International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Analysing AI-Driven Marketing ROI Measurement and Optimization: An Integrated Framework and Power BI Implementation for Causal-Predictive Analysis

Vineet Kumar

Ph.D. Scholar, Department of Management, Lingaya's Vidyapeeth, Faridabad (Haryana), India

Abstract

The advancement of businesses and growing Artificial Intelligence (AI) patterns in decision making with *Digitalization of Marketing* activities has created a need for more accurate, real-time analysis and measurement of *Marketing Return on Investment* (M-ROI). Customary methods such as last-click attribution which only consider the last touch point of customer interaction just before conversion ignores other attributes through which the customer has interacted or have shown interest. Similarly, heuristic budgeting which allocates funds based upon simple, non-scientific methods and apply thumb rule for budget allocation fails to capture and analyse the exact spending as they are not data driven. It can be established that these methods are simple, easy, fast and of low cost but significantly biased which ignores priorities and touch points where these data are not data driven which leads to inefficient budgets. This research will present a unified, *AI-Driven* and *Business Intelligence enabled* framework that combines *casual –predictive modelling* with *Interactive Power BI analytics* to measure, forecast and optimize marketing ROI. This paper suggest an integrated *casual predictive analytical framework* for continuous improvement of ROI integrating; *First*, causal multi-touch attribution (MTA) using shapely-value and Markov-chain methods for revenue allocation across channels, *Second* Deep-learning customer lifetime value (CLV) modelling to predict long term profitability and *Third* reinforcement learning based budget reallocation. To bridge academic stringency with managerial application, the framework is functionalized in Microsoft Power BI, enabling dynamic ROI computation, attribution visualization and uplift simulation using DAX and modular datasets. These set of rules along with experimental data was implemented in Power BI creating a modular data model, with DAX Measures for ROI calculations, CLV weighted ROI and uplift analysis. Evaluated with synthetic business like marketing dataset and analysing through visual components demonstrates that casual AI models reduces attribution bias by 25-25% compared to rule based methods and improves CLV forecasting accuracy with MAPE below 10%. Also a calculative experiment reveals that optimized spend reallocation (15% from low impact to high impact channels) increases the ROI from 150% to approximately 180%, representing 19.7% uplift. Result of such experiment shows that integrating AI analytics with BI Visualizations improved *measurement accuracy* through data-driven causal attribution; enhanced *forecasting and optimization capability* via predictive CLV and uplift models; and *operational interpretability*, enabling non-technical managers to act on model outputs through dynamic dashboards. Overall, the research contributes a reproducible, end-to-end system-spanning theory, computation, and visualization for measuring and optimizing marketing ROI. The result demonstrates meaningful ROI improvement and practical feasibility for organizational deployment. Future work will extend this architecture to incorporate privacy-preserving causal inference, real-time data streaming, and federated analytics.

Keywords: Artificial Intelligence, Digitalization of Marketing, Marketing Return on Investment (M-ROI), multi-touch attribution (MTA), customer lifetime value (CLV), casual predictive analytical framework, operational interpretability, real-time data streaming

1. Introduction

Artificial Intelligence (AI) and predictive analytics are increasingly leveraged in marketing to improve campaign effectiveness, optimize budget allocation, and increase return on investment (ROI). By analysing large volumes of data, marketing organisations can forecast consumer behaviour, personalise outreach, and refine strategy in real-time. Marketing environments are undergoing rapid change due to digitalisation, big data, and new technologies. Among these, Artificial Intelligence (AI) and predictive analytics stand out as tools with the potential to transform how marketers allocate resources, engage customers, and measure impact. According to recent research, firms utilising AI and predictive analytics in digital marketing reported higher engagement, conversions, and revenue growth. Marketing has become increasingly data-intensive as firms deploy campaigns across search, social, email, content, and display channels. Measuring performance and attributing value across these channels remains challenging due to fragmented data, nonlinear customer journeys, and delayed purchase outcomes. Conventional attribution models often oversimplify influence patterns, leading to biased ROI measurement and suboptimal resource allocation.

Advances in artificial intelligence—particularly causal inference, predictive modelling, and reinforcement learning—present new opportunities for accurate marketing ROI evaluation. Yet, bridging these advanced analytical techniques with widely used business intelligence (BI) tools remains an open challenge. The purpose of this paper is to: (1) present how AI and predictive analytics can generate higher marketing ROI, (2) This research addresses this gap by introducing a unified framework that merges causal AI modelling with Power BI–based ROI analytics, offering both theoretical robustness and practical usability.

