebook to Instagram generated a statistically meaningful causal effect on campaign lead outcomes.

The dataset used in this study is data from a herbal product advertising campaign running in Meta Ads Manager. The pre-intervention period ran from January to July 2025, during which the campaign ran solely on Facebook, with 8,000 rows of observations. The post-intervention period occurred in August 2025, when the campaign ran simultaneously on Facebook and Instagram, with 1,865 rows of observations. The sample dataset is shown in Tables 1 and 2.

Table 1. Sample Dataset of Ads Pre-Intervention

Date	Platform	Placement	Reach	Impressions	Views	Link Clicks	CPC	Spends	Lead
2025-01-01	Facebook	Stories	1607	1776	1981	37	2417	89430	4
2025-01-01	Facebook	Stories	2617	2919	2663	90	2513	226182	4
2025-01-01	Facebook	Reels	3662	4594	465	39	619	24150	2
⋮		⋮	⋮	⋮	⋮	⋮	⋮		⋮
2025-07-31	Facebook	Feed	623	664	665	7	2753	19272	2

Table 2. Sample Dataset of Ads Post-Intervention

Date	Platform	Placement	Reach	Impressions	Views	Link Clicks	CPC	Spends	Lead
2025-08-01	Facebook	Feed	120	122	104	1	12849	12849	1
2025-08-01	Instagram	Feed	119	120	112	4	2962	11847	1
2025-08-01	Instagram	Stories	107	107	124	2	686	1371	2
⋮		⋮	⋮	⋮	⋮	⋮	⋮		⋮
2025-08-31	Facebook	Reels	2840	3631	3805	38	2561	97332	3

4. Results

This section presents the results of the TabTransformer predictive modeling and Causal Impact analysis used to evaluate the effect of adding the Instagram platform on digital campaign performance. The findings include model performance evaluation, baseline prediction results, and the estimated causal impact on lead generation after the intervention.

Table 3. Data Before and After Normalization

Category	Variable	Mean	Std	Min	Max
Before	Reach	2.685.00	3.129.31	23	30.432
	Impressions	3.045.19	3.682.65	5	34.215
	Views	2.726.81	3.385.31	5	27.093
	Link Clicks	33.90	48.80	2	430
	CPC	2.989.81	1.740.70	29	24.905
After	Reach	0.000	1.000	-0.851	8.867
	Impressions	0.000	1.000	-0.826	8.464
	Views	0.000	1.000	-0.804	7.198
	Link Clicks	0.000	1.000	-0.654	8.117
	CPC	0.000	1.000	-1.701	12.590

Table 3 shows the data before normalization; numeric variables have significant scale differences and tend to be skewed in distribution. The maximum values for the reach, impressions, and link clicks variables reached 30,432, 34,215, and 27,093, respectively, while the average values were much lower (2,685–3,045). suggesting that using raw data without normalization may impact the modeling process (Huang et al., 2020).

The numeric variables after normalization were standardized to a mean near zero and a standard deviation near one for better comparability in model training. The TabTransformer predictions and spends variables were then used as covariates in a Causal Impact analysis to help the Bayesian Structural Time Series (BSTS) model construct a counterfactual, while actual Leads data from the pre- and post-intervention periods served as the response variable (Matheus et al., 2020).

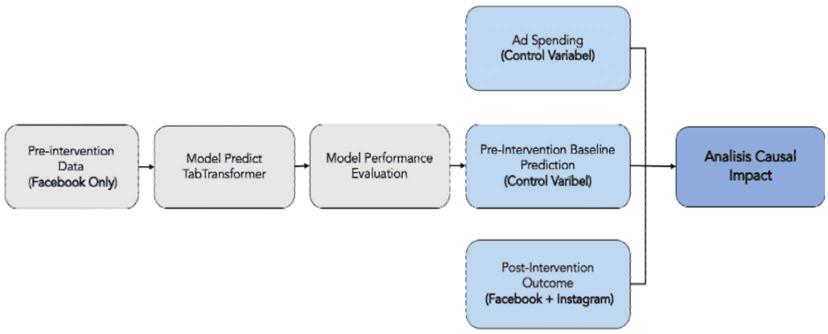


Figure 1. Analytical Workflow Integrating Predictive Modeling and Causal Impact

Figure 1 illustrates the analytical framework integrating machine learning–based prediction and causal impact analysis. The process begins with pre-intervention advertising data collected from Facebook-only campaigns, which are used to train the TabTransformer model. After the model is developed, its predictive performance is evaluated to ensure the reliability of baseline predictions. The resulting pre-intervention baseline predictions are then combined with ad spending as a control variable and compared with post-intervention outcomes from campaigns conducted on both Facebook and Instagram. These inputs are subsequently analyzed using the Causal Impact framework to estimate the causal effect of adding the Instagram platform on campaign lead generation performance.

