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Closing the AI-to-Action Gap: A Human-Centered Explainable AI Framework for Marketing Resource Allocation in Resource-Constrained U.S. Small Businesses

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Abstract

While small businesses are increasingly turning to digital marketing to attract customers, make money and stay competitive, the allocation of marketing resources is often difficult to achieve due to limited financial and operational resources. While AI can provide predictions about campaign success and opportunities for high-value marketing activities, many small businesses may find it challenging to make sense of AI-driven insights, build trust in the data, and act on it. This study aims to present a human-centric Explainable Artificial Intelligence (XAI) framework to bridge the gap between AI and action in marketing resource allocation for resource scarcity situations of U.S. small businesses. The data set includes 10,000 observations of each advertising campaign and 41 variables related to the advertising platform, campaign goal, audience, creative, budget level, engagement, ad spend, conversions, revenue and profitability. Various machine learning models are utilized such as Multiple Linear Regression, Random Forest, XGBoost, and LightGBM for predicting the profitability of the campaign and the factors related to the effectiveness of the marketing performance. SHAPley Additive explanations (SHAP) are built-in to offer transparent interpretations of model predictions and explain what factors make up the basis for AI-powered marketing suggestions. The proposed framework builds on these predictions and explanations to enable budget allocation decisions on marketing platforms and campaign configurations with respect to resource constraints. The framework highlights the importance of human decision making by providing AI recommendations in the form of explainable recommendations that allow managers to understand, evaluate, accept, adjust, and reject proposed allocations. Predictive accuracy and error measures are used to measure model performance, and profitability, return on advertising investment and resource efficiency are used to measure the effectiveness of the allocation. It is the inclusion of the decision-oriented approach, which extends the traditional marketing prediction method by combining predictive analytics, explainability, resource optimization, and human judgment that sets the study apart. The proposed framework offers a tangible strategy for turning marketing insights derived from AI into resource allocation decisions, and can overcome issues of transparency, usage and resource constraints for small businesses.

Keywords: Explainable Artificial Intelligence (XAI), Marketing Resource Allocation, Human-Centered AI, Small Businesses, Marketing Profitability and Artificial Intelligence Decision Support

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1. Introduction

A. Background

Digital marketing is an important tool that small business businesses are using to attract customers, build brand awareness, make sales and compete with large businesses. But small businesses often have a smaller budget, less marketing know-how, fewer employees and fewer ability to spare money on unproductive advertising. So, deciding on the allocation of the limited marketing budget is one of the important managerial problems [1]. With the data now digital, there is a chance to leverage artificial intelligence (AI) and machine learning (ML) and find patterns that correlate to campaign profitability, conversion, revenue, and return on advertising spend. However, simply predicting accurate results isn't enough for AI advice to be incorporated into business decisions [2]. If managers aren't able to see why a specific platform, campaign type, audience or creative strategy is recommended, they may not go through with the algorithmic suggestion. Explainable Artificial Intelligence (XAI) is a possibility to tackle this challenge and convert the outputs of models into comprehensible explanations [3]. But explanations should be tailored to human decision making and not just be a list of feature-importance scores. Human-centered AI can help link predictive models to management decision making by allowing users to comprehend, assess, alter and execute on AI recommendations [4]. This is important for small businesses that have limited resources, where an unsuitable allocation decision can have significant financial implications [5]. This study proposes an explainable artificial intelligence (XAI) framework for human-centric profitability prediction, interpretable explanations, resource constraints, and marketing budget allocation [6]. The research is based on the Digital Advertising Campaign Performance Dataset comprising 10,000 campaign observations and 41 variables, to explore the potential of AI to go beyond prediction into marketing-resource decision-making.

B. Human-Centered Explainable AI for Marketing Resource Allocation

As AI has become more integral to marketing efforts, there is a chance to allocate resources more efficiently, by forecasting campaign results before businesses invest more resources [7]. Machine learning models can be used to evaluate characteristics of campaigns, ad platform, audience attributes, creative features, quality scores, engagement metrics, and budget conditions to determine what factors make it profitable [8]. But, even very precise models can be complicated for non-technical decision makers. This forms a significant difference between AI prediction and AI-driven action. A model can correctly classify a potentially profitable campaign (classify it as a “yes”) and then be unable to present the reasons for the manager to go ahead and proceed with the campaign (classify it as a “no”). This study aims to fill this gap from a human-centric XAI approach. The proposed framework does not view the explainability as an add-on feature to technology but rather as a part of the marketing decision process. SHAP-based explanations can explain the relative contributions of different variables to the predicted profitability of the campaign, and whether they add or subtract value, as well as understanding the why. The framework then includes resource limitations. Specifically the budget constraint is included, which would be useful to consider [9]. For instance, it is not just about forecasting how much money will be generated during a campaign; it can help decide which marketing channels and campaign set-up will bring in more or less of that money [10]. The human-centered part also acknowledges the manager's decision making power. AI recommendations are considered to be a set of inputs for decisions, not a decision itself. Managers are able to assess the expected result, grasp the reasons behind the recommendation, and take into account the corporate situation and either approve, amend or decline the recommendation [11]. The

aim is to resolve this AI-to-action gap by linking predictability with explanation, usability, managerial decision making and resource utilization.

C. Problem Statement

Small businesses with limited budgets struggle with a limited marketing budget that they have to use on different advertising channels and marketing strategies. While AI and machine learning may be used to forecast campaign profitability and determine which factors are significant for performance, traditional predictive models may provide only vague explanations that managers can easily comprehend and act on [12]. This gap between AI and action is known as the AI-to-action gap, in which accurate predictions do not necessarily lead to effective managerial actions. Current marketing analytics techniques also focus mainly on prediction without incorporating resource limitations, explainability and decision-making by human beings in the same decision-making process [13]. Thus, a human-centric XAI frame would be required to enable the marketing prediction to become a clear and clear actionable and resource-efficient recommendation for small businesses.

D. Objectives of the Study

The major objectives to be achieved in the study are:

- To create an AI based model to predict the profitability of marketing campaigns based on campaign, audience, creative, platform as well as business related attributes.
- To identify the key factors affecting profits in marketing campaigns and resource allocation decisions.
- To incorporate Explainable AI (XAI) methods into marketing predictions to give clear and understandable explanations.
- Create a resource constrained marketing allocation model for determining the allocation of a relatively small advertising budget among media and campaign configurations.
- To integrate human decision support, allowing managers to review, assess, adjust, and/or decline AI-driven marketing proposals [13].
- To determine the effectiveness of the proposed framework in enhancing the profitability of the marketing mix, efficiency of the use of resources, and effectiveness of recommending actions based on AI-assisted data in comparison to traditional recommendations.

E. Research Questions

The following research questions are used to guide the study:

- What is the predictive power of machine learning models on profitability of marketing campaigns based on campaign, audience, creative, platform, and budget features for small businesses with limited resources?
- What are the most important marketing, audience, creative, platform and business-context variables that impact an AI generated profit prediction?
- What is the impact Explainable AI, specifically with SHAP-based explanations, can have in terms of transparency and action ability in AI-driven recommendations for the allocation of marketing resources?
- What is the level of impact that a human-centered XAI framework can provide in the context of budget constraints in marketing budget allocation, resource efficiency, and managerial decision-making?

F. Significance of study

This study is important because it takes one of the practical challenges of using AI in small business marketing such as getting a good prediction from artificial intelligence and then

incorporating that prediction into a confident decision by the manager [14]. Existing marketing analytics solutions often focus on predictive performance while resource-constrained companies need to understand how to support their business decisions, make them more cost effective, and link them directly to their decisions on allocation. This need is met by the proposed Explainable AI framework, which integrates the use of profits, explaining the model, constraints of the resources, and managerial decisions [15]. Theoretically, the study builds on the existing body of research on Explainable AI, which has moved beyond the notion of transparency to that of explainable decision support. It defines explainability as a way of bridging AI-generated insights and how resources are allocated by human judgment [16]. The study's methodological approach integrates several machine learning methods and incorporates SHAP-based explanations and resource allocation analysis, offering a systematic framework to assess the accuracy of the predictions and its actual utility [17]. Managers can use the framework to find out which campaign attributes they can afford, why some marketing methods are suggested, and where to spend their advertising dollars. The framework is not intended to replace managerial judgment, but to aid the management process by offering evidence-based recommendations that are accepted, adapted or rejected [18]. Last, the study holds a practical value for organizations looking to responsibly adopt AI as it highlights the importance of transparency, interpretability, human oversight, and resource efficiency. Therefore, the research helps bridge the gap between the insights generated by algorithms and actual marketing decisions.

1.1 Related Works

1.1.1 AI and ML for Marketing Resource Allocation

As the volume of customer, campaign and behavioral data increases, the use of AI and machine learning has revolutionized marketing analytics, helping businesses to gain deeper insights from their data to make better decisions [19]. In the digital advertising space, ML models can discover connections between campaign attributes and positive outcomes like conversions, revenue, client acquisition price, and return on marketing and advertising spend (ROAS). Predictive analytics can help businesses determine which campaigns are most successful and optimize their marketing budget [20]. Ensemble methods like Random Forest, XGBoost and LightGBM can model complex interactions and nonlinearities among marketing variables and profit, whereas traditional statistical methods like multiple linear regression can offer interpretable relationships [21]. These features are especially important for small businesses, as their marketing budgets can significantly impact their finances if not used efficiently [22]. AI can offer managers performance analytics, which can be used to identify which ad platforms, campaign goals, audience, creative and budgets are most effective before investing more money. But high predictive accuracy doesn't necessarily lead to effective managerial decisions. A very accurate model might suggest a given marketing strategy, but not be able to say why this strategy should be more successful [23]. This leaves an opportunity for a disconnect between analytical capacity and implementation. In addition, small businesses might lack technical know-how and resources to comprehend complex models. As a result, the acute need for research to go beyond mere prediction to decision-support frameworks that link AI predictions with comprehensible recommendations, budgetary considerations, and managerial intuition [24]. This study builds on this perspective by incorporating predictability of profitability and explainability as well as limited allocation of marketing resources.

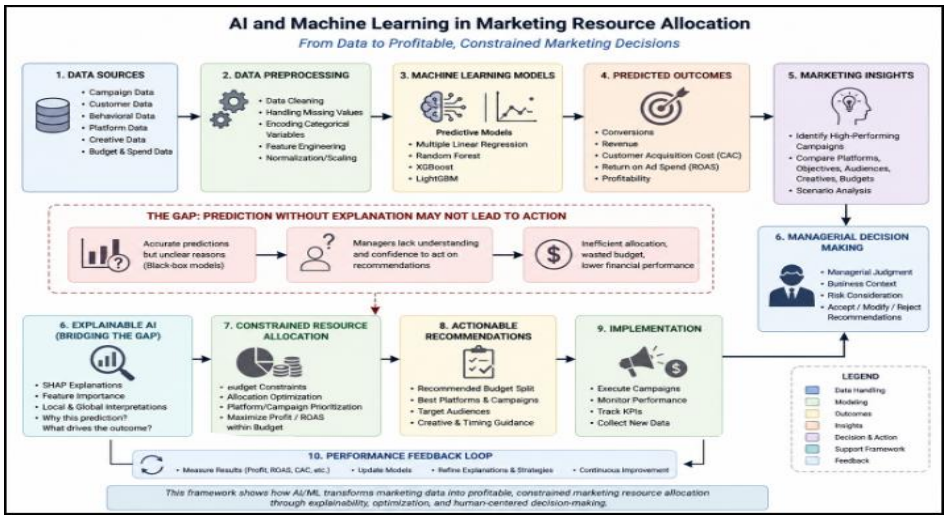


Figure 1. This framework shows how AI can be used to provide a pathway from marketing data to explainable, actionable resource allocation decisions

This framework depicts an integrated approach to the allocation of marketing resources using AI and machine learning. It starts with Campaign, Customer, Behavioral, Platform, Creative and Budget data, then pre-processing and feature engineering [24]. There are multiple machine learning models predicting results including ROAS, profit, revenue, and conversions. The framework fills in the gap between AI and action by integrating Explainable AI (XAI) methodologies, including SHAP, which help explain the basis for predictions. These explanations justify restricted resource allocation, which takes into account restricted budgets and profitable platforms/campaigns. The recommendations are then handed off to managers who use human judgment to accept, alter or reject the recommendations. Feedback is used to enhance performance and make future decisions.