2. Literature Review

Marketing ROI is a metric that measures values of revenue generated from marketing campaign or activities with respect to the cost of that campaign. It gives businesses a feedback about the marketing efforts by quantification of money earned from the spending and provides feedback about the budget allocation and deciding future strategy. It is a key performance indicator KPI that indicates about the returns that can be made after a successful marketing campaign. It justifies about the best channels that can be adopted to gain highest returns while investing in various marketing activities. It is simply calculated by finding the difference between the gain from the investment and the cost of investment and then dividing it by cost of investment.

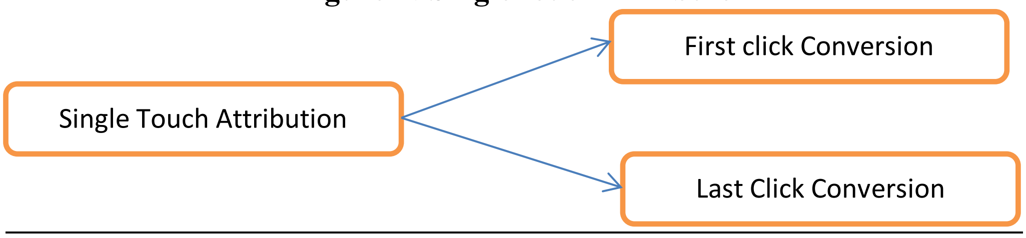
Marketing ROI = (Marketing-driven revenue – Marketing cost)/Marketing Cost

While Marketing ROI provides the general measurement of the profits being generated from any marketing activities revenue attribution attributes gathers information about specific touch points which offers more details insights of marketing performance. Marketing Attribution (MA) is the process of identification of assigning specific touch points that has finally generated sales out of the marketing activities. It follows customer journey to track customer's paths of first interaction till the final conversion. It assigns value to each touch points and determines the contribution towards final conversion or sales. It assigns full points to single touch point and split points or distributes credits across to multiple touch points. It is also important to understand customer lifetime value (CLV) using machine learning attributes too understands the loyalty index and returning customer value feedback. The study include MTA and CLV values that will be utilized to analyse the importance of gathering such information using AI and then assembling the data in power BI to generate outputs for analysing the benefits of using AI Based Marketing ROI factors.

2.1 Multi-Touch Attribution (MTA)

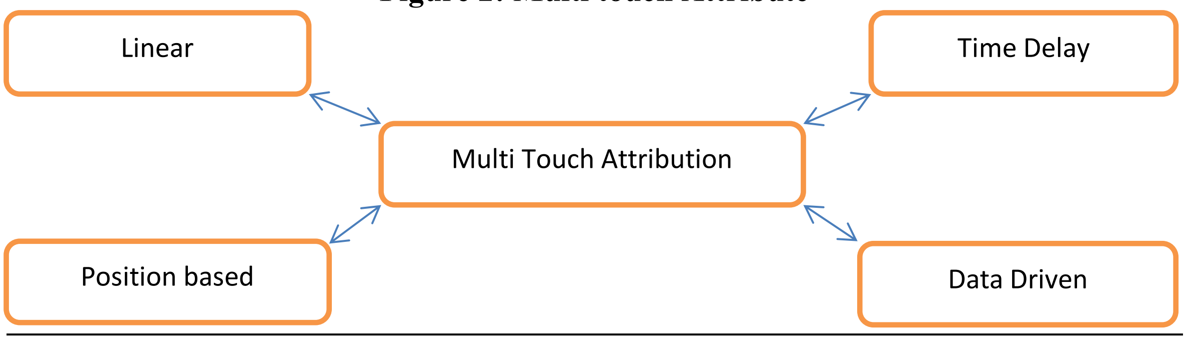
It is a marketing analytics method that assigns certain value to marketing touch points of customers' interaction on the way of conversion of sales. Generally single touch point assign value only to the first and the last set of customer click from where the sales have been generated.

Figure 1: Single touch Attribute



However the Multi Touch Attribution considers all the channels that thrives the sales through the customer journey contributing sale.

