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Developing Ad Impact Assessment Models Using Pre/Post-Survey Data Analytics

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ABSTRACT

This paper presents a comprehensive study on developing advanced advertising impact assessment models leveraging pre- and post-survey data analytics. Advertising effectiveness measurement remains crucial for optimizing marketing investments, yet conventional methods often fail to capture nuanced consumer behavior shifts. Our proposed framework integrates statistical, machine learning, and causal inference approaches to analyze survey data collected before and after ad exposure. This approach enables deeper understanding of consumer perception changes, purchase intent, and brand awareness, supported by large-scale empirical validation. Results demonstrate improved accuracy and interpretability over traditional models, offering practical implications for marketing professionals and researchers. Future directions include integrating multi-modal data sources and real-time adaptive assessment mechanisms.

Keywords: advertising effectiveness, pre/post survey, data analytics, causal inference, consumer behavior, machine learning

1. Introduction

Advertising serves as a pivotal driver in shaping consumer attitudes, brand awareness, and purchase decisions [1]. In the rapidly evolving media landscape, marketers face growing challenges to accurately measure advertising impact and justify budget allocations [1], [2], [3], [4], [5], [6]. Traditional metrics such as reach, and frequency provide limited insights into actual consumer behavior changes or long-term brand equity effects [7], [8], [9]. Consequently, there is increasing interest in sophisticated impact assessment models that harness rich data sources including consumer surveys conducted both prior to and following ad exposure [10], [11], [12], [13], [14], [15].

Pre/post survey data represent a vital resource, capturing changes in awareness, attitudes, and purchase intent attributable to specific campaigns [16], [17], [18], [19], [20]. Yet, extracting actionable insights from such data is non-trivial due to the complexities of survey design, sampling biases, confounding factors, and temporal effects. Existing ad impact evaluation methods, including simple lift analysis and matched control comparisons, often oversimplify these dynamics and fail to robustly quantify causal effects [21], [22], [23], [24]. This limitation undermines marketers' ability to optimize creative strategies and media mix decisions based on reliable evidence.

Recent advances in data analytics, machine learning, and causal inference provide promising avenues to develop more accurate and interpretable models for ad impact assessment [20], [25], [26]. By combining these approaches with pre/post survey designs, it becomes feasible to disentangle advertising effects from external influences, quantify heterogeneous consumer responses, and predict longer-term outcomes [27], [28], [29], [30]. Moreover, automated analytic frameworks enable scalable processing of large survey datasets from diverse markets and channels, enhancing generalizability and operational utility [31], [32], [33], [34], [35].

This paper aims to address the critical gap in integrated modeling methodologies for ad impact evaluation using pre/post survey data. We propose a novel framework encompassing data preprocessing, feature engineering, causal effect estimation, and predictive analytics tailored to advertising contexts. The framework is empirically validated on multiple real-world datasets spanning digital, TV, and cross-media campaigns. Our contributions include:

- A detailed literature synthesis on survey-based ad effectiveness measurement and advanced analytic methods.
- Development of hybrid causal and machine learning models to assess ad impact with improved accuracy and explanatory power.
- Implementation of a practical analytic pipeline addressing common survey data challenges such as missingness, bias, and sample representativeness.
- Comprehensive evaluation using multiple performance metrics and sensitivity analyses across campaign types and consumer segments.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on advertising effectiveness metrics, survey methodologies, and analytic models. Section 3 outlines the data sources and preprocessing techniques used. Section 4 details the proposed ad impact assessment framework and modeling approaches. Section 5 presents empirical results and discussion. Section 6 discusses practical implications, limitations, and future research directions. Finally, Section 7 concludes with a summary of findings and contributions.

2. Literature Review

Advertising effectiveness measurement has been a cornerstone of marketing research for decades, evolving in complexity alongside technological and methodological advances. This literature review systematically examines key domains relevant to developing ad impact assessment models using pre/post-survey data analytics. It covers foundational advertising metrics, survey methodologies, statistical and causal inference models, machine learning applications, integration of multi-modal data, and identifies existing research gaps.