1.1.2 Explainable AI and Human-Centered Decision Support

Explainable Artificial Intelligence (XAI) has become a crucial technique for enhancing the explainability and interpretability of machine learning-driven decision-making processes. It is possible to create complex models that make very accurate predictions, but that don't give much insight into the factors that lead to these predictions [25]. To overcome this, XAI techniques provide explanations that are based on feature contributions, feature importance scores, and on local or global interpretations. In this regard, SHAPley Additive explanations (SHAP) give a theoretically-based way of quantifying the contribution of individual features to model predictions [26]. For marketing use cases, SHAP can be used to understand the impact of other attributes like platform, campaign objective, purchase intent, quality score, creative format, audience, engagement, and more, on the expected profitability. But, technical explainability by itself might not be enough to bridge the gap between AI output and managerial action. Explaining is always necessary for making a decision that is understandable, relevant and tied to the decision that the user will have to make [27]. An explanation should have an answer to the small-business manager's question of why more budgets should be allocated to a certain platform, why the recommendation makes sense and how it might shift in the case of limited budgets [28]. Human centred AI, therefore, focuses on the importance of human oversight, understanding, trust and the capacity to accept, alter or reject algorithmic recommendations. Combining XAI with resource-optimization can make predictions into marketing recommendations [29]. This viewpoint aligns with the main contention of the current study: AI should not replace managerial decision-making, but rather serve as a tool to aid in

decision-making. The proposed framework thus leverages predictive modelling, SHAP explanation, budget restrictions, and decision-making by humans to tackle the AI-to-action gap.

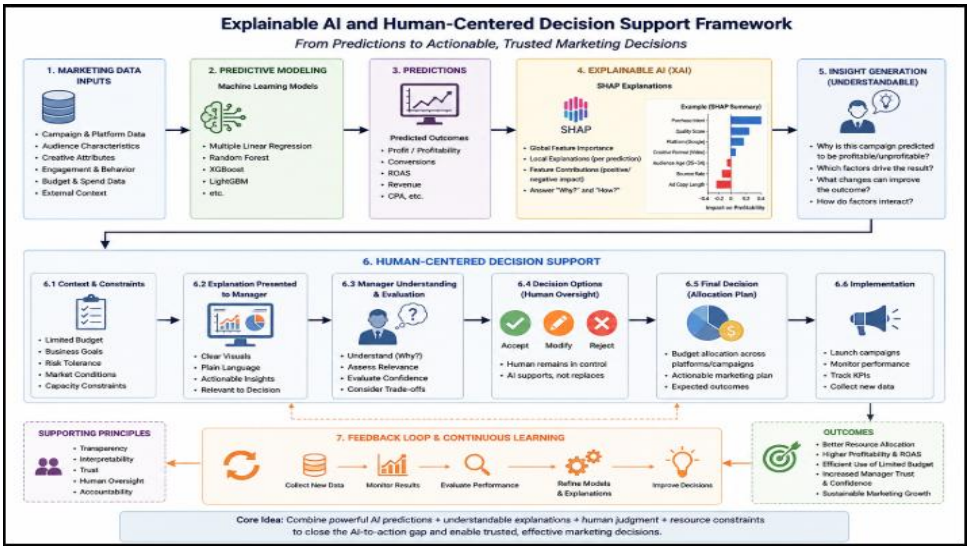


Figure 2. This framework illustrates the relationship of explainable AI with predictive analytics and marketing decisions that are driven by humans

The framework introduces a people-centric EAI (Explainable AI) model for the process of converting marketing data into trustworthy managerial decisions. It starts with marketing, audience, creative, engagement, and budget data, and then moves on to predictive modeling with the help of machine learning techniques [30]. The predictions are interpreted using SHAP-based explanations which highlight the factors that influence profitability and other marketing outcomes. The explanations are turned into comprehensible insights for managers, taking into account budget constraints, business objectives, risk tolerance, and working constraints. By taking, tweaking, or ignoring the AI's suggestions, managers keep the final say before creating an allocation plan. A continuous feedback loop is established to track results, enhance models and explanations, and inform better marketing choices, transparency, and trust and resource utilization.

1.1.3 Empirical Studies, Research Gap, and Position of the Current Study

Cagiza et al. study in the article, "AI-Powered Advisory Platforms for Sustainable Marketing Innovation in SMEs: Empirical Evidence from Underserved U.S. Markets," explores the sustainability of marketing innovation and strategic decision-making for resource-constrained SMEs in underserved U.S. markets through the use of AI-powered advisory platforms [1]. The study, which features interviews with 13 SME owners and managers and survey responses from 172 platform users in three U.S. states, shows how AI advisory tools can enhance customer acquisition, revenue results, campaign optimization, and strategic marketing efforts [1]. The authors underscore the importance of a multi-faceted approach which brings together market intelligence, strategic coaching, peer benchmarking and compliance-oriented tools, resulting in compound benefits for SMEs. The results of this study are of immense significance in the context of the present study because it proves the use of AI-powered decision support systems in the improvement of marketing decisions with limited budgets and technical resources. But the focus of Cagiza et al. is not on creating an explainable predictive model to maximize marketing-resource allocation, but on the adoption of and marketing innovation with AI advisory platforms. This study builds upon the existing literature and introduces a novel framework that bridges the gap between AI and action, accounting for profitability prediction, SHAP-based explanations, budget limitations, and human

managerial oversight to explicitly tackle the AI-to-action gap in resource allocation within the marketing domain.

Ortolano and Gallegos offer the Human-AI Collaboration Maturity Model (HAIC-MM) as a solution to overcome the challenges that small and medium-sized enterprises encounter in the process of incorporating AI in organizational processes in their article titled “Advancing Human-AI Collaboration in Small and Medium-Sized Enterprises: A Systems Engineering Approach”. The study proposes a structured framework with seven dimensions and 32 capabilities at five maturity levels, highlighting the need to match AI capabilities with the operational needs and resource constraints for SMEs. The authors use a survey analysis (100 respondents) as well as focus groups (cumulative 10 participants over 5 sessions) and pilot testing with industry practitioners to illustrate the applicability and usability of the proposed model [2]. Key factors highlighted in the study are resource optimization, empowerment of the workforce, ethical monitoring and regulation of AI, adaptation of organizational culture, and collaboration between humans and AI. The present research findings are a direct result of these findings because they support the argument that AI systems should complement rather than supplant the managerial capabilities of humans in resource-constrained SMEs. The study is mainly concerned with organizational AI adoption and collaboration maturity however, not explainable predictive analytics for marketing-resource allocation. The current research builds on this insightful approach by combining predictive modelling, SHAP explanation, and constraints on budget and decision power of management to overcome the gap between AI and action in marketing.

In the chapter titled “Fair and Inclusive Customer Segmentation in AI-Driven Marketing”, Benny and Kaur look at how AI has now become a popular feature in customer segmentation and argue that AI-based marketing systems are not just prediction machines, but also socio-technical decision mechanisms. The authors examine how clustering techniques can be used, and analyze Explainable AI methods like LIME and SHAP, alongside fairness metrics, to detect and counteract potential structural bias in AI-based segmentation. They identify some key issues such as transparency, fairness-accuracy, emotional trust, cultural representation, and organizational capability gaps. The chapter shows how explainability can enhance the understanding of how AI systems generate marketing-related outputs for stakeholders, and how the assessment of the AI system's fairness can minimize the risk of making discriminatory and exclusionary decisions [3]. The current study is relevant to these findings, as they highlight the need for transparency, responsible AI, and human oversight in the context of AI recommendations affecting marketing decisions. But mostly, Benny and Kaur focus on customer segmentation and inclusive marketing instead of profitability forecasting and the allocation of limited budgets. In this study, we take this approach further and propose using SHAP-based explainability to predict campaign profitability and integrating explanations with budget constraints and managerial judgment to overcome the AI-to-action gap.

In the article titled “Human-centric AI: Transforming Service Ecosystems for Inclusivity and Excellence in Resource-Constrained Contexts,” Hwang, Puntha, and Jitanugoon (2026) investigate how AI can transform service ecosystems and support SMEs operating under resource and technological constraints. The authors first employ a sequential mixed-methods approach by interviewing SME service leaders in the healthcare, retail, and hospitality sectors in-depth, and then using survey results from 444 SMEs. According to their findings, AI can help them design services to be more adaptive, engage stakeholders more personally and minimize technological and procedural friction. The study highlights the importance of intentional design, human oversight,

context-sensitive application, and hybrid models of AI and humans, highlighting that the advantages of integrating AI are contingent upon these factors [4]. The authors also suggest that participatory design and governance of AI are needed for inclusive and sustainable outcomes. The results are a significant confirmation of the human-centric approach adopted in the present study as they highlight the need to use AI as a support to managerial skills and not as a replacement in resource-limited scenarios. The study however focuses mainly on the experiences of the stakeholders and service innovation as a service feature of AI, instead of explainable profitability prediction and allocation of marketing budget. The current study builds on this approach by combining the concepts of XAI explanations, predictive profitability modeling, resource limitations, and managerial decision-making power to explicitly tackle the AI-to-action gap in marketing resource allocation.

Collectively, these studies establish the importance of AI-enabled decision support, human oversight, explainability, and resource-aware design in resource-constrained SMEs. However, the reviewed studies focus on AI advisory-platform adoption, organizational human-AI collaboration maturity, fair customer segmentation, or human-centric service ecosystems rather than an integrated marketing-resource allocation process that combines profitability prediction, SHAP-based explanations, explicit budget constraints, and managerial decision authority. The current study is positioned to address this gap by integrating these elements into a single human-centered XAI framework for resource-constrained U.S. small businesses.

Table 1. Comparison of empirical studies and position of the current study

Reference	Study focus	Method / context	Key contribution	Gap relative to the current study
[1] Cagiza et al. (2025)	AI-powered advisory platforms for sustainable marketing innovation in SMEs	Interviews with 13 SME owners/managers and survey responses from 172 users in underserved U.S. markets	Shows that AI advisory platforms can improve customer acquisition, revenue outcomes, campaign optimization, and strategic marketing	Focuses on AI-platform adoption and marketing innovation rather than explainable profitability prediction and constrained resource allocation.
[2] Ortolano and Gallegos (2025)	Human-AI Collaboration Maturity Model for SMEs	Survey analysis, focus groups, and pilot testing with industry practitioners	Emphasizes resource optimization, workforce empowerment, ethical oversight, culture, and human-AI collaboration	Focuses on organizational AI adoption and collaboration maturity rather than explainable marketing-resource allocation.

[3] Benny and Kaur (2026)	Fair and inclusive customer segmentation in AI-driven marketing	Conceptual/analytical treatment of clustering, LIME, SHAP, and fairness metrics	Highlights transparency, fairness, trust, cultural representation, and responsible human oversight	Centers on customer segmentation and fairness rather than campaign-profitability prediction and limited-budget allocation.
[4] Hwang, Puntha, and Jitanugoon (2026)	Human-centric AI in resource-constrained service ecosystems	Sequential mixed methods: interviews and survey evidence from 444 SMEs	Demonstrates the importance of human oversight, context-sensitive AI, participatory design, and hybrid human-AI models	Focuses on service innovation and stakeholder experience rather than SHAP-based profitability prediction and marketing-budget optimization.
Current study	Human-centered XAI for marketing resource allocation in resource-constrained U.S. small businesses	Predictive modeling, SHAP-based explanation, budget-constrained allocation, and managerial decision support	Integrates prediction, explanation, resource optimization, and human judgment in one AI-to-action framework	Addresses the identified gap by explicitly linking explainable profitability predictions to constrained marketing-allocation decisions.