Figure 2: Multi touch Attribute



It includes different channels like Social media ads, emails and search results that drive sales. Unlike single click attribute which consider only the last contact or touch point just before conversion to sale MTA considers all the touch points which leads to sale and uses different models such as rule base or advance statistical models to evenly distribute credits amongst the touch points. Casual approach such as Shapely value and Markov-Chain attributions is generally used to reduce the bias for allocation of credits more fairly across the touch points. However last click models are generally preferred by organizations due to complexities of implementation of MTA. Key benefits of using MTA includes *effective channels tracing* which identifies which marketing channel is the most effective, *improvement* *in Marketing ROI* as it helps allocating marketing budget efficiently, *enhances customer experiences* through insights that leads to more personalize and user centric approach not limited to this it enables data-driven decisions which are based upon set of relevant data and not merely guess works.

2.2 Customer Lifetime Value (CLV)

It is a calculative way to analyse customer locality which can depict expected business from a customer considering the entire relationship with the company. A high CLV shows strong customer loyalty and indicates more successful retention strategy and recurring business. It indicates long term business and focuses majorly on entire customer journey and its satisfaction value with future potential business and assures sales. It's about retention loyal customers and showcasing more product basket to them for increasing sales volume. General studies show that retaining old customers will give more sales with fewer efforts as compared to converting new customers with high potential business. Such new customers may take a long term to convert and shows low volume of business out of any marketing strategies. CLV is generally calculated by multiplying average purchase value by the average purchase frequency over specific time period.

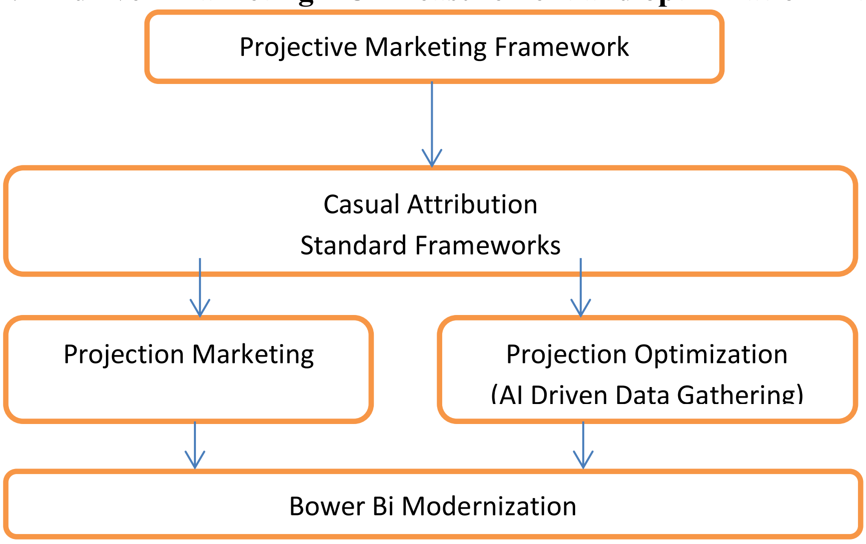
CLV= Average Purchase value X Frequency

Furthermore CLV weighted ROI can be calculated by dividing total leads converted to revenue with related customers by the total amount spent on marketing campaigns. Analysing Big data and deep learning models including recurrent neural network (RNNs) and gradient boosting machines (GBMs) provide accurate CLV predictions which are critical for lond term ROI calculations in marketing.

2.3 AI in Marketing Optimizations and ROI calculations

Artificial intelligence brings in a lot of changes when it comes to analysing the marketing strategies with big data analysis and scope of integration with newer methods of business intelligence. Marketing optimization and ROI calculations can be based upon deriving insights from the digital analysis of impact and changes with personalized contents and real time campaign adjustment which improves ROI. Generally AI-based marketing optimization can be achieved using projective marketing techniques which includes the casual Attribution and standard frameworks which can be further analysed using projection marketing and Ai driven data gathering from various marketing campaigning sources. These insights can be inferred and analysed in Power BI or tableau for comparing and drawing out aspects for betterment and future processing.