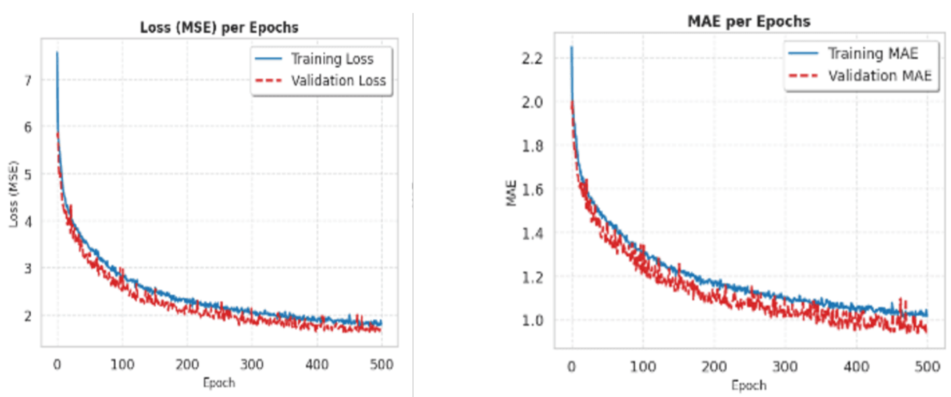
4.1. TabTransformer-Based Prediction

In this study, the TabTransformer model was developed using five configuration scenarios, in which key hyperparameters, including embedding dimension, number of attention heads, transformer layer depth, learning rate, and batch size, were systematically varied. These scenarios were designed to explore how differences in model complexity and training dynamics influence prediction performance and the model's ability to capture complex patterns in tabular data. Model performance across all five scenarios was evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2), offering complementary insights into both the magnitude of prediction errors and overall model fit. Results evaluation for the five scenarios is summarized in Table 3.

Table 4. Evaluation Metrics of TabTransformer Model

Parameter	**Test 1**	**Test 2**	**Test 3**	**Test 4**	**Test 5**
Embed dim	32	16	64	32	32
Num heads	4	2	4	4	4
Num transformer blocks	2	1	3	2	2
FF dim	128	64	256	128	128
Dropout rate	0.1	0.1	0.2	0.3	0.1
Learning rate	0.001	0.001	0.0005	0.001	0.0001
Batch Size	64	32	64	64	64
Epoch	500	500	500	500	500
MSE	1.94	1.84	2.42	2.57	1.80
MAE	1.01	0.95	1.19	1.25	0.99
R^2	77%	80%	70%	69%	78%

Based on the experimental results presented in Table 4, the performance of the TabTransformer model shows variations in performance influenced by the combination of hyperparameters tested. Among the five configurations evaluated, the scenario 2 configuration (16-dimensional embedding, 2 attention heads, 1 transformer block, 64 feed-forward units, dropout 0.1, batch size 32, and learning rate 0.001) produced the best performance based on the evaluation metrics used. This configuration obtained the lowest Mean Squared Error (MSE) value of 1.84, Mean Absolute Error (MAE) of 0.95, and coefficient of determination (R^2) value of 0.80. These results indicate that the model is able to capture most of the variation in leads during the pre-intervention period. The pattern of loss reduction observed during the training process for the best-performing configuration is illustrated in Figure 2.