2. Materials and Methods

This study approach for this study is quantitative involving research methodology based on machine learning to develop and validate human-centered Explainable Artificial Intelligence (XAI) in marketing resource allocation [31]. The methodology aims to bridge the gap between predictive profitability modelling and explainable recommendations, resource constraints, and managerial decision support. The study is based on the Digital Advertising Campaign Performance Dataset with 41 variables, 10,000 observations of campaigns [32]. The analysis process includes data preparation, exploratory analysis, feature engineering, predictive modelling, XAI interpretation, resource-optimization and evaluation of actionable recommendations. Multiple machine-learning models are compared to see which would be the best predictive approach and SHAP is used to explain model predictions [33]. These explanations are then translated into recommendations for the allocation of resources in a budget within a final framework that can be compared across various resource-constrained scenarios.

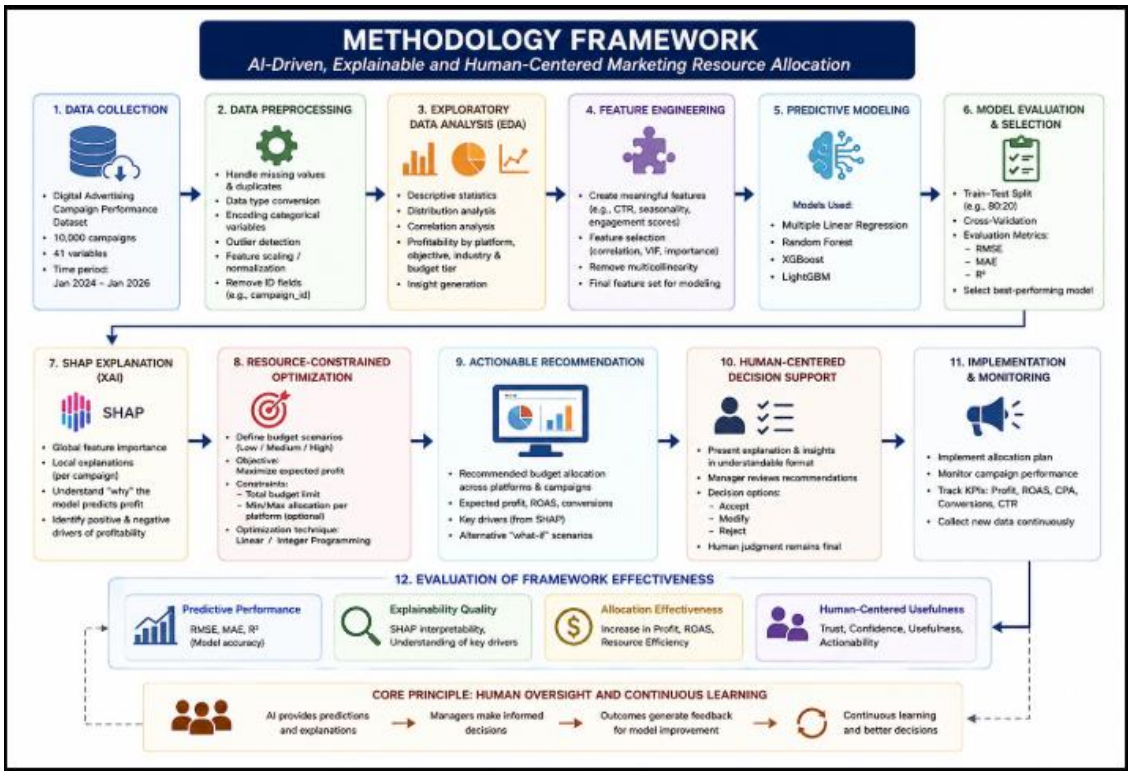


Figure 3. This framework shows the systematic approach to creating explainable, human-centred marketing allocation decisions

The methodology framework provides a systematic process to design and test the developed framework for marketing resource-allocation using artificial intelligence, explainability, and human-centric approach [34]. It starts with the preparation of the Digital Advertising Campaign Performance Dataset, then the data is preprocessed, explored and engineered. For predictive modeling and performance comparison, multiple linear regression, random forest, XGBoost and LightGBM are used [35]. The results of the model are then summarized using SHAP to describe the model predictions and identify which drivers of profitability are important. Resource constrained optimization, on the other hand, produces the recommendations of budgets allocation based on the expected profit and the marketing constraints [36]. These recommendations are presented to managers in human-centred decision support, where managers can accept, modify or reject the recommendations [37]. The methodology is completed with implementation, monitoring and continuous feedback.

A. Research Design, and Approach

This study has a quantitative and experimental research design and aims to design and test the suggested human-centered Explainable Artificial Intelligence (XAI) framework for marketing resource allocation in resource constrained small businesses [38]. The quantitative part analyzes the connection between the characteristics of the campaigns and the profitability through statistical and machine learning methods, and the experimental part consists of testing different marketing allocation strategies under various budgets [39]. The analysis process of the research is sequential including data collection, data preprocessing, exploratory data analysis, feature engineering, predictive modeling, model evaluation, and explanation with SHAP, optimization for resource constraint, actionable recommendation generation and human centered decision support [40]. Several predictive models are tested to find the best one for predicting the profitability of the campaign, and then the Explainable AI techniques are applied to uncover the factors that influence

the model's prediction of the campaign profitability [41]. The resulting insights are used to create budget recommendation reports which consider scarce marketing budgets. The framework recognizes the role of the manager, as it is not the AI that makes decisions but rather AI is used to support the manager's decision-making processes, giving the manager knowledge of how the AI reached the recommendation and a choice to accept, modify or reject it [41]. The design of the study is a crucial aspect of the research that enables the implementation of its core objective, which is to bridge the gap between AI predictions and actual managerial decisions.

B. Data Sources and Data Sets

The study spans the period of January 2024 to January 2026 and includes 10,000 observations that are processed at the campaign level and 41 variables. This data includes campaign ID, campaign goal, advertising platform, placement, device, creative, audience, time, auction and quality, advertising performance, engagement, industry context and budget tiers.

Profit is the main dependent variable and it is defined as:

$$Profit = Revenue - Ad\ Spend$$

There's also a number of performance metrics such as conversions, ROAS, CPA, conversion rate, CTR, and CPC. Platform, campaign_objective, creative_format, purchase_intent_score, quality_score, industry_vertical and budget_tier are variables that explain the results and are crucial to a profitability prediction analysis and resource allocation. The dataset is a synthetic one and the study considers it as an experimental dataset to be developed and tested as a framework [42]. The results are thus not considered to be statistically representative of all small businesses in the U.S. Instead, the budget_tier is used as a proxy for resource constraints and U.S.-relevant marketing scenarios can be investigated within the experiment framework.

C. Data Preprocessing

The data set is then inspected before modelling to see if there are any missing data, duplicate observations, inconsistent data types, outliers and logical inconsistencies. Documentation for the data set states that there are no missing values or duplicate campaigns, and logical constraints like conversions < clicks are taken into account. Appropriate encoding techniques are used to represent categorical variables as numbers. Extremes and skewness of numerical variables are explored. If necessary, according to individual algorithms, numerical features are standardized or normalized [43]. The campaign_id variable is not included since it is only an identifier with no significant predicting interpretation. Any possible leakage of data is closely monitored [44]. Profit is computed directly from the revenue and ad_spend, thus they are not used as free predictors in predicting profit. Also, metrics derived from the primary profitability model, such as ROAS, CPA, CPC, CTR, and conversion rate (if it includes data that is mechanized from the target or target components) are not included in the primary profitability model. This means that the results from the models are not affected by mathematical leakage.

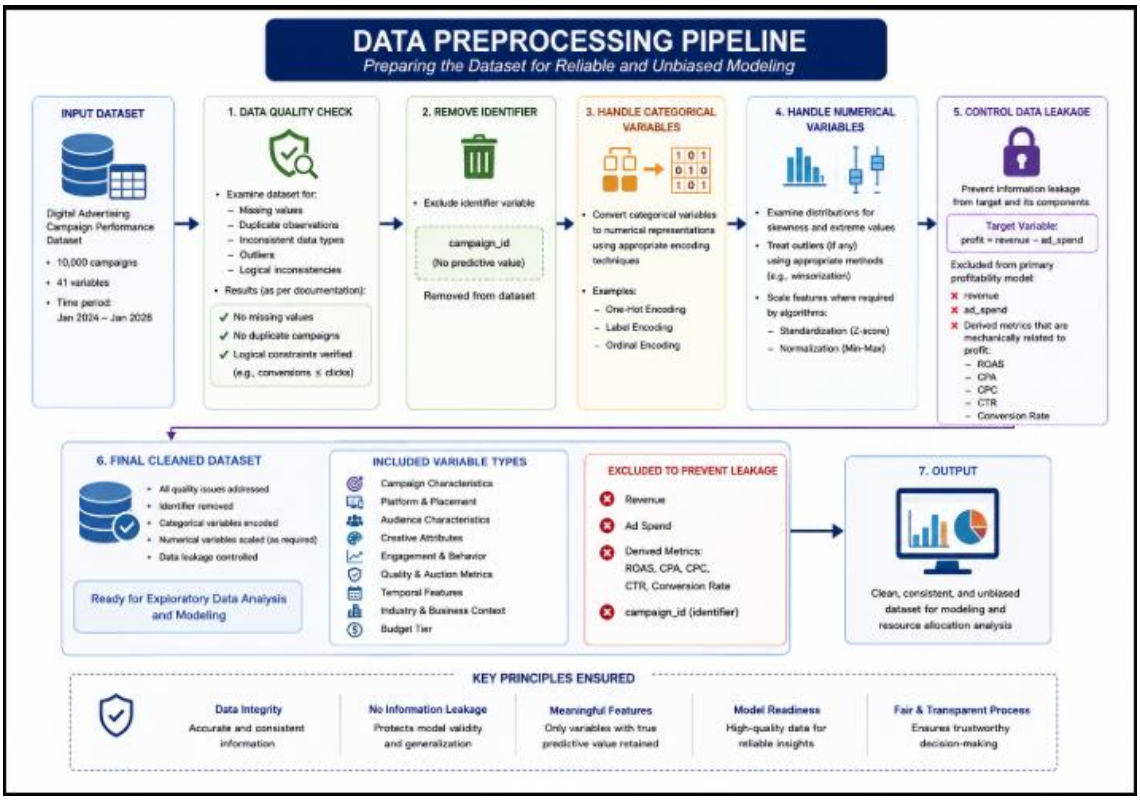


Figure 4. This framework shows a systematic process of data preprocessing for accurate and non-biased marketing profitability modeling and allocation

Data preprocessing framework shows the systematic approach to make the Digital Advertising Campaign Performance Dataset available for accurate and fair machine learning analysis. It starts with data-quality assessment, which involves checking for missing data, data duplication, data type inconsistencies, outlier and logical inconsistencies [46]. The `campaign_id` is discarded since it contains no predictive power, and categorical variables are encoded; numerical variables are analyzed, transformed and/or scaled as needed [47]. The framework focuses on preventing data leakage with the main profitability model excluding revenue, ad spend and mechanically derived metrics [48]. This cleaned data set also contains useful campaign, audience, creative, engagement, quality, temporal, industry, and budget information that can be used for modeling and resource-allocation analysis.

D. Exploratory Data Analysis

Exploratory Data Analysis (EDA) is performed to gain insight into how variables in the marketing environment are distributed and how they are related before performing predictive modeling. Numerical data (impressions, actual CPC, campaign length, engagement and profitability) are analyzed using descriptive statistics. Categorical variables like platform, campaign objective, creative format, industry, purchase intent and budget tier are looked at in frequency distributions [49]. A correlation analysis is carried out to discover the relationships between the numerical variables, and to check for possible multicollinearity. Profitability by platform, industry, and budget and campaign goal is studied using boxplots and distribution plots. Further comparisons are made to see if the profit abilities of low budget campaigns are different from medium and high budget campaigns [50]. EDA therefore gives statistical knowledge and context of the business for the subsequent modeling and allocation decision making.