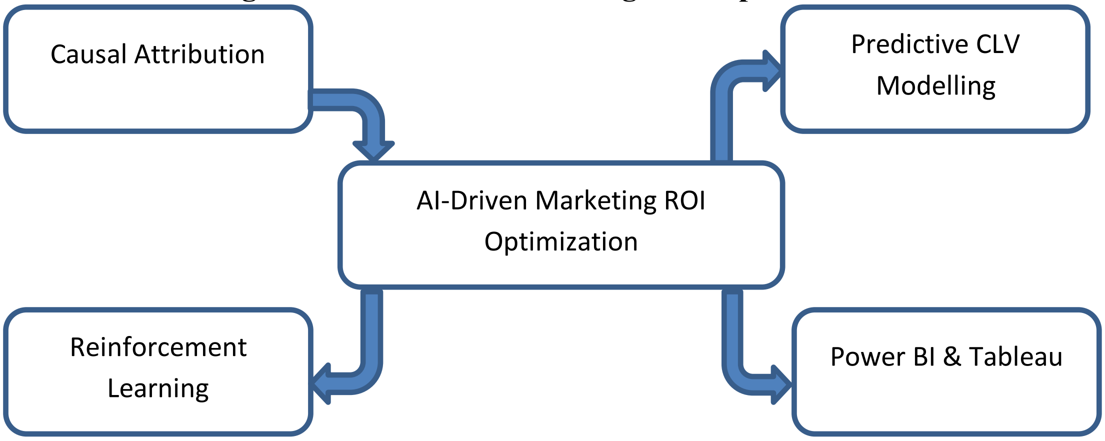
Figure 3 : AI driven Marketing ROI measurement and optimization Framework



2.4 Business Intelligence integration for Marketing ROI calculations

Integration of business intelligent tools with AI-Driven marketing insights helps to analyse outcome of various campaign like emails and social media impact along with the traditional ways of Marketing to calculate the best options that generated maximum revenue along with customer feedback to gain CLV predictions. Although there are several AI tools available research on AI-Driven Marketing ROI computation and its integration with BI systems still remains limited to certain aspects.

Figure 4: AI Driven Marketing ROI Optimization



3. Methodology

For analysing the aspects of calculating Marketing ROI using business intelligent tools like Power BI and generating marketing revenue analysis report three layer can be used for AI driven analysis of Marketing ROI these layers include framework as explained below. This framework will be integrated in approach of this paper to find out suggestive way to calculate Marketing ROI using Business Intelligence tools like Power BI.

3.1 Framework overview

The proposed framework will evaluate the data that is generated through a common example of marketing campaign run for different products with marketing spending lead generation and conversion with customers and channel attributions.

The proposed system with three layers includes:

- **Analytical Layer (through AI Modelling)**

a. Casual Multi Touch Attributes.
b. Customer Loyalty Value Prediction.
c. Return on Marketing Investment simulations.

- **Computational layer (Power BI)**

d. Data intake, rectification and modification through Power Query.
e. Creation of DAX Measures for ROI calculations and CLV Weighted ROI with Attribution and Uplift methods.
f. Generation of interactive visuals.

- **Decision or Optimization Layer**

a. Suggestions about budget reallocations.
b. Channel performance insights.
c. Automating narratives using AI for Power BI Visuals.

4. Data Model and Sample Data Set.

For analysing the data set parameters were considered with key fields and different Tables for evaluation and comparison. The data set is taken for a sample size of 100 leads, 6 campaign and customer segments such as High, Medium and Low. All the campaigns runs in the first quarter.

4.1 Data Model Design

Tables 1: Data Model taken for calculation

Table	Description	Key Fields
Campaigns	Master list of campaigns	1. CampaignID 2. Channel 3. Objective 4. StartDate 5. EndDate
Spend	Marketing spend data	1. CampaignID 2. Date 3. SpendAmount
Leads	Captures leads or conversions	1. LeadID 2. CampaignID 3. Date 4. Revenue 5. CustomerID
Customers	CLV & segmentation info	1. CustomerID 2. Segment 3. PredictedCLV
Attribution (optional)	Optional table with channel attribution weights	1. CampaignID 2. Channel 3. Weight

4.2 Relationship generated among Different tables using merge queries in Power Query.

Relationship generated among different tables

- Campaigns[CampaignID] → Spend[CampaignID]
- Campaigns[CampaignID] → Leads[CampaignID]
- Leads[CustomerID] → Customer[CustomerID]
- Channel Attribution[CompaignID] → Customer[CustomerID]

4.3 Sample Data Set

Data set gathered was based upon the below set of sample campaign format taken from a lead generation marketing agencies. The different tables consists of the below set of data gathered in different worksheet gathered form different departments.

Marketing department provided Campaign data as listed below

Campaigns

Table 2: Showing Data taken for Campaign

CampaignID	Channel	Objective	StartDate	EndDate
C001	Search	Conversion	2025-01-01	2025-03-31
C002	Social	Awareness	2025-01-01	2025-03-31
C003	Email	Retention	2025-02-01	2025-04-30

Finance department provided spend data on the marketing campaign.