(a) (b)

Figure 2. (a) MSE Loss Curve over Epochs (b) MAE Error Curve over Epochs

Figure 2 shows that the training loss and validation loss (MSE) values consistently decrease with increasing epochs, indicating that the model is able to learn the data patterns well. The two curves, training and validation, are relatively close together without significant divergence, thus indicating no indication of overfitting. The MAE per epoch graph shows that the training MAE and validation MAE values consistently decrease with increasing epochs, indicating an increase in the model's prediction accuracy. The two curves remain close together without significant divergence, indicating no indication of overfitting. After approximately the 300th to 400th epoch, the MAE decline begins to slow and tends to stabilize, indicating that the model has reached a state of convergence and that further performance improvements are relatively small. The decreasing pattern in Figure 2, along with the proximity of the training loss and validation loss values for both metrics, indicates that the model training process is proceeding steadily and does not indicate overfitting.

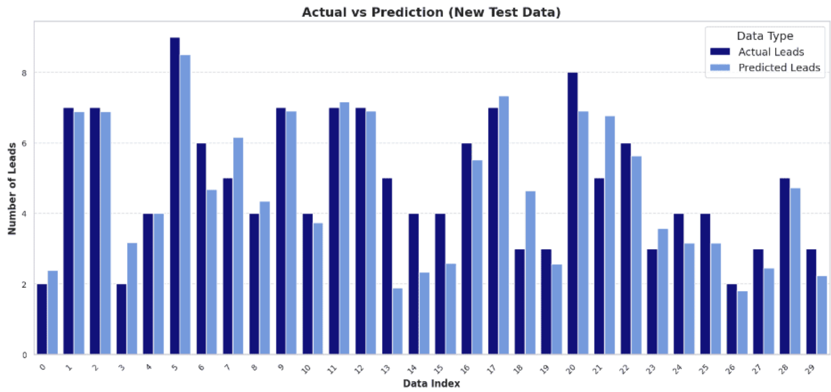


Figure 3. Actual vs. Predicted Gap on New Test Data

The best model in scenario 2 was tested using 30 new test datasets and demonstrated good predictive performance. Figure 3 shows that the predicted pattern accurately follows the trend of the actual values without any extreme deviations. The Mean Absolute Error (MAE) value of 0.6321 indicates that the average prediction error is only about 0.63. This relatively small and insignificant error indicates that the model's predictions are very close to the actual values, making the model suitable for predicting the number of leads as a covariate.

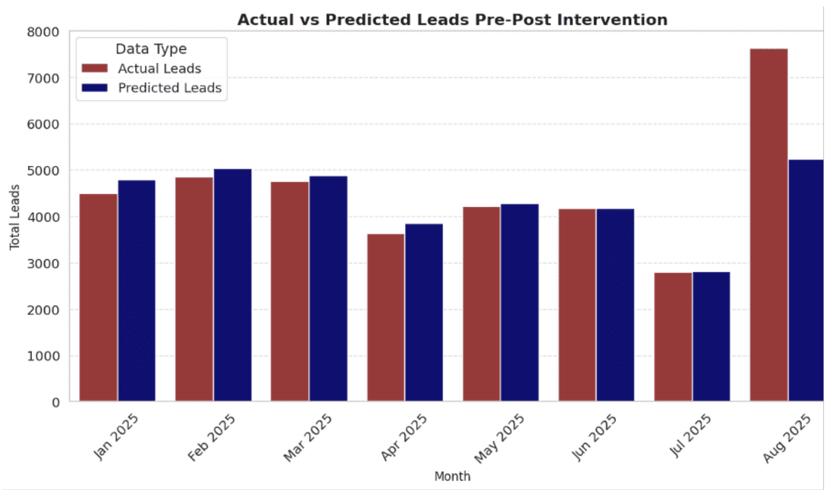


Figure 4. Actual vs. Predicted Values (Pre- and Post-Intervention)

Figure 4 shows that in the pre-intervention period (January – July), the Tab Transformer model's predictions closely followed the actual values, demonstrating its ability to capture the historical pattern of the pre-intervention data. In the post-intervention period (August), the actual values were higher than the predictions, which continued to follow the pre-intervention pattern, indicating a potential impact of the intervention, which will be further confirmed through causal impact analysis.

4.2. Causal Impact Analysis

The causal impact analysis was conducted to evaluate whether the addition of the Instagram platform generated a measurable improvement in lead generation performance. The results are presented through causal impact visualization, quantitative effect estimation, and comparative analysis of leads and advertising spending across observation periods.