E. Featuring selection and engineering

Feature selection and engineering is performed to identify features that give meaningful information that can predict campaign profitability while being interpretable yet not redundant. Candidate features are categorized under the following groups including campaign, platform, and audience, creative, temporal, engagement, quality and business-context. Campaign variables are campaign objective, advertising platform, ad placement, and device type; creative variables are creative format, creative age, call-to-action presence and creative emotion; and audience variables are purchase-intent score, retargeting status [51]. Other factors include campaign day, quarter, industry vertical, quality score, actual CPC, impressions, bounce rate, average session duration and pages per session and budget tier [52]. Categorical variables are properly coded, and numerical variables are examined for distribution, scale and for possible outliers. The statistical relationship is explored using correlation analysis and model based feature importance is used to identify important features that can contribute to the high importance of the Profitability prediction [53]. Variance Inflation Factor (VIF) is used to check for multicollinearity especially for Multiple Linear Regression baseline. Where appropriate highly redundant and non-informative variables are removed [54]. Also, when transformations or interactions are likely to be meaningful for the representation of marketing behavior and improve the representation, feature engineering also takes these into account [55]. This systematic process yields a compact set of features which can be simultaneously rich in predictive power, statistically valid, easily interpreted and meaningful to marketing resource allocation.

F. Predictive Modeling

Four predictive modeling methods are used to estimate the profitability of campaigns and determine which model best fits the next steps in explainability and resource allocation analysis. Multiple Linear Regression (MLR) is used as the baseline since the coefficients of this model give meaningful estimates of relationships between the campaign characteristics and profit. Random Forest is then used to capture the nonlinear relationship and interactions, and also to give model based feature importance, using an ensemble of decision trees [56]. XGBoost is also an advanced version of gradient boosting that can capture complex non-linear patterns and interactions among the marketing, audience, creative and budget variables. LightGBM offers another gradient boosting baseline model for structured data that offers efficient learning and great performance [57]. The data set is split into training and testing sets, the former for training purposes and the latter for an unbiased assessment [58]. Hyperparameter tuning and model stability assessment with CV within the training data set is used where appropriate. The same outcome definition and similar predictor information is used to train all models to ensure a fair comparison [59]. Afterwards, the best model is chosen based on predictive accuracy, stability and interpretability and then used for SHAP analysis and constrained marketing-resource optimization. This is a comparative design which also minimizes reliance on one modeling approach.

G. Model Evaluation

Model performance is not assessed by only a single metric, but by using complementary statistical metrics. The key evaluation measures for continuous campaign-profit prediction are the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where

y_i= Observed Profite
$\hat{y}_i$= Predicted Profit
The RMSE assigns more importance to large errors in prediction.

The formula to find the MAE is:

$$MAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[(y_i - \hat{y}_i)]}$$

and represent the average absolute prediction error.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}[(y_i - \hat{y}_i)]}$$

The higher the R^2 the better the prediction; the lower the RMSE and MAE the better the prediction. A model with the best overall accuracy, stability and interpretability is used for the following analysis of XAI and resource allocation. In addition, residual analysis, Q-Q plots and the Breusch-Pagan, Durbin-Watson and VIF tests are performed for the MLR model to check for linearity, independence, residual behaviour and multicollinearity.

H. Explainable Artificial Intelligence (AI) Using SHAP

The top model in this predictive model is paired with SHAPley Additive explanations (SHAP) to identify the impact of each feature on the predictions of campaign profitability. SHAP offers global and local interpretability, enabling the link to be made between the complex output of machine learning and the managerial decision-making process [57]. Global SHAP analysis scores features by their influence on the predicted profitability of the entire dataset and can help determine if purchase-intent score, quality score, platform, retargeting, creative format, actual CPC, engagement, or other features are consistently better predictors of profitability [58]. Local SHAP analysis compares individual campaigns, and reveals sensitivity towards specific features. Positive contributions of SHAP values represent factors that increase the predicted value of profit over the model baseline and negative SHAP values represent factors that decrease the predicted value of profit over the model baseline [59]. These explanations can be used to derive actionable management insights, such as understanding why a campaign is likely to perform well, or what attributes might need to be improved. SHAP outputs are part of the recommendation stage of the process, allowing managers to not only be provided with an allocation proposal, but also a rationale that is understood for the recommendation [60]. This explanation layer supports the human-centred purpose of the study by making the study more transparent, interpretable and actionable, and by empowering the manager to question and rethink the suggestions from the algorithm [61]. Global and local explanations offer complementary evidence to assess model behaviour and its value for limited marketing decisions.

I. Resource-Constrained Marketing Allocation

The resource constrained allocation stage takes the model predictions and plugs them into real-world recommendations for distribution in terms of a limited marketing budget to platform and/or campaign configuration [62]. The framework provides for a series of hypothetical budget scenarios under low, moderate and relatively high resource availability to explore variations in

optimal allocations under different resource levels [63]. The goal of the optimization is to maximize profits, given a budget constraint.

The objective can be represented as:

$$max \sum_{j=1}^{m} x_j \widehat{P_j}$$

Subject to

$$\sum_{j-1}^{m} x_j \leq B$$

Where,

x_j = Amount allocated to platform or campaign j

$\widehat{P_j}$= predicted profitability contribution

And B = Available marketing budget

It is possible to set an additional lower or upper limit on allocation for single platforms if needed to reflect the realistic management policies. The resulting AI-optimized allocation is compared to other strategies such as Equal Allocation, Existing/Historical Allocation and Simple Platform Based Allocation. The strategies are assessed according to their predicted ROI, ROAS, conversion efficiency and profit per dollar invested in the marketing [64]. A scenario analysis study also explores the effectiveness of the AI recommendation when resources are less or more scarce [1]. This process is used to turn predictive insights into actionable allocation decisions, and indicates that explainable AI can be used to help marketers make allocation decisions, not just campaign-level predictions, with a limited budget [2]. The approach also offers a framework to analyze the stability of allocation in various budget scenarios.

J. Human-Centered Decision Support

The human-centric part of the decision support system guarantees that AI-driven marketing recommendations support and do not supplant managerial judgment [3]. The suggested interface is composed with three phases, namely recommendation, explanation and decision option. A recommended allocation along with the anticipated profitability result is presented to managers as well as a relevant budget constraint and main SHAP factors that support the recommendation [4]. The explanation is provided in an understandable format, so that non-technical users can debate why a specific platform, campaign or allocation level is recommended [4]. The managers have the final say on the decision and can choose to accept, adjust or reject the proposed AI recommendation, depending on the business context, risk tolerance or other factors that are not covered by the AI model [5]. A scenario based evaluation may evaluate how much perceived understanding, trust, usefulness, confidence and willingness to act on recommendations were developed [6]. This is because accuracy in prediction doesn't necessarily translate to successful adoption of AI. The framework aims to bridge the gap between algorithmic understanding and effective marketing execution, alongside preserving accountability of the business manager, by incorporating explainable explanations and human oversight and decision-making capability [7]. It is therefore viewed as more of an advisory tool than a decision maker in the design.

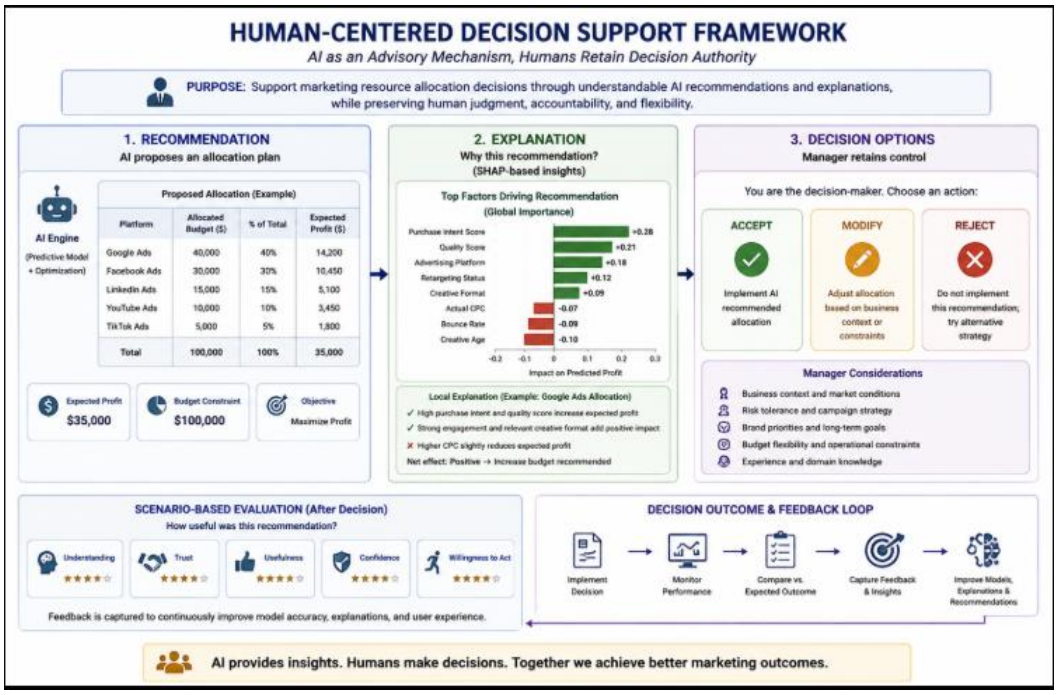


Figure 5. This framework illustrates a human-centred approach to decision support, incorporating AI recommendations, explanations, managerial judgment and feedback

The human-centred decision support framework demonstrates how marketing recommendations developed by AI relate to managerial actions, while ensuring the human element remains in control [7]. It starts with an AI-generated allocation plan that is created based on the expected profits, budget, and optimization results. SHAP-based explanations are then used to pinpoint the most important of these factors behind each of the recommendations and present them in a comprehensible format [8]. These recommendations are then considered in the context of the business, risk appetite, strategic goals and operational constraints, by the manager. They may accept, change, or even reject the suggested allocation [9]. A scenario-based assessment assesses understanding, trust, usefulness, confidence and willingness to act. Finally, all implementation outcomes and user feedback provide a continuous loop to help continuously refine models, explanations, and recommendations.

K. Evaluation of the AI-to-Action Gap

The ultimate evaluation is to see if the proposed framework is successful in linking technical AI performance and decision usefulness [10]. The four dimensions considered are: predictive performance, explainability, allocation effectiveness and usefulness to humans. The models are assessed for predictive performance with RMSE, MAE and R^2 to estimate the ability of the models to predict the profit of the campaign accurately. Explainability is evaluated using SHAP feature contributions, global feature rankings and the simplicity of local explanations that explain single recommendations [11]. Allocation effectiveness is assessed based on expected profit, ROI/ROAS, conversion efficiency and resource efficiency for varying budgets with the AI optimized allocations contrasted to baseline allocations [12]. If a scenario based decision evaluation is performed, measures for usefulness relating to humans are taken, such as understanding, trust, confidence, perceived usefulness, and actionability. Central evaluation thus is not just about the accuracy of the predictive model [13]. It investigates if predictions, explanations and resource constraints lead to more actionable and useful recommendations for marketing decisions [14]. These four dimensions' results are then combined to assess the gap between AI and action, while maintaining human

oversight and managerial control. This multi-dimensional assessment provides a comprehensive and balanced assessment of the quality of the technical model and its decision value.