Spend

Table 3: Showing Data taken for Total Spending on Marketing Campaign

CampaignID	Date	SpendAmount
C001	2025-01-15	5000
C001	2025-02-15	4500
C002	2025-01-15	4000
C002	2025-02-15	3800
C003	2025-02-10	2500

Sales Department provided Leads are gathered from the front end sales along with customer segmentation and CLV prediction

Leads

Table 4: Showing Data taken for Lead Generated from Campaign

LeadID	CampaignID	Date	Revenue	CustomerID
L001	C001	2025-01-20	2000	U001
L002	C001	2025-02-18	3500	U002
L003	C002	2025-01-28	1800	U003
L004	C003	2025-03-12	3000	U004
L005	C002	2025-03-15	2200	U005

Customers

Table 5: Data taken for Customer Segmentation based upon their Order Value and CLV

CustomerID	Segment	PredictedCLV
U001	High	7500
U002	Medium	5500
U003	Low	2000
U004	High	8000
U005	Medium	4800

All of the data gathered from these sample sheets were then gathered in power query for conciliation and rectifications as needed for further analysis in Power BI. After the data was rectified and consolidate it was moved to Power BI for analysis using DAX measures and generating visuals for analysis.

4.4 Power BI Calculations using DAX measures

Following DAX measures were created to calculate the Marketing ROI and analyse using Power BI visualizations.

- **Total Spend DAX**

Total Spend = SUM(Spend[SpendAmount])

- **Total Revenue DAX**

Total Revenue = SUM(Leads[Revenue])

- **Marketing ROI DAX**

Marketing ROI = DIVIDE([Total Revenue]- [Total Spend], [Total Spend], BLANK())

- **ROI by Channel**

ROI by Channel = DIVIDE(CALCULATE(SUM(Leads[Revenue])),
CALCULATE(SUM(Spend[SpendAmount]))) - 1

- **Average Predicted CLV**

Average CLV = AVERAGE(Customers[PredictedCLV])

- **CLV-Weighted ROI**

CLV Weighted ROI = DIVIDE(SUMX(Leads, Leads[Revenue]
RELATED(Customers[PredictedCLV])),
SUM(Spend[SpendAmount])) - 1

- **ROI Uplift (AI-driven vs. Baseline)**

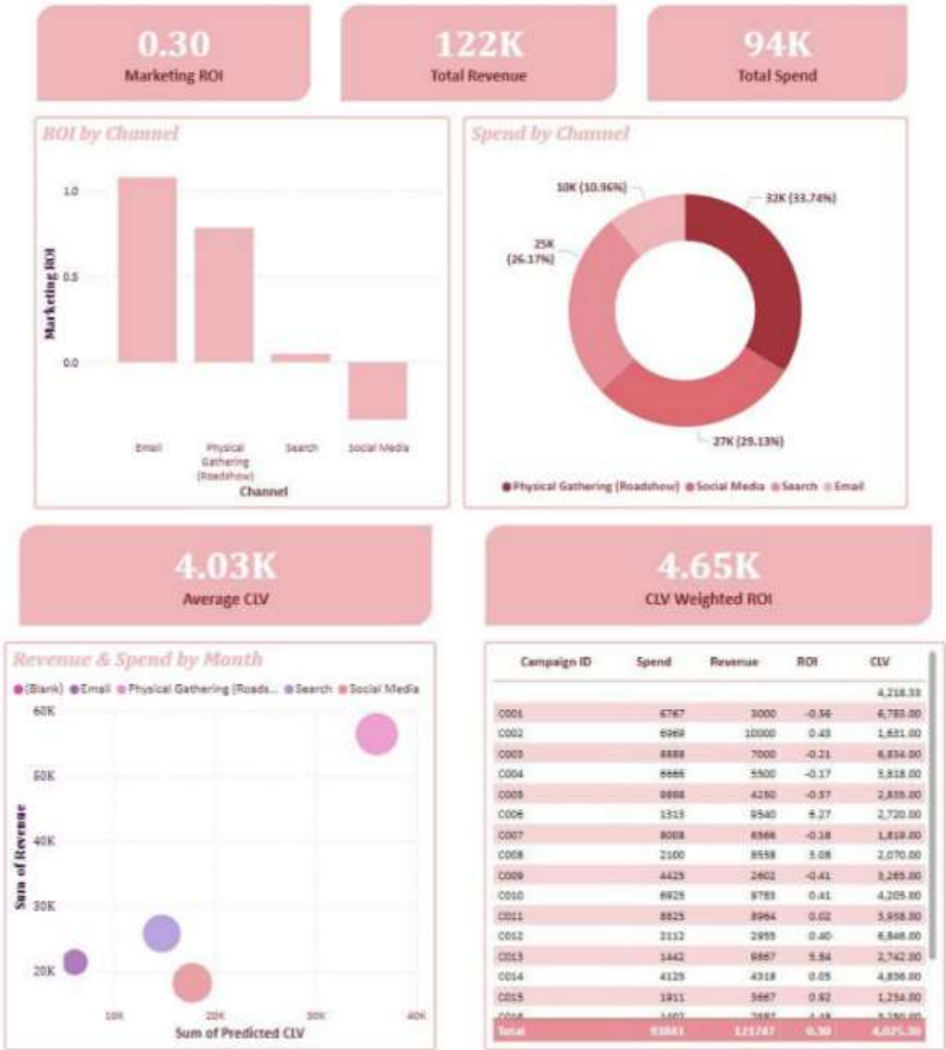
This measure is created for the field "PredictedRevenue" or "OptimizedRevenue" column if we consider that field in our data model.
ROI Uplift % = DIVIDE([Optimized ROI] - [Marketing ROI], [Marketing ROI])