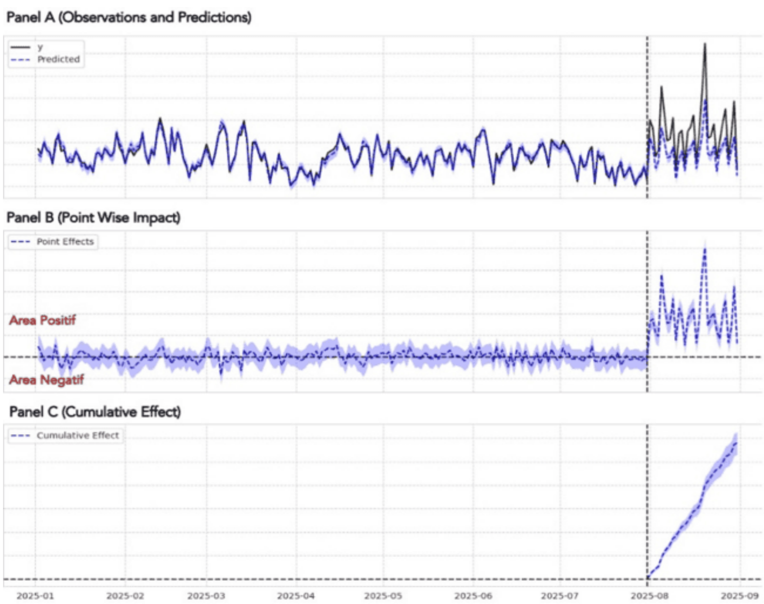


Figure 5. Output Causal Impact

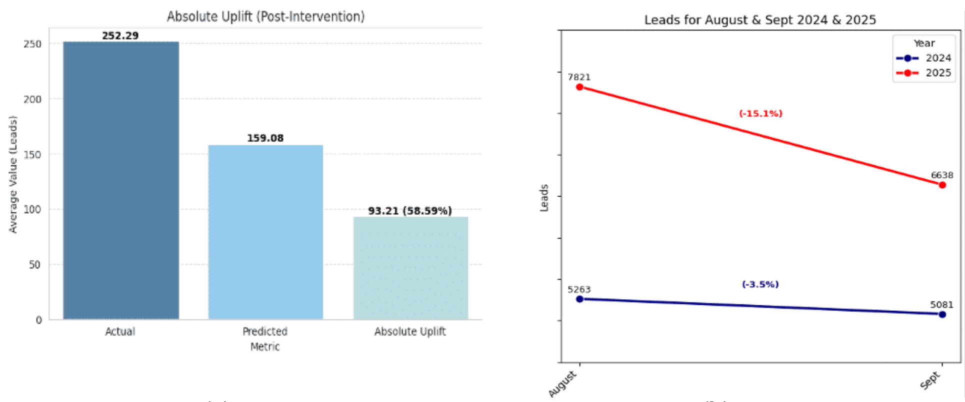
Based on the causal impact output shown in Figure 5, the analysis indicates a consistent positive effect of the intervention across all evaluation panels. In Panel A (Observation vs Prediction), the actual observations represented by the black line consistently exceeded the counterfactual predictions shown by the dashed blue line during the post-intervention period, indicating that the implemented intervention generated higher lead outcomes than the estimated no-intervention scenario (Samartsidis et al., 2024). Panel B (Pointwise Daily Impact) further demonstrates that the intervention effect was predominantly positive, as reflected by the dominance of positive impact areas where actual values surpassed predicted values, suggesting that the intervention consistently improved campaign performance daily. Meanwhile, Panel C (Cumulative Impact) shows a steadily increasing cumulative impact curve throughout the post-intervention period, indicating that the positive effects of the intervention were sustained and accumulated over time rather than occurring temporarily. These findings demonstrate that the addition of the Instagram platform significantly enhanced lead generation performance beyond the expected baseline, providing strong evidence of a stable and continuous improvement in digital campaign effectiveness following the intervention (Du et al., 2021).

Based on the quantitative summary in Table 5, the addition of the Instagram platform demonstrated a statistically significant positive impact on campaign performance. Without intervention, the model predicted an average of 159.08 leads, with a 95% credible interval of 151.41 to 167.21. After the intervention was implemented, the average observed actual leads increased to 252.29 leads. This corresponds to an absolute increase of 93.21 leads, with a credible interval of 85.08 to 100.88, indicating that the increase far exceeded the expected baseline variation (Arslan et al., 2024).