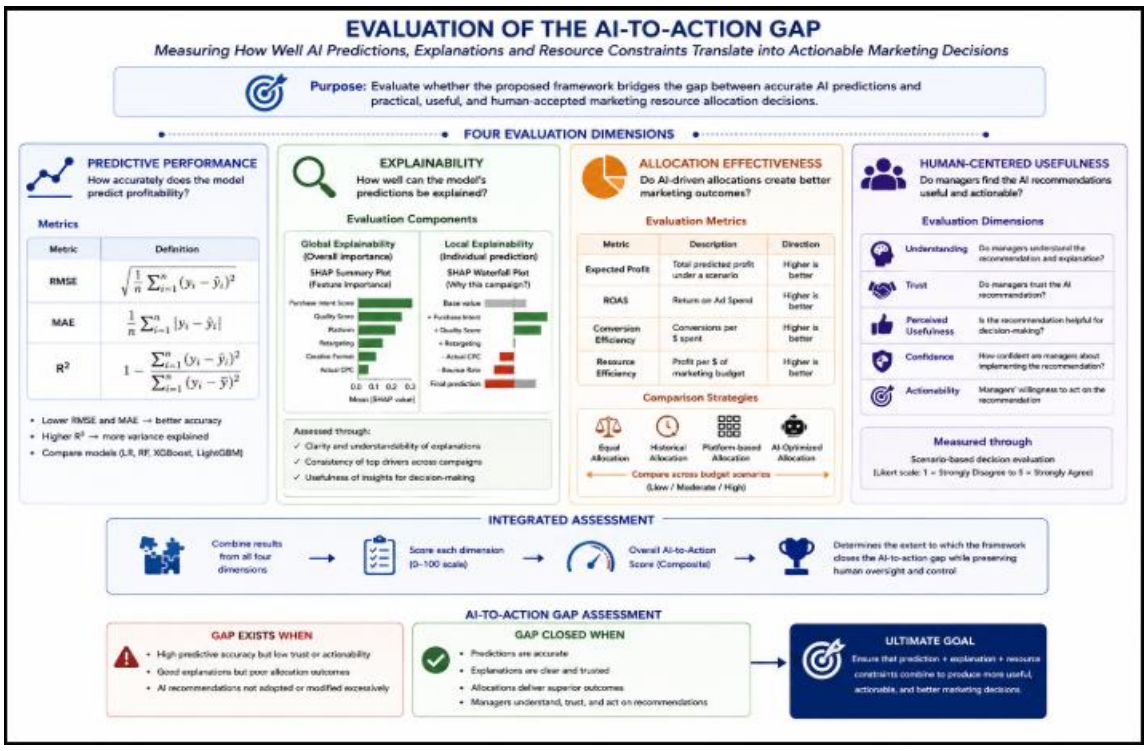


Figure 6. This framework presents the multi-dimensional assessment of AI predictions, explanations, effectiveness of allocation, and actionability for humans

The framework assesses the proposed AI-to-action approach on four complementary dimensions: predictive performance, explainability, allocation effectiveness and human-centered usefulness. Predictive performance evaluates the ability to predict profitability in terms of RMSE, MAE and R^2 of the machine learning models. Explainability assesses global and local SHAP contributions and aims for clarity, consistency, and usefulness of model explanations. Allocation effectiveness is measured against both expected profit and ROAS, conversion efficiency, and resource efficiency for various budget scenarios when compared to AI optimized marketing allocations, equal marketing allocations and historical marketing allocations and platform allocations [15]. Human-centered usefulness focuses on understanding, trust, perceived usefulness, confidence, and actionability using a scenario evaluation. The results of all dimensions are aggregated to an overall AI-to-action gap.

Conceptual Framework

This study's conceptual framework sheds light on the interplay between these key factors: AI, Explainable AI (XAI), resource constraints, and human-centric decision-making processes, to connect AI with action in marketing resource allocation [15]. It starts with digital advertising campaign characteristics as the major input, such as platform, campaign objective, audience characteristics, creative attributes, engagement measures, quality indicators, industry context and budget tier [16]. These are fed into machine learning models to forecast the profitability of campaigns and uncover patterns that relate to successful marketing results. The most successful predictive model is then linked to a layer of SHAP which provides an explanation of the global and campaign-specific factors that lead to predictions of profitability [17]. It then adds another layer of constraints to the process, including constraints on marketing budgets, to make the insights

actionable for recommendable allocations [18]. The recommendations that are generated result in potentially profitable platforms, campaigns and the allocation level within set budget constraints. The human-centered decision-support layer is the core of the framework, as it enables the manager to comprehend explanations, assess recommendations and accept, adapt or reject the allocation strategies suggested by AI. Last but not least, marketing results like profit, ROAS, conversion effectiveness, and resources effectiveness give back input data to gauge the effectiveness of the framework [19]. The conceptual framework thus outlines a linear sequence of: data, prediction, explanation, constrained allocation, human decision, outcome and feedback, with the goal of having AI support the human decision-making process as an interpretable tool rather than an independent decision-maker.

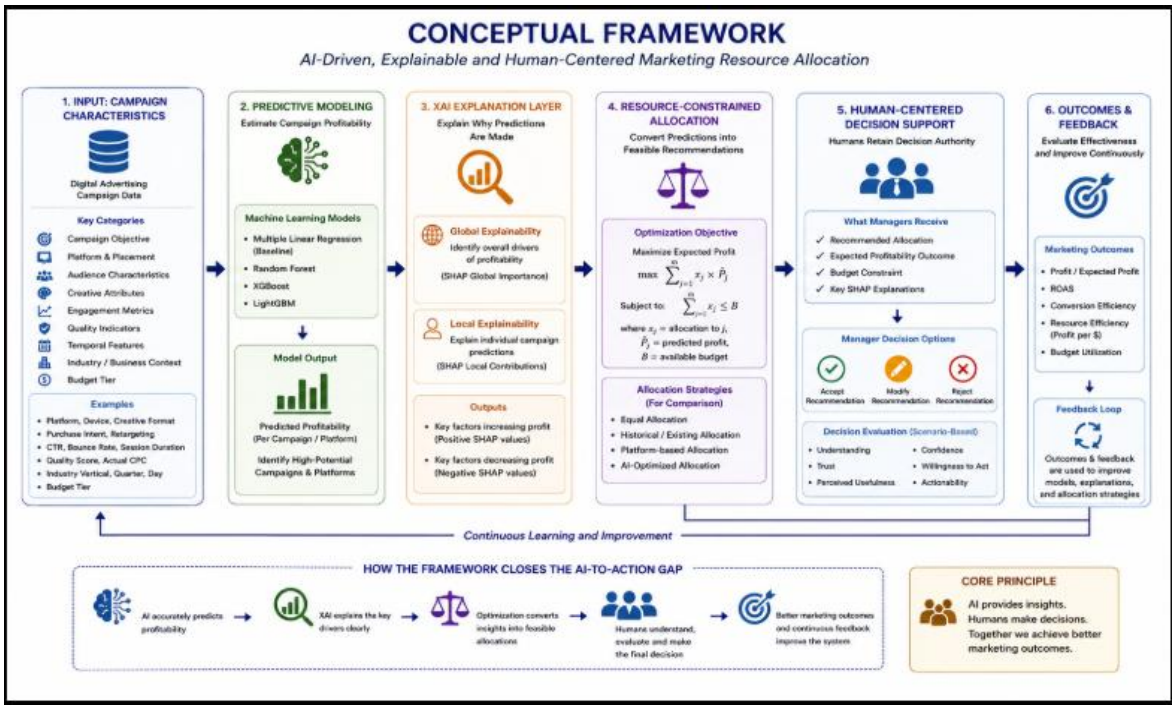
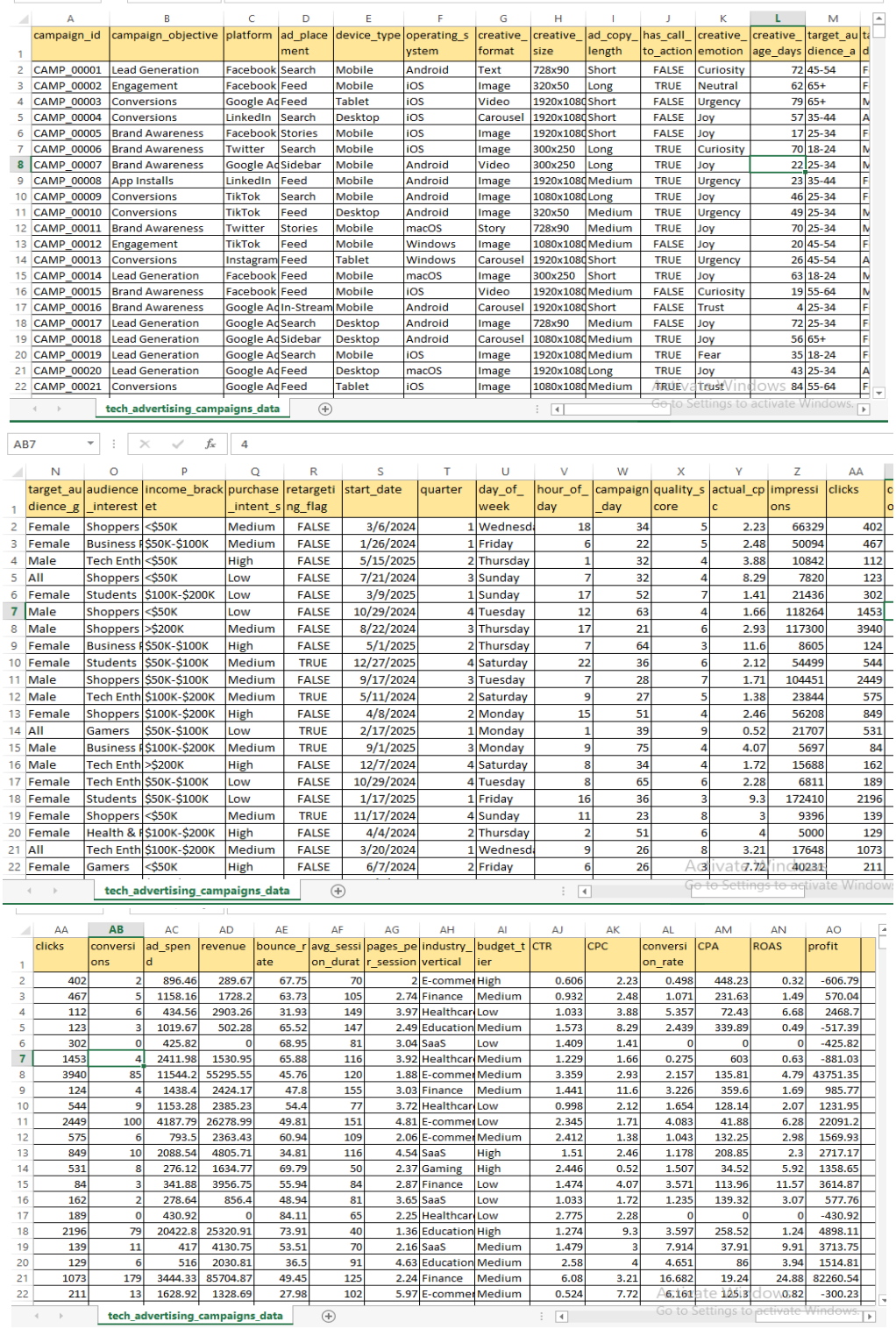


Figure 7. This framework outlines the concept of predictive AI, explainability, optimization, and human insights working together to make marketing resource allocation actionable

The conceptual framework provides a representation of how AI-driven predictive analytics can be not only a tool for making marketing decisions but also a set of explanations that are understandable to humans [20]. It starts with campaign properties such as platform, audience, creative, engagement, quality, temporal, industry and budget details. The machine learning models forecast the profit of a campaign and provide high-potential campaigns and platforms. Global and local SHAP explanations are used in the XAI layer to explain the factors that contribute to predictions [21]. These insights are used in resource constrained optimization to come up with feasible allocation strategies. Managers are presented with recommendations, along with projected impacts, budgetary considerations and explanations, and have the discretion to approve, revise, and/or reject recommendations. The marketing results and feedback complete a continuous learning loop which leads to the improvement of the framework.