2.1 Traditional Advertising Effectiveness Metrics and Models

Historically, advertising effectiveness was evaluated primarily through simple metrics such as reach, frequency, gross rating points (GRPs), and recall measures [1], [2]. Early models, including the hierarchy of effects frameworks, emphasized sequential consumer responses starting from awareness, interest, desire, to action (AIDA) [3], [4]. While these metrics offered useful insights into media exposure levels, they provided limited understanding of actual behavior change or the incremental value generated by advertising efforts.

Regression-based attribution models emerged to correlate advertising spend with sales or brand metrics, but suffered from endogeneity and confounding biases, limiting causal interpretability [5], [6]. Econometric approaches such as marketing mix modelling (MMM) allowed for decomposing sales drivers across media channels but typically operated at aggregate market-level data, missing individual consumer heterogeneity [7], [8]. These limitations stimulated the adoption of experimental and quasi-experimental designs for more robust impact evaluation.

2.2 Pre/Post Survey Designs: Principles and Challenges

Pre/post survey designs have long been used to measure changes in consumer attitudes, awareness, and behavioral intentions due to advertising exposure [36], [37], [38]. By collecting baseline measures prior to ad exposure and follow-up data afterwards, researchers can directly estimate incremental lift within individuals or groups [39], [40], [41]. This design is widely considered superior to cross-sectional surveys for isolating the effect of advertising campaigns, particularly when complemented by control groups [42], [43], [44], [45].

However, several challenges impact the reliability and validity of pre/post surveys. Panel attrition, wherein participants drop out between waves, can introduce non-random sample bias [15]. Response biases such as social desirability effects, recall decay, and acquiescence distort true attitudinal shifts [46], [47], [48], [49]. The timing between pre and post surveys critically influences measured effects, as too short intervals may not capture full ad impact, while longer delays risk contamination from other marketing activities [50], [51].

Methodological advancements to address these challenges include employing balanced panel designs, incentivizing participation, using validated scales for attitude measurement, and incorporating behavioural intent proxies [52], [53], [54]. Advanced weighting schemes compensate for demographic imbalances and non-response bias, enhancing generalizability [55], [56], [57]. Nevertheless, survey data remain inherently noisy, necessitating robust analytic approaches for impact assessment.

2.3 Statistical and Econometric Methods for Impact Estimation

To estimate causal advertising effects from survey data, a rich body of literature explores econometric techniques that adjust for confounding and selection bias. [58], [59], [60], [61] Difference-in-differences (DiD) is a popular quasi-experimental method that compares outcome changes over time between exposed and unexposed groups [62]. DiD assumes parallel trends, which may be violated if unobserved factors differentially affect groups [36], [63]. Extensions include triple differences and synthetic control methods to relax assumptions and improve robustness [64], [65], [66].

Instrumental variables (IV) methods leverage exogenous variation in exposure, such as ad scheduling or geographic rollouts, to isolate causal impacts [67], [68]. While powerful, valid instruments are challenging to identify, and weak instruments can bias estimates [30]. Structural equation modeling (SEM) provides a framework for modeling latent constructs such as brand attitude or emotional response, incorporating measurement error and mediating variables [31], [32]. SEM has been applied to evaluate indirect and direct effects of advertising [33].

Propensity score matching (PSM) and inverse probability weighting (IPW) further adjust for observable confounders by balancing covariate distributions between treatment and control groups [69]. Despite methodological rigor, these techniques rely on strong ignorability assumptions and are sensitive to model specification [36]. Combining multiple econometric approaches has been advocated for triangulating effect estimates [37].

2.4 Machine Learning and Causal Machine Learning in Advertising Analytics

With the explosion of digital advertising data, machine learning (ML) techniques have gained prominence for modelling consumer behaviour and ad response patterns [70], [71], [72], [73], [74]. Supervised learning methods such as random forests, gradient boosting machines, and deep neural networks can uncover complex nonlinear relationships and interaction effects beyond traditional regression [75], [76]. For example, gradient boosting frameworks have demonstrated superior performance in predicting purchase intent and churn following ad exposure [42].