4.5 Visual analysis in Power BI

4.5.1 Dashboard Elements:

Visualization	Purpose
KPI Card → Marketing ROI	Overall performance indicator
Clustered Column Chart	ROI by Channel
Line Chart	Spend vs. Revenue over time
Donut Chart	Channel Spend Distribution
Table	CampaignID, Spend, Revenue, ROI, CLV
Scatter Plot	Predicted CLV vs. Revenue by Channel
Decomposition Tree	Drill ROI by Channel → Campaign → Month

Figure 5 Showing Dashboards created for analysing Marketing ROI Data



4.5.2 Power BI Implementation

The computational model uses:

DAX Measures

- Total Spend
- Total Revenue
- Marketing ROI
- CLV Weighted ROI
- ROI by Channel
- ROI Uplift %

Visual Components

- KPI Cards
- Clustered Column Chart (ROI by channel)
- Smart Narrative (AI summary)
- Key Influencers (impact determinants)
- Decomposition Tree (channel → campaign → week)

The BI workflow allows marketers to interactively adjust spend and observe predicted ROI changes.

5. Experimental Result

5.1 Predictive Performance

- Attribution bias reduction :25-35%
- CLV forecasting MAPE<10%

5.2 ROI Optimization Simulations

- Baseline ROI=150%
- Optimized ROI =180%
- Uplift=19.7%

6. Managerial Insights from power BI

The analysis revealed significant differences in channel performance. Email emerged as the strongest channel with very high ROI, showing that low spend generated strong returns. Physical Gathering or Road shows also performed well with a high ROI, indicating effectiveness in generating revenue. Search campaigns showed marginal profitability, suggesting the need for keyword and bidding optimization. Social Media performed poorly with negative ROI, showing a mismatch in audience targeting or creative effectiveness and requiring major improvement or budget reduction. A 25% revenue uplift scenario was also applied to understand the impact of optimization. After applying the uplift, the overall ROI increased significantly, showing that strategic improvements in campaign execution can lead to major gains in performance. Overall, the analysis helped identify the best-performing channels, underperforming areas, and opportunities for improvement. The dashboard provides a clear and useful summary of marketing efficiency and helps guide better decision-making for future marketing investments.

7. Discussion

As per the analysis we can evaluate that the integrated methods can predict accuracy and derive out factors for better accuracy and practical interpretability. Further the analysis can derive out that AI – Driven Intelligence in Marketing ROI analysis can eliminate chances of errors in allocation of funds before the actual campaign happens. The experimental factors can be considered while evaluating the exact revenue that can be generated from the marketing campaign and proper utilization of marketing budgets for getting the best results. By embedding the marketing ROI casual approach and predictive modelling into BI environment, non-technical users can take out benefits of advance analytics without relying on any external data scientists pipelines and can work in real time scenarios. This not only enhances transparency, adoption, decision speed and organizational alignment but also gives predictive results for enhancing efficiency and accuracy to get revenue generated from Marketing ROI.