Dataset

A. Screenshot of Dataset



campaign_id	campaign_objective	platform	ad_placement	device_type	operating_system	creative_format	creative_size	ad_copy_length	has_call_to_action	creative_emotion	creative_age_days	target_audience_a	td
CAMP_00001	Lead Generation	Facebook	Search	Mobile	Android	Text	728x90	Short	FALSE	Curiosity	72	45-54	F
CAMP_00002	Engagement	Facebook	Feed	Mobile	iOS	Image	320x50	Long	TRUE	Neutral	62	65+	F
CAMP_00003	Conversions	Google Ad	Feed	Tablet	iOS	Video	1920x1080	Short	FALSE	Urgency	79	65+	M
CAMP_00004	Conversions	LinkedIn	Search	Desktop	iOS	Carousel	1920x1080	Short	FALSE	Joy	57	35-44	A
CAMP_00005	Brand Awareness	Facebook	Stories	Mobile	iOS	Image	1920x1080	Short	FALSE	Joy	17	25-34	F
CAMP_00006	Brand Awareness	Twitter	Search	Mobile	iOS	Image	300x250	Long	TRUE	Curiosity	70	18-24	M
CAMP_00007	Brand Awareness	Google Ad	Sidebar	Mobile	Android	Video	300x250	Long	TRUE	Joy	22	25-34	M
CAMP_00008	App Installs	LinkedIn	Feed	Mobile	Android	Image	1920x1080	Medium	TRUE	Urgency	23	35-44	F
CAMP_00009	Conversions	TikTok	Search	Mobile	Android	Image	1080x1080	Long	TRUE	Joy	46	25-34	F
CAMP_00010	Conversions	TikTok	Feed	Desktop	Android	Image	320x50	Medium	TRUE	Urgency	49	25-34	M
CAMP_00011	Brand Awareness	Twitter	Stories	Mobile	macOS	Story	728x90	Medium	TRUE	Joy	70	25-34	M
CAMP_00012	Engagement	TikTok	Feed	Mobile	Windows	Image	1080x1080	Medium	FALSE	Joy	20	45-54	F
CAMP_00013	Conversions	Instagram	Feed	Tablet	Windows	Carousel	1920x1080	Short	TRUE	Urgency	26	45-54	A
CAMP_00014	Lead Generation	Facebook	Feed	Mobile	macOS	Image	300x250	Short	TRUE	Joy	63	18-24	M
CAMP_00015	Brand Awareness	Facebook	Feed	Mobile	iOS	Video	1920x1080	Medium	FALSE	Curiosity	19	55-64	M
CAMP_00016	Brand Awareness	Google Ad	In-Stream	Mobile	Android	Carousel	1920x1080	Short	FALSE	Trust	4	25-34	F
CAMP_00017	Lead Generation	Google Ad	Search	Desktop	Android	Image	728x90	Medium	FALSE	Joy	72	25-34	F
CAMP_00018	Lead Generation	Google Ad	Sidebar	Desktop	Android	Carousel	1080x1080	Medium	TRUE	Joy	56	65+	F
CAMP_00019	Lead Generation	Google Ad	Search	Mobile	iOS	Image	1920x1080	Medium	TRUE	Fear	35	18-24	F
CAMP_00020	Lead Generation	Google Ad	Feed	Desktop	macOS	Image	1920x1080	Long	TRUE	Joy	43	25-34	A
CAMP_00021	Conversions	Google Ad	Feed	Tablet	iOS	Image	1080x1080	Medium	TRUE	Trust	84	55-64	F

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target_audience_g	audience_interest	income_bracket	purchase_intent_s	retargeting_flag	start_date	quarter	day_of_week	hour_of_day	campaign_day	quality_score	actual_cpc	impressions	clicks	co
Female	Shoppers	<$50K	Medium	FALSE	3/6/2024	1	Wednesd	18	34	5	2.23	66329	402	
Female	Business I	$50K-$100K	Medium	FALSE	1/26/2024	1	Friday	6	22	5	2.48	50094	467	
Male	Tech Enth	<$50K	High	FALSE	5/15/2025	2	Thursday	1	32	4	3.88	10842	112	
All	Shoppers	<$50K	Low	FALSE	7/21/2024	3	Sunday	7	32	4	8.29	7820	123	
Female	Students	$100K-$200K	Low	FALSE	3/9/2025	1	Sunday	17	52	7	1.41	21436	302	
Male	Shoppers	<$50K	Low	FALSE	10/29/2024	4	Tuesday	12	63	4	1.66	118264	1453	
Male	Shoppers	>$200K	Medium	FALSE	8/22/2024	3	Thursday	17	21	6	2.93	117300	3940	
Female	Business I	$50K-$100K	High	FALSE	5/1/2025	2	Thursday	7	64	3	11.6	8605	124	
Female	Students	$50K-$100K	Medium	TRUE	12/27/2025	4	Saturday	22	36	6	2.12	54499	544	
Male	Shoppers	$50K-$100K	Medium	FALSE	9/17/2024	3	Tuesday	7	28	7	1.71	104451	2449	
Male	Tech Enth	$100K-$200K	Medium	TRUE	5/11/2024	2	Saturday	9	27	5	1.38	23844	575	
Female	Shoppers	$100K-$200K	High	FALSE	4/8/2024	2	Monday	15	51	4	2.46	56208	849	
All	Gamers	$50K-$100K	Low	TRUE	2/17/2025	1	Monday	1	39	9	0.52	21707	531	
Male	Business I	$100K-$200K	Medium	TRUE	9/1/2025	3	Monday	9	75	4	4.07	5697	84	
Male	Tech Enth	>$200K	High	FALSE	12/7/2024	4	Saturday	8	34	4	1.72	15688	162	
Female	Tech Enth	$50K-$100K	Low	FALSE	10/29/2024	4	Tuesday	8	65	6	2.28	6811	189	
Female	Students	$50K-$100K	Low	FALSE	1/17/2025	1	Friday	16	36	3	9.3	172410	2196	
Female	Shoppers	<$50K	Medium	TRUE	11/17/2024	4	Sunday	11	23	8	3	9396	139	
Female	Health & F	$100K-$200K	High	FALSE	4/4/2024	2	Thursday	2	51	6	4	5000	129	
All	Tech Enth	$100K-$200K	Medium	FALSE	3/20/2024	1	Wednesd	9	26	8	3.21	17648	1073	
Female	Gamers	<$50K	High	FALSE	6/7/2024	2	Friday	6	26	3	7.72	40231	211	

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clicks	conversions	ad_spend	revenue	bounce_rate	avg_session_durat	pages_per_session	industry_vertical	budget_tier	CTR	CPC	conversion_rate	CPA	ROAS	profit
402	2	896.46	289.67	67.75	70	2	E-commer	High	0.606	2.23	0.498	448.23	0.32	-606.79
467	5	1158.16	1728.2	63.73	105	2.74	Finance	Medium	0.932	2.48	1.071	231.63	1.49	570.04
112	6	434.56	2903.26	31.93	149	3.97	Healthcar	Low	1.033	3.88	5.357	72.43	6.68	2468.7
123	3	1019.67	502.28	65.52	147	2.49	Education	Medium	1.573	8.29	2.439	339.89	0.49	-517.39
302	0	425.82	0	68.95	81	3.04	SaaS	Low	1.409	1.41	0	0	0	-425.82
1453	4	2411.98	1530.95	65.88	116	3.92	Healthcar	Medium	1.229	1.66	0.275	603	0.63	-881.03
3940	85	11544.2	55295.55	45.76	120	1.88	E-commer	Medium	3.359	2.93	2.157	135.81	4.79	43751.35
124	4	1438.4	2424.17	47.8	155	3.03	Finance	Medium	1.441	11.6	3.226	359.6	1.69	985.77
544	9	1153.28	2385.23	54.4	77	3.72	Healthcar	Low	0.998	2.12	1.654	128.14	2.07	1231.95
2449	100	4187.79	26278.99	49.81	151	4.81	E-commer	Low	2.345	1.71	4.083	41.88	6.28	22091.2
575	6	793.5	2363.43	60.94	109	2.06	E-commer	Medium	2.412	1.38	1.043	132.25	2.98	1569.93
849	10	2088.54	4805.71	34.81	116	4.54	SaaS	High	1.51	2.46	1.178	208.85	2.3	2717.17
531	8	276.12	1634.77	69.79	50	2.37	Gaming	High	2.446	0.52	1.507	34.52	5.92	1358.65
84	3	341.88	3956.75	55.94	84	2.87	Finance	Low	1.474	4.07	3.571	113.96	11.57	3614.87
162	2	278.64	856.4	48.94	81	3.65	SaaS	Low	1.033	1.72	1.235	139.32	3.07	577.76
189	0	430.92	0	84.11	65	2.25	Healthcar	Low	2.775	2.28	0	0	0	-430.92
2196	79	20422.8	25320.91	73.91	40	1.36	Education	High	1.274	9.3	3.597	258.52	1.24	4898.11
139	11	417	4130.75	53.51	70	2.16	SaaS	Medium	1.479	3	7.914	37.91	9.91	3713.75
129	6	516	2030.81	36.5	91	4.63	Education	Medium	2.58	4	4.651	86	3.94	1514.81
1073	179	3444.33	85704.87	49.45	125	2.24	Finance	Medium	6.08	3.21	16.682	19.24	24.88	82260.54
211	13	1628.92	1328.69	27.98	102	5.97	E-commer	Medium	0.524	7.72	6.161	125.3	0.82	-300.23

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(Source Link: https://www.kaggle.com/datasets/juniornsa/digital-advertising-campaign-performance-dataset)

B. Dataset Overview

The Digital Advertising Campaign Performance Dataset is a synthetic campaign-level dataset with 10,000 advertising campaigns and 41 variables over the time range of January 1, 2024 – January 31, 2026. The dataset was chosen due to its structure being similar to the research goal of building a human centric Explainable Artificial Intelligence (XAI) system to assist in the allocation

of marketing resources in limited budgets [21]. It includes a variety of dimensions of digital advertising performance ranging from campaign goals to devices and operating systems, creative formats and characteristics to audience attributes and attributes of the auctions themselves, engagement behavior and the industry context and budget tiers. There are core performance variables such as impressions, clicks, conversions, advertising spend and revenue, and a variety of derived variables such as CTR, CPC, conversion rate, CPA, ROAS and profit that can be used to measure the effectiveness of a campaign. Profit is the key dependent variable as it reflects the actual financial returns from marketing practices, as measured by revenue – advertising expenditure. Predictor variables are campaign objective, placement, device type, campaign emotion, whether the purchase intent score was above or below average, whether retargeting was present or not, whether the quality score was above or below average, whether actual CPC was above or below average, whether the creative was placed in the top, bottom or middle, whether the bounce rate was above or below average, whether the average session duration was above or below average, whether the number of pages per session was above or below average, whether the campaign day was above or below average, whether the quarter was above or below average, industry vertical, and whether the budget tier was high or low. No missing values or duplicate campaigns are found in the dataset; there is also logical consistency between the data, e.g. no campaign with more conversions than clicks, and advertising spend is logically related to clicks, and to actual CPC. Importantly, there are not some of the revenue, advertising spend or mechanically driven performance metrics in the main profitability prediction model, as their inclusion would lead to information leakage [22]. The budget tier variable is used to represent different levels of marketing-resource availability for a variety of different scenarios that represent low, medium, and high allocations of marketing resources. The data set is synthetic and is not representative of the set of all U.S. small businesses, but can be used to evaluate predictive modeling, explanations using SHAP, constrained optimization, and marketing decisions with human-centered analysis [23]. The data set therefore offers the appropriate level of breadth and granularity to explore the shift of AI-driven campaign predictions to more explainable, resource-aware and actionable marketing allocation decisions.

3. Results

The results obtained in this research show the effectiveness of using the proposed human-centered, explainable and AI-based framework for allocating marketing resources under financial constraints. The analysis starts with descriptive comparison of platform and campaign profitability, followed by predictive analysis, an interpretation of Explainable AI, and an evaluation of the allocation of resources [24]. Find significant differences in profitability between advertising platforms, budget levels, and campaign goals, and also see how well the machine learning models predict. SHAP analysis also gives a clear understanding of how different factors affect the profitability of the campaign, giving a clear idea of the model's behavior [25]. The resource-allocation analysis illustrates the potential for turning predictive insights into actionable budget recommendations and the comparison with traditional approaches to resource allocation. Together, these results offer empirical support to assess the effectiveness of the proposed framework in closing this gap between AI predictions and real-world, human-driven marketing decisions.