However, conventional ML models primarily optimize predictive accuracy and often lack causal interpretability, limiting their utility for policy and budget decisions [77], [78], [79], [80]. To address this, causal machine learning (CML) methods have emerged, integrating causal inference with ML to estimate heterogeneous treatment effects (HTEs) at individual or subgroup levels [44], [45]. Techniques such as causal forests, Bayesian additive regression trees (BART), and targeted maximum likelihood estimation (TMLE) allow estimation of conditional average treatment effects (CATEs) with uncertainty quantification [46], [47].

Recent studies have demonstrated the application of CML to advertising contexts, revealing significant heterogeneity in ad effectiveness across demographics, browsing behaviour, and prior brand engagement [48], [49]. These insights enable marketers to tailor campaigns and optimize targeting strategies. However, adoption is still limited by the complexity of model training, validation, and the need for rich feature sets derived from survey and behavioural data [50].

2.5 Multi-Modal and Real-Time Analytics for Ad Impact

Increasingly, advertising impact assessment benefits from integrating multiple data modalities beyond survey responses. Social listening data, digital tracking metrics (e.g., clickstreams, impressions), point-of-sale data, and customer relationship management (CRM) systems enrich understanding of consumer journeys [81], [82], [83], [84]. Combining these heterogeneous sources poses challenges in data harmonization, temporal alignment, and privacy compliance [53].

Real-time analytics and streaming data platforms enable dynamic campaign optimization by monitoring live consumer responses and adjusting creatives or targeting accordingly [85], [86], [87], [88]. Techniques such as reinforcement learning and bandit algorithms have been proposed to balance exploration and exploitation in ad allocation [89]. Despite potential, real-time systems require robust integration with traditional survey frameworks to ensure accurate baseline comparisons and causal validity [90], [91].

2.6 Research Gaps and Future Directions

Despite the extensive literature, several gaps remain in developing robust, scalable ad impact models using pre/post survey data. Most existing studies focus narrowly on either statistical causal inference or predictive machine learning, lacking unified frameworks that combine their strengths. Handling survey-specific issues such as missing data, measurement error, and panel attrition within these models is insufficiently addressed.

Moreover, few studies systematically validate models across diverse campaign types (digital, TV, cross-media) and consumer segments, limiting generalizability. Integration of multi-modal data, including social listening and sales data, is still in early stages, and practical pipelines for real-time adaptive assessment are underdeveloped.

Addressing these gaps requires interdisciplinary approaches drawing from marketing science, statistics, computer science, and behavioral economics. This paper contributes by proposing such an integrated framework and validating it empirically on large, heterogeneous datasets.

3. Methodology

This section details the methodological framework developed for assessing advertising impact by leveraging pre/post survey data analytics. The framework integrates rigorous survey design, advanced data processing, and robust modeling techniques combining causal inference and machine learning methods. The methodological approach is structured into four key phases: data collection and preprocessing, model development, validation, and implementation for decision support.

3.1 Data Collection and Survey Design

Central to the framework is the deployment of a carefully designed pre/post survey protocol to capture consumer attitudes, perceptions, and behaviors before and after exposure to advertising campaigns. The survey instruments include standardized psychometric scales for brand awareness, brand favorability, purchase intent, and emotional engagement, complemented by demographic and media consumption variables. Participants are recruited through stratified sampling to ensure representation across key consumer segments, with attention to minimizing panel attrition. The pre-survey collects baseline measures prior to campaign launch, while the post-survey is administered after a pre-defined exposure window typically 2 to 4 weeks depending on campaign length and media channel.

To mitigate biases, the survey employs randomized question ordering, validated response scales, and anonymity assurances. Additionally, attention checks and response time metrics identify low-quality responses for exclusion. Survey data are augmented with campaign metadata including ad impressions, frequency, and channel to enable linkage between self-reported exposure and actual ad delivery.

3.2 Data Preprocessing and Feature Engineering

Raw survey responses undergo preprocessing to handle missing data, outliers, and inconsistencies. Missing values are imputed using multiple imputation techniques, preserving the distributional characteristics of variables [59]. Outlier detection employs robust statistical methods, including Mahalanobis distance for multivariate anomalies [60]. Responses are standardized and transformed where appropriate. Key variables are aggregated to form composite indices (e.g., brand favorability index) using confirmatory factor analysis (CFA) to ensure measurement validity and reliability [61]. Behavioral variables such as purchase intent are binarized or categorized for modeling convenience.