Table 5. Quantitative Summary Causal Impact Results

Component	Average	Cumulative	95% CI (Average)	95% CI (Cumulative)
Actual	252.29	7.821.00	–	–
Prediction (s.d.)	159.08 (4.03)	4.931.58 (124.96)	[151.41. 167.21]	[4.693.61. 5.183.46]
Absolute Effect (s.d.)	93.21 (4.03)	2.889.42 (124.96)	[85.08. 100.88]	[2.637.54. 3.127.39]
Relative Effect (s.d.)	58.59% (2.53%)	58.59% (2.53%)	[53.48%. 63.42%]	[53.48%. 63.42%]

Based on a cumulative perspective, the predicted number of leads without intervention was 4,931.58, while the actual cumulative result reached 7,821.00 leads during the post-intervention period. This results in a cumulative absolute effect of 2,889.42 additional leads, with a 95% credible interval ranging from 2,637.54 to 3,127.39. The relative effect, averaging 58.59% with a narrow uncertainty range, indicates that the impact is substantial and consistent over time. These results provide strong quantitative evidence that adding Instagram as an additional advertising channel leads to a significant increase in lead generation performance.

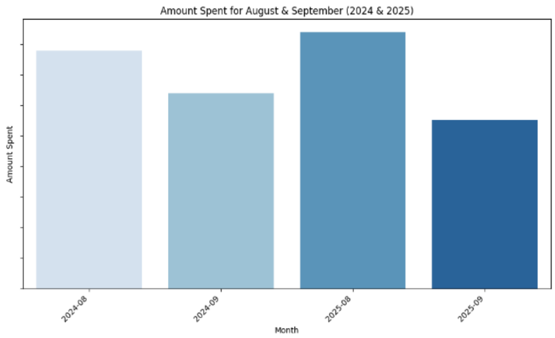


(a) (b)

Figure 6. (a) Cumulative Absolute Uplift (b) Leads in August–September 2024 and 2025

Figure 6(a) visualizes the absolute uplift in the post-intervention period by comparing the actual value and the counterfactual prediction. The average number of actual leads was recorded at 252.29, which is higher than the 159.08 predicted without intervention, resulting in an absolute uplift of 93.21 leads, equivalent to a 58.59% increase. This visualization quantitatively confirms the results of the causal impact analysis, which clearly shows that the observed increase in leads is a real and measurable impact of the intervention of adding the Instagram platform.

Figure 6(b) presents a comparative analysis of lead generation during August–September in both 2024 and 2025. The total number of leads in August–September 2025 significantly exceeds that of the same period in 2024. In contrast, the results in 2024 remained relatively stable, showing only a slight decline between the two months. Meanwhile, although there is a decrease from August to September in 2025, the overall lead volume still surpasses that of the previous year. This comparison indicates that the increase observed in 2025 is not merely a short-term fluctuation



or temporary spike but rather suggests a sustained improvement, likely driven by the implemented intervention.

Figure 7. Amount Spent in August–September 2024 and 2025

Figure 7 compares advertising spending between years and shows that the campaign budget in September 2025 was lower than in September 2024. This budget decrease was one of the factors that contributed to the decrease in the number of leads in September 2025. However, the number of leads in September 2025 remained higher than in the same period the previous year. This shows that the intervention by adding the Instagram platform was quite effective and indicates that the increase in August was not just a temporary spike.

5. Discussion

The findings of this study demonstrate that the integration of the Instagram platform into an existing Facebook-based advertising campaign significantly improves lead generation performance. Based on the Causal Impact analysis, the intervention produced a substantial positive effect, with an average uplift of 93.21 leads and a relative increase of 58.59% compared to the counterfactual baseline. This result confirms that expanding cross-platform advertising reach can generate meaningful incremental value beyond single-platform campaigns, consistent with the argument that digital marketing effectiveness is highly dependent on multi-channel integration and data-driven optimization (Du et al., 2021; Liu et al., 2025).