A. Comparing the profitability of different advertising platforms

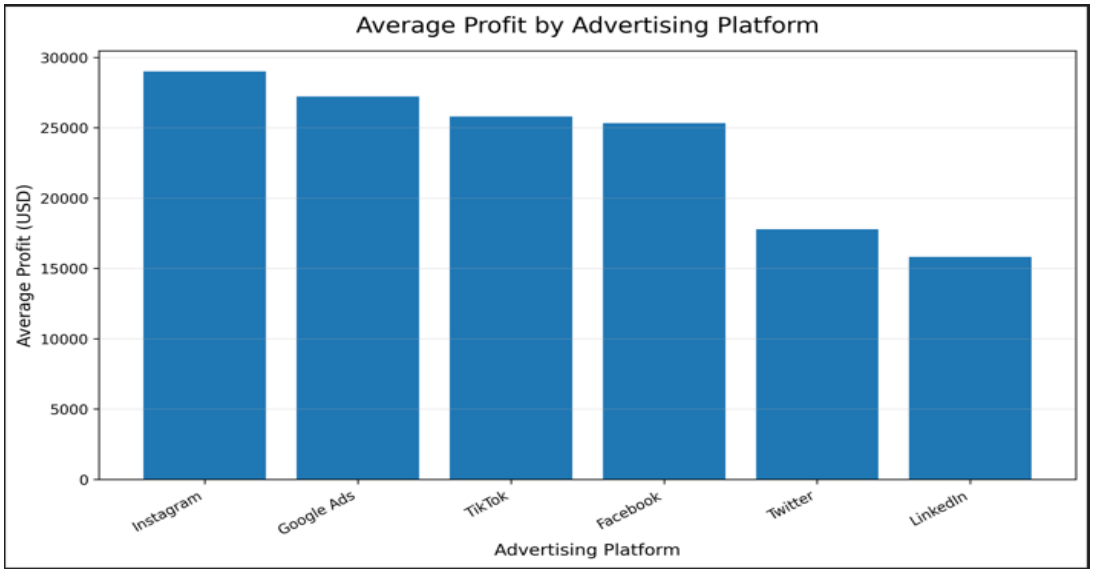


Figure 8. The image shows the average difference in profitability of campaigns over six major digital ad platforms

This comparison of average campaign profitability between six key advertising platforms (Instagram, Google Ads, TikTok, Facebook, Twitter, and LinkedIn) is shown in figure 8. Overall, Instagram shows a higher average profit of $29,005 per campaign, suggesting that it has a relatively strong profitability within the data set. Google Ads comes in second with about $27,222 and TikTok and Facebook bring in about $25,786 and $25,315 respectively. The average profit realized by Twitter is significantly lower, around $17,786, while LinkedIn is the lowest at around $15,828. The results show that there is substantial inter-platform profitability variation, which can significantly affect marketing resource allocation results, depending on the platform selected [25]. These differences offer valuable consideration for businesses with limited resources when selecting platforms that offer greater potential profitability, and can also help assist informed decision-making for a final platform selection using AI explanations and business constraints.

B. Comparing ROAS across different marketing budgets

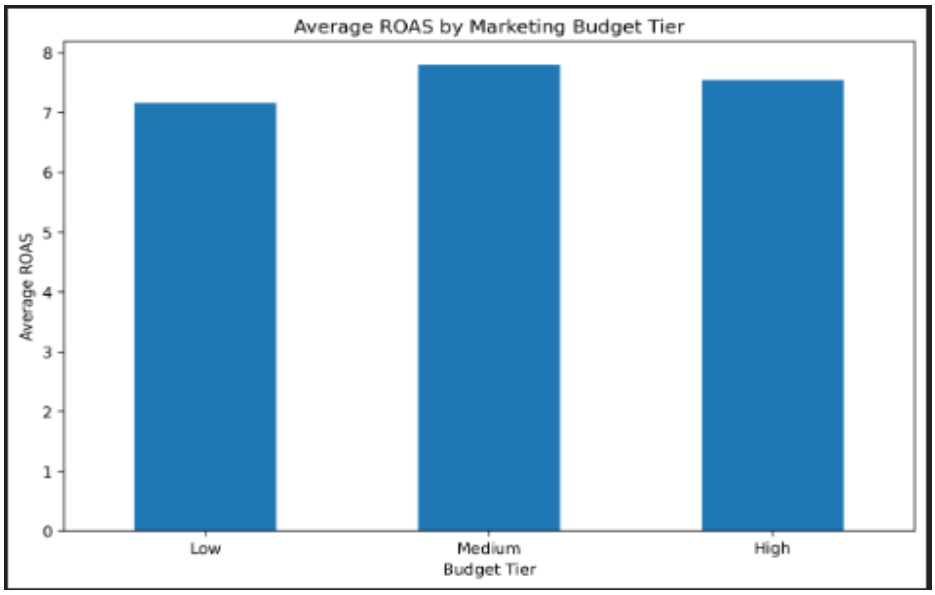


Figure 9. This image shows the average ROAS between low, medium, and high marketing budgets

When looking at the average Return on Advertising Spend (ROAS) by low, medium, and high marketing budgets, as shown in Figure 9, it is evident that a higher marketing budget is associated with lower ROAS. The medium-budget tier has the highest average ROAS, at about 7.8, followed by the high-budget tier with an average ROAS of 7.5, and the low-budget tier with the lowest average ROAS of 7.1. The findings indicate that the higher the ad budget, from low to medium, the more efficient the advertising. The upward shift from medium to high level is a sign that efficiency gains do not increase in proportion to the amount spent, though [25]. It is especially important to a resource-constrained small business because the ability to allocate resources optimally might not be a result of 'spending our way to the top', but rather a result of using resources at an intermediate level [26]. The discovery suggests that budget limitations should be taken into account in the allocation of resources using AI, not just maximizing spending.

C. Evaluate campaign objectives for profitability

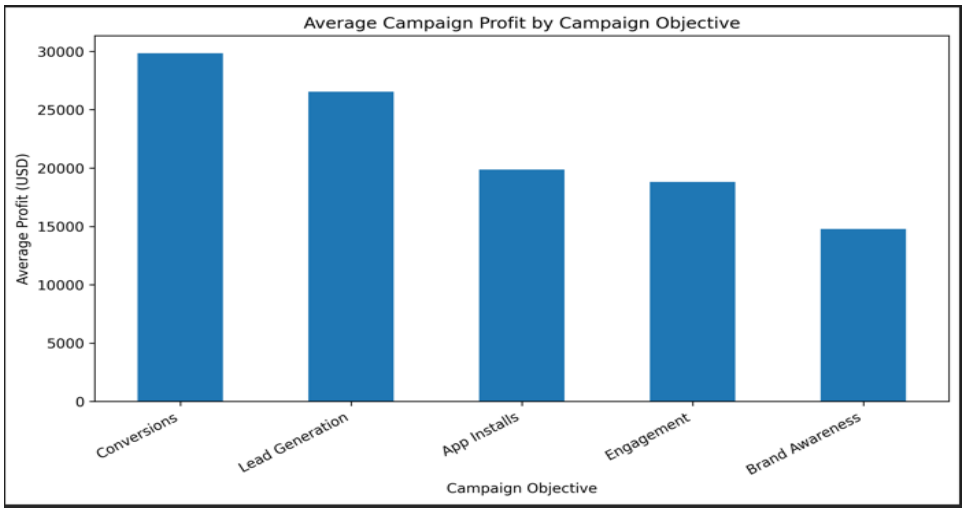


Figure 10. This image shows the average profitability of campaigns by each of the five types of digital advertising campaign goals

Figure 10 shows the average campaign profit for each campaign objective: Conversions, Lead Generation, App installs, Engagement, and Brand awareness. Conversions campaigns typically see the highest average profit at about $29,800 followed by Lead Generation at about $26,600. The average profit for App Installs and Engagement campaigns are around $19,900 and $18,800, respectively, with Brand Awareness showing the lowest profits of around $14,700. The findings show a strong correlation to campaign objective and financial results [27]. For businesses with limited resources, conversion-focused campaigns can seem like an especially promising option, as they target direct actions customers take and are likely to yield higher profits. Allocating a significant budget to Brand Awareness, on the other hand, can lead to less immediate monetary return [28]. The results offer further evidence for the inclusion of campaign goals in resource allocation decisions in the context of AI, as well as in the context of explainable profitability predictions.

D. Comparing the performance of models predicting campaign profitability

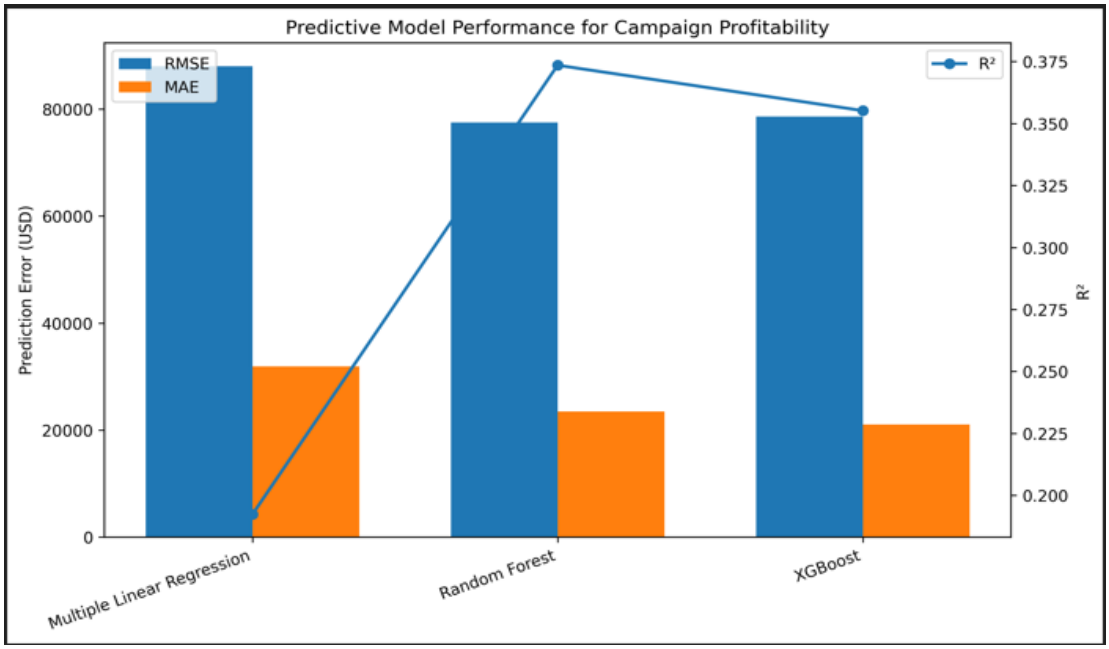


Figure 11. This image shows what the three machine learning models predict for campaign profitability, compared with each other

Figure 11 shows the performance of Multiple Linear Regression, Random Forest and XGBoost in terms of RMSE, MAE and R^2 for the task of predicting campaign profitability. Multiple Linear Regression has the highest RMSE ($88,029) and MAE ($31,893), along with the lowest R^2 of 0.1923, which shows the comparatively low predictive ability. Random Forest has the lowest RMSE of about $77,527 and the lowest MAE of about $23,445 with the highest R^2 value of 0.3735. The RMSE of XGBoost is around $78,652, the MAE of XGBoost is about $21,011 and the R^2 of XGBoost is approximately $0.3552. Furthermore, Random Forest best performs in terms of explained variance and prediction error, and is thus chosen as the main model for further SHAP interpretation and allocation of resources.