Feature engineering incorporates interaction terms (e.g., demographic × exposure frequency), temporal variables capturing time between surveys, and categorical encoding for media channels. This enriched feature set supports nuanced modeling of heterogeneous treatment effects.

3.3 Model Development

The core of the methodology is the development of impact assessment models that estimate the incremental effect of advertising on consumer outcomes using pre/post survey data. The approach combines traditional econometric models with state-of-the-art causal machine learning techniques to balance interpretability and predictive power.

3.3.1 Difference-in-Differences (DiD) Analysis

A baseline model employs DiD to estimate average treatment effects by comparing outcome changes over time between exposed and control groups. The model specification controls for observed covariates and includes fixed effects for individual and time periods to mitigate unobserved heterogeneity [62], [92].

3.3.2 Propensity Score Matching (PSM)

To address selection bias in non-random exposure, PSM is used to create matched samples of exposed and unexposed respondents with similar covariate profiles. Nearest neighbor and kernel matching algorithms are applied, and balance diagnostics verify the quality of matching [69].

3.3.3 Causal Machine Learning Models

Building upon these foundations, causal forests and Bayesian additive regression trees (BART) are employed to estimate heterogeneous treatment effects at the individual level [93], [94], [95]. These nonparametric models automatically capture nonlinearities and interactions, providing insights into which consumer segments benefit most from advertising.

Model training incorporates cross-validation and hyperparameter tuning to prevent overfitting. Feature importance measures and partial dependence plots elucidate key drivers of ad impact.

3.4 Model Validation and Evaluation

Model performance is evaluated through multiple complementary metrics. For causal inference models, average treatment effect (ATE) estimates are benchmarked against ground truth or experimental results where available. Heterogeneity analyses assess subgroup consistency.

Predictive accuracy is measured using root mean squared error (RMSE) and area under the receiver operating characteristic curve (AUC) for classification-based outcomes. Sensitivity analyses evaluate robustness to varying assumptions and sample compositions.

External validity is tested by applying models to holdout datasets from different campaigns and media formats. Statistical significance is assessed via bootstrapping and permutation tests.

3.5 Implementation for Marketing Decision Support

The final phase translates model outputs into actionable insights for marketers. Impact estimates are integrated into dashboards and reporting tools that visualize lift metrics, segment-level responsiveness, and ROI projections.

Scenario analysis modules enable forecasting of incremental outcomes under different budget allocations and targeting strategies. Alerts highlight unexpected shifts in consumer sentiment or engagement, facilitating agile campaign adjustments.

Data governance protocols ensure compliance with privacy regulations and ethical standards, supporting transparent and responsible use of consumer data.

This comprehensive methodological framework establishes a rigorous foundation for reliable and scalable advertising impact assessment using pre/post survey data analytics. The following sections present empirical results and case studies demonstrating its efficacy.

4. Results and Analysis

This section presents the empirical findings from applying the proposed ad impact assessment framework to multiple advertising campaigns spanning diverse industries and media channels. The analysis covers descriptive statistics of the survey data, model estimation results, validation outcomes, and insights into heterogeneous treatment effects.

4.1 Descriptive Statistics and Survey Data Overview

The combined dataset comprises pre/post surveys from five distinct campaigns conducted over a 12-month period, encompassing a total sample size of 8,500 respondents. Table 1 summarizes key demographic characteristics and baseline brand metrics across campaigns.

Table 1: Summary of key demographic characteristics

Variable	Mean (SD) / %
Age	35.7 (12.4) years
Gender (Female)	52.3%
Baseline Brand Awareness	42.6%
Purchase Intent (Pre)	21.9%
Exposure Rate	65.4%

The pre-survey baseline indicated moderate brand awareness and low purchase intent, consistent with campaign objectives focused on brand introduction and consideration. Exposure rates measured through self-report and cross-validated with ad impression logs showed high concordance (Pearson $r = 0.78$).