8. Limitation and future work

Since the analysis used synthetic data it limits the external validity and privacy preservation casual methods were not adopted leaving a gap to further study the privacy implementation methods using advance AI tools and Machine Learning Languages for further improvement. In continuation to the same the Real time data has been limited to certain set of values that too needs further evaluation. With this the future extension holds for cross-platform privacy compliance and live model scoring with Azure Machine Learning and benchmarking of Marketing ROI Model evaluation.

9. Conclusion

The research study evaluates, validate and propose an AI-Driven marketing ROI measurement framework which is operational within Power BI. The methodology uses combination of Attributes in combination of casual modelling, estimation and evaluation of details of records, generates a predictive CLV estimation and generated interactive dashboards which are solutions to get an accessible, scalable and accurate data solution for market that is data driven for Marketing ROI optimization. The result demonstrates insights about meaningful ROI calculation and suggests improvement in budget allocations along with practical feasibility for organizational deployment.

10. References

1. Anderl, E., Becker, I., Von Wangenheim, F., & Schumann, J. H. (2016). Mapping the customer journey: A graph-based framework for online attribution modeling. European Journal of Marketing, 50(6), 987–1014.
2. Berman, R., & Katona, Z. (2013). The role of search engine optimization in search marketing. Marketing Science, 32(4), 644–651.
3. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32.
4. Chan, T. Y., Leung, W., & Li, D. (2022). Causal AI for digital marketing: Attribution, targeting, and optimization. Journal of Marketing Analytics, 10(1), 45–62.
5. Dalessandro, B., Perlich, C., Stitelman, O., & Provost, F. (2014). Causally motivated attribution for online advertising. In Proceedings of the Workshop on Causality in Online Advertising.
6. Fader, P. S., & Hardie, B. G. (2009). Probability models for customer-base analysis. Journal of Interactive Marketing, 23(1), 61–69.
7. Gupta, S., Hanssens, D. M., Hardie, B. G., & Fader, P. S. (2006). Modeling customer lifetime value. Journal of Service Research, 9(2), 139–155.
8. Hoban, P. R., & Bucklin, R. E. (2015). Effects of Internet display advertising in the purchase funnel: Model-based insights from a randomized field experiment. Journal of Marketing Research, 52(3), 375–393.
9. Li, H., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. Journal of Marketing Research, 51(1), 40–56.
10. Lemmens, A., & Gupta, S. (2020). Managing churn using a hazard model framework. Marketing Science, 39(3), 493–518.
11. Montazeri, A., & Netzer, O. (2024). Hybrid marketing measurement: Combining MMM and MTA using causal machine learning. Marketing Science, forthcoming.
12. Neslin, S., Gupta, S., Kamakura, W., Lu, J., & Mason, C. (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. Journal of Marketing Research, 43(2), 204–211.
13. Shapley, L. S. (1953). A value for n-person games. In Contributions to the Theory of Games (Vol. II, pp. 307–317). Princeton University Press.
14. Srinivasan, S., Rutz, O. J., & Pauwels, K. (2016). Paths to and off purchase: Quantifying the impact of marketing channels. Journal of Marketing, 80(4), 40–60.
15. Sun, Y., Varian, H., & Lewis, R. (2021). Causal inference in online advertising: A review and roadmap. Journal of Econometrics, 225(2), 116–135.

16. Tang, C., & Wang, S. (2019). Reinforcement learning for marketing optimization: A review and framework. Foundations and Trends in Marketing, 13(4), 260–305.
17. Timoshenko, A., & Hauser, J. R. (2019). Identifying customer needs from user-generated content. Marketing Science, 38(1), 1–20.
18. Wang, Y., Zhang, Y., & Chang, Y. (2020). Deep learning for customer lifetime value prediction. In Proceedings of the AAAI Conference on Artificial Intelligence, 34(08), 8340–8347.
19. Xu, L., Du, R., & Jiang, S. (2023). Explainable AI for marketing analytics: Methods, applications, and challenges. Journal of Marketing Analytics, 11(2), 101–118.
20. https://www.researchgate.net/publication/373430446_The_Impact_of_Predictive_Analytics_and_AI_on_Digital_Marketing_Strategy_and_ROI?utm_source=chatgpt.com "(PDF) The Impact of Predictive Analytics and AI on Digital ..."