The observed improvement aligns with prior empirical evidence that Meta-based advertising ecosystems, such as Facebook and Instagram, can significantly enhance conversion and sales performance when used in combination rather than isolation. Andhyka et al. (2025) emphasize that Meta Ads optimization contributes directly to improved MSME sales performance, highlighting the importance of platform synergy in digital marketing strategies. Similarly, Setiawan et al. (2025) argue that sustainable digital marketing performance is strongly influenced by multi-platform strategies that enable broader audience targeting and more efficient engagement pathways. The results of this study extend these findings by quantifying not only performance improvement but also the causal magnitude of Instagram's incremental contribution using a counterfactual-based framework.

From a methodological perspective, the use of Bayesian Structural Time Series (BSTS) strengthens causal interpretation by constructing a robust counterfactual scenario. This approach is consistent with Brodersen et al. (2015) and Scott and Varian (2014), who highlight BSTS as an effective method for estimating intervention effects in observational time-series data. Furthermore, the significant divergence between predicted and actual post-intervention outcomes supports the robustness of causal inference, addressing limitations of traditional regression-based approaches that often fail to capture nonlinear and dynamic advertising effects (Athey & Imbens, 2017; Rahardja & Aini, 2025).

The integration of TabTransformer further enhances the analytical framework by improving the representation of complex tabular advertising data. The model achieved strong predictive performance ($R^2 = 0.80$), indicating its ability to capture nonlinear relationships between marketing variables and lead generation. This supports previous findings that deep learning models for tabular data outperform traditional statistical approaches in handling high-dimensional and heterogeneous marketing datasets (Huang et al., 2020; Badaro et al., 2023). However, consistent with Hair and Sarstedt (2021), predictive strength alone is insufficient for causal interpretation, reinforcing the importance of combining machine learning with causal inference frameworks.

The results demonstrate a clear methodological advancement by integrating TabTransformer-based prediction with BSTS causal impact estimation. This hybrid approach addresses the gap identified in prior studies, where machine learning is primarily used for prediction rather than causal attribution (Vdovichena et al., 2024; Xie, 2025). The findings confirm that Instagram not only improves engagement metrics but also produces a statistically and practically significant increase in lead generation, validating its strategic role in cross-platform digital advertising optimization.

6. Conclusion

This study demonstrates that the integration of TabTransformer and Causal Impact analysis provides an effective framework for evaluating the causal effectiveness of digital advertising interventions. The TabTransformer model was implemented through multiple architectural and training configurations to optimize predictive performance and construct reliable baseline predictions from historical campaign data. The findings indicate that the introduction of the Instagram platform generated a statistically significant and sustained increase in lead generation, as reflected by the consistent positive intervention effects and high posterior probabilities obtained from the Causal Impact analysis. These results suggest that combining machine learning–based tabular representation with Bayesian causal inference can improve the evaluation of digital marketing performance beyond conventional descriptive or correlation-based approaches.

The study also provides practical implications for digital marketing practitioners and business decision-makers. The proposed framework enables advertisers to estimate the actual contribution of platform expansion strategies while separating intervention effects from normal fluctuations in campaign performance. This can support more accurate budget allocation, cross-platform optimization, and evidence-based decision-making in digital campaign management. In addition, the integration of predictive modeling and causal inference offers a scalable analytical approach for handling complex and nonlinear advertising data environments.

Despite these contributions, this study has several limitations. The analysis was conducted using data from a single herbal product campaign and within a relatively short post-intervention observation period, which may limit the generalizability of the findings across industries, products, and longer campaign durations. Furthermore, the study focused primarily on Meta advertising platforms and did not incorporate external variables such as seasonality, competitor activity, or broader market trends that could also influence campaign performance.

Future research is recommended to extend this framework by applying it to larger and more diverse datasets across multiple industries and advertising ecosystems. Further studies may also compare TabTransformer with other deep learning architectures for tabular data, such as DeepFM or TabNet, and incorporate additional contextual variables to improve counterfactual estimation accuracy.

Moreover, future research could explore real-time causal impact monitoring and multi-intervention analysis to support adaptive and dynamic digital marketing strategies.

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Acknowledgment

We gratefully acknowledge the contributions of individuals who supported the completion of this article.

Funding Information

This research did not receive any funding.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

Ethical Approval and Originality Statement

Ethical approval was obtained for this study. The manuscript represents original work and has not been previously published, nor is it under consideration by another journal.

Data Disclosure Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.