4.2 Model Estimation Results

4.2.1 Difference-in-Differences (DiD) Analysis

DiD models estimate an average lift of 7.8 percentage points ($p < 0.01$) in purchase intent attributable to ad exposure across campaigns. The inclusion of covariates such as age, gender, and media channel improved model fit (adjusted $R^2 = 0.32$).

4.2.2 Propensity Score Matching (PSM)

PSM successfully balanced covariates between treatment and control groups, as evidenced by standardized mean differences below 0.1 for all key variables post-matching. The average treatment effect on the treated (ATT) was estimated at 8.3 percentage points (95% CI: 6.2–10.4), slightly higher than DiD estimates, reflecting reduced selection bias.

4.2.3 Causal Machine Learning Models

Causal forests yielded heterogeneous treatment effects ranging from 3% to 15% lift in purchase intent across consumer subgroups. Feature importance rankings identified prior brand familiarity, age group, and exposure frequency as primary moderators. Bayesian additive regression trees (BART) corroborated these findings, with improved predictive accuracy (RMSE = 0.12).

Partial dependence plots reveal nonlinear relationships, such as diminishing returns for high exposure frequency beyond five ad impressions. Segment analysis highlighted younger consumers (18–34 years) and females as more responsive to advertising stimuli.

4.3 Model Validation and Robustness Checks

Cross-validation procedures confirmed model stability, with consistent ATE estimates across folds (variation < 2%). Applying the models to holdout campaigns with differing media mixes demonstrated external validity, yielding lift estimates within 1.5 percentage points of original campaigns.

Sensitivity analyses showed results robust to alternative imputation strategies and exclusion of low-quality respondents. Bootstrapped confidence intervals remained narrow, underscoring statistical reliability.

4.4 Marketing Insights and Implications

The integrated modeling approach enables marketers to quantify incremental advertising impact with high precision and uncover nuanced consumer segment responses. Findings suggest optimization opportunities in budget allocation towards demographic segments exhibiting higher ad sensitivity.

The observed nonlinear exposure effects inform frequency capping strategies to maximize ROI while minimizing ad fatigue. Additionally, the framework supports scenario planning for multi-channel campaigns by simulating incremental lifts under varying media mixes.

4.5 Limitations

While the framework demonstrates strong empirical performance, certain limitations merit consideration. Reliance on self-reported exposure introduces measurement error despite cross-validation efforts. The time lag between surveys may not fully capture long-term brand effects.

Moreover, unobserved confounders such as competitor activity remain potential sources of bias. Future work incorporating experimental or panel data can further enhance causal inference robustness.

The results validate the efficacy of the proposed ad impact assessment framework and underscore its practical utility in data-driven marketing decision-making. The next section discusses these findings in the context of current literature and outlines avenues for future research.

5. Discussion

The findings presented in Section 4 underscore the significant value of integrating pre/post survey data with advanced analytical models to derive actionable insights into advertising effectiveness. This section contextualizes these results within the broader literature on ad impact assessment, evaluates methodological strengths and limitations, and explores implications for marketing practice and future research directions.

5.1 Integration with Existing Literature

The demonstrated average treatment effects, quantified through both traditional econometric techniques such as difference-in-differences (DiD) and propensity score matching (PSM), align closely with seminal studies highlighting the incremental impact of advertising on brand metrics [62], [96]. The lift in purchase intent observed in this study corroborates prior findings indicating that targeted media exposure positively influences consumer behavior when controlling for confounding factors [97], [98], [99].

Importantly, the incorporation of causal machine learning approaches such as causal forests and Bayesian additive regression trees (BART) advances the methodological frontier by enabling estimation of heterogeneous treatment effects (HTE). These techniques complement earlier research demonstrating the limitations of average treatment effects for guiding precision marketing strategies [100], [101], [102]. The identification of demographic and exposure frequency moderators echoes contemporary studies emphasizing the necessity of personalized ad targeting to maximize return on investment [103], [104].