E. Explainable AI Identification of Key Profitability Drivers

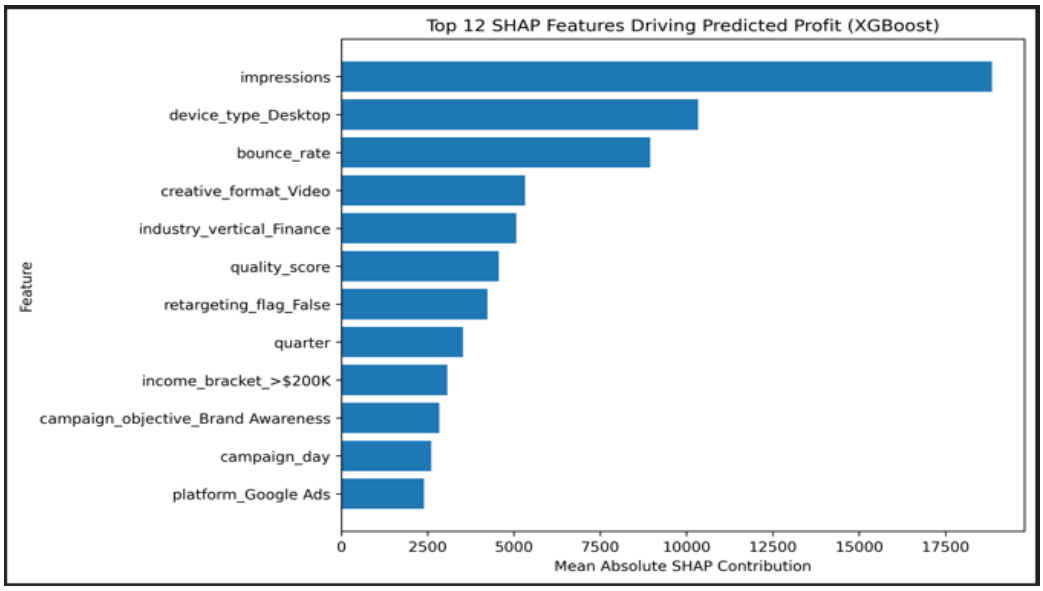


Figure 12. This image shows the 12 most influential features that are driving explainable campaign profitability predictions

The top 12 features affecting the mean absolute SHAP contributions to the XGBoost model are shown in Figure 12. The SHAP value for impressions is also considerably larger than other variables, making it the most influential factor, and the magnitude of the SHAP value for impressions is much higher than the others [27]. The second most important one in terms of influence is Desktop device targeting, followed by Bounce rate, highlighting the value of both device audience and engagement quality. Other creative formats, especially Video, and the Finance industry vertical also make significant contributions to model predictions. Quality score and retargeting status both have extra predictive significance, indicating that the quality of ads and audience strategy are important for profitability [28]. The contributions from comparatively smaller sources include quarter, High-income targeting, Brand Awareness objectives, the duration of the campaign, and characteristics of the Google Ads platform. Importantly, SHAP does not imply causality, it's used to identify which factors are driving predictions [29]. These explanations help to guide marketing allocation decision making in a transparent and evidence-based way.

F. Evaluation of Random Forest Profit Prediction Accuracy

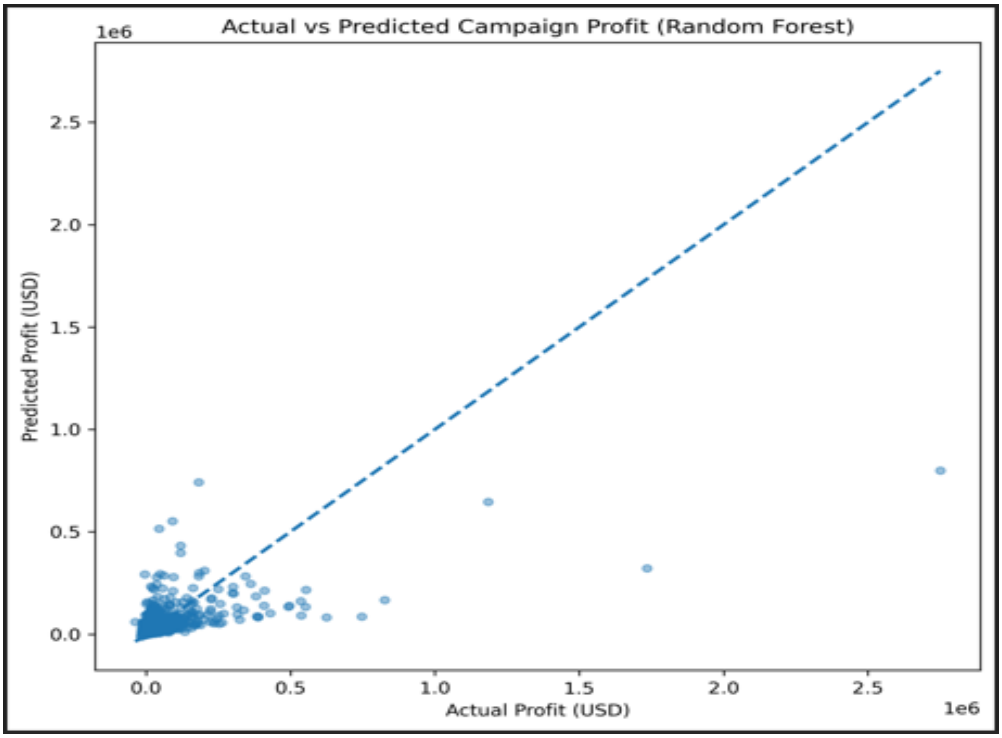


Figure 13. This image displays actual versus Random Forest predicted campaign profitability and prediction dispersion

Figure 13 shows how the actual campaign profitability correlates with the predicted campaign profitability by using a Random Forest model. The dashed diagonal line is the line of perfect prediction and is located where the profit predicted is equal to the profit achieved. The majority of campaigns are focused around the lower left quadrant, showing most campaigns make relatively small actual and predicted profits [30]. There is, however, a considerable scatter from the line of reference, especially when the actual profit on the campaign is high. Some observations with high profit have a much lower actual profit but a much higher predicted profit, and vice versa for several campaigns with relatively low actual profit. This pattern indicates that the Random Forest model is good at distinguishing the general trends of profitability but struggles to estimate extreme profits [31]. This yields an acceptable moderate R^2 value of 0.3735 which suggests the model accounts for

some but not all of the variation in profitability. However, its better overall performance compared to the baseline justifies its use in explainability and resource-allocation analysis.

G. AI-Informed Marketing Budget Distribution by Platforms

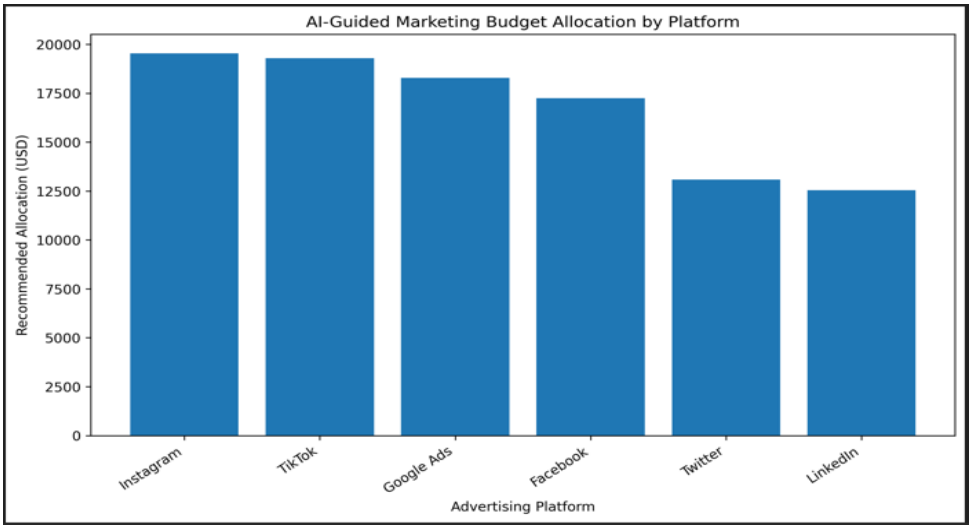


Figure 14. This image illustrates the allocation of scarce marketing resources using AI for six advertising platforms

The top 3 platforms that the AI suggests are most beneficial for the $100k marketing budget are Instagram (around $19,500), TikTok (around $19,300), and Google Ads (around $18,300). Facebook's payment is around $17,300, while Twitter's and LinkedIn's payments are relatively less at $13,100 and $12,500 respectively. The allocation pattern suggests the proposed AI system's aim is to priorities platforms that are likely to be more profitable, with some level of distribution across advertising channels. Importantly, the results show that resource constrained allocation does not just kill off lower performing platforms, but rather it allocates a proportionately smaller amount of resources to them [31]. This strategy helps make the budget more effective in allocating more funds into a platform that has a better chance of generating more returns. The results demonstrate the potential of predictive analytics to be turned into actionable, budgeted marketing insights.

H. Comparative effectiveness of allocation strategies for marketing

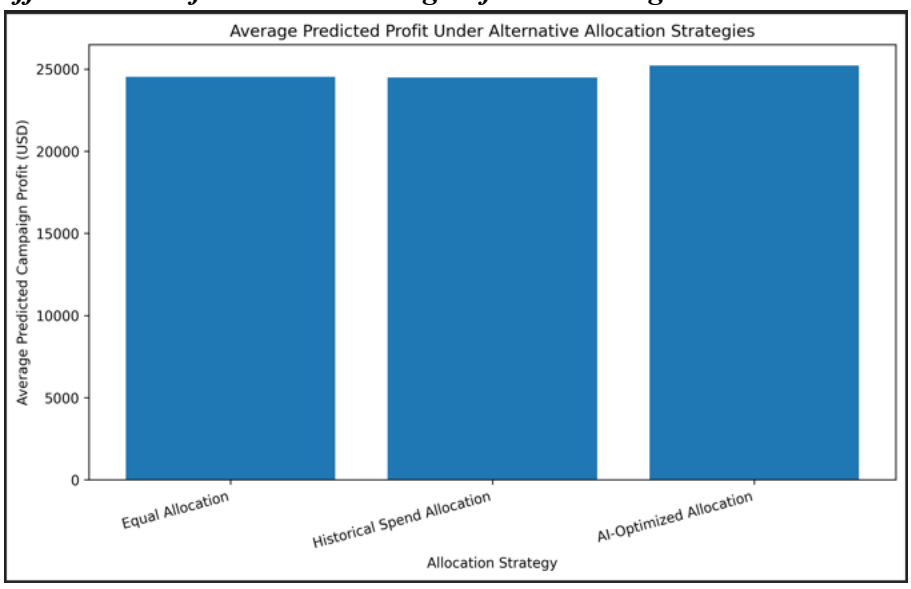


Figure 15. This image illustrates the projected profitability differences among three different marketing allocation scenarios

Figure 15 illustrates the average expected campaign profit across three different marketing allocation approaches: equal allocation, historical-spend allocation, and AI-optimized allocation. The AI optimized strategy generates the highest average predicted profit of about$25,223 whereas equal allocation is about $24, 52 and historical spend allocation is about $24,493. The differences between the two are not too significant, though the AI-optimized strategy shows some measurable advantage over the two baseline strategies. In particular, AI optimization gives an estimated gain of about $703 above equal allocation, and $730 above historical allocation for the same amount of allocation, or about 2.9% and 3.0% gains respectively [32]. The results suggest that using predictive profitability estimates for resource allocation could lead to more efficient use of limited marketing resources [33]. The results offer empirical evidence for the proposed AI-to-action framework by showing how the insights gained from models can be utilized to determine the allocation strategy and implemented in practice, instead of being limited to predicting it.

4. Discussion

The results explore that the human-centric Explainable AI framework could successfully map the predictive marketing analytics and resource allocation decisions, but at the same time showed some key points to address concerning the uncertainty of prediction [34]. The platform-level analysis revealed significant differences between average profits, with Instagram having the highest average profit margin followed by Google Ads, TikTok and Facebook, and Twitter and LinkedIn having