The nonlinear dose-response relationships detected in partial dependence analyses reflect findings from media mix modeling and ad fatigue literature, which caution against excessive ad frequency diminishing marginal returns [105], [106], [107]. These nuanced insights reinforce the value of dynamic frequency capping and channel optimization informed by granular data analytics [108], [109], [110], [111].

5.2 Methodological Contributions and Strengths

The framework's strength lies in its holistic integration of survey methodology, rigorous data preprocessing, and multi-model analytical strategies. By employing robust imputation and matching techniques, the approach mitigates common pitfalls such as sample selection bias and measurement error pervasive in observational ad effectiveness research [112], [113], [114].

The use of causal machine learning models represents a critical advancement, bridging the gap between interpretable econometric estimates and predictive accuracy required for operational deployment. Moreover, the modular nature of the framework facilitates adaptation to varied campaign contexts and data availability scenarios, enhancing its generalizability.

5.3 Practical Implications for Marketers

The actionable insights derived from this framework empower marketers to optimize ad spend allocation, refine media strategies, and tailor messaging for high-value consumer segments. By quantifying incremental lifts and identifying key moderators, decision-makers can move beyond aggregate performance metrics toward precision targeting that improves campaign ROI and consumer engagement.

Furthermore, scenario simulation capabilities support proactive budget planning and agile adjustments in response to real-time market dynamics. This dynamic responsiveness is essential in today's rapidly evolving digital advertising ecosystem characterized by fragmented media consumption and diverse consumer preferences.

5.4 Limitations and Future Research Directions

Despite its contributions, the study has limitations warranting attention. The reliance on self-reported survey data may introduce recall bias and social desirability effects, potentially attenuating true exposure measures. Future studies could integrate passive measurement technologies such as digital ad tracking and biometric response monitoring to enhance exposure accuracy.

The temporal separation between pre and post surveys, while necessary for causal inference, constrains assessment of longer-term brand effects and customer lifetime value impacts. Longitudinal panel designs and repeated measurement models can provide richer insights into ad durability and delayed responses.

Finally, expanding the framework to incorporate cross-channel attribution and real-time adaptive learning algorithms could further augment its strategic value, addressing the complexity of omnichannel consumer journeys.

5.5 Summary

In summary, this study demonstrates that combining pre/post survey data with advanced causal modeling offers a powerful means of accurately assessing advertising impact. The approach aligns with evolving marketing analytics paradigms emphasizing data integration, causal inference, and personalized insights. By advancing both theory and practice, the framework supports more effective, efficient, and accountable advertising investments.

6. Conclusion and Future Work

This study presents a comprehensive framework for developing ad impact assessment models leveraging pre/post-survey data analytics. Through a combination of traditional econometric techniques and cutting-edge causal machine learning approaches, the framework effectively quantifies the incremental effects of advertising on key consumer metrics such as purchase intent and brand awareness. The integration of rigorous data preprocessing, propensity score matching, and heterogeneous treatment effect modeling enables marketers to gain deeper insights into campaign performance, optimize media allocation, and tailor targeting strategies to specific consumer segments.

Empirical results from multiple real-world campaigns validate the framework's robustness, with consistent treatment effect estimates across diverse industries and media channels. The identification of nonlinear dose-response patterns and key moderator variables further enriches understanding of ad frequency optimization and audience responsiveness, supporting dynamic campaign management and ROI maximization.

Despite these advances, the study acknowledges limitations related to self-reported exposure measures, survey timing constraints, and potential unobserved confounders. Addressing these challenges through integration of passive exposure tracking, longitudinal designs, and real-time adaptive learning represents promising avenues for future research.

Future work will also focus on extending the framework to incorporate cross-channel attribution models, enabling holistic evaluation of omnichannel advertising effectiveness. Additionally, leveraging advances in artificial intelligence and real-time data streams to develop automated, scalable impact assessment systems will enhance the practical utility and responsiveness of ad analytics in fast-paced digital environments.

In conclusion, this research contributes both theoretically and practically by offering a flexible, scalable, and methodologically rigorous approach to ad impact assessment. It equips marketers with actionable intelligence to drive smarter advertising investments and supports ongoing innovation in marketing analytics methodologies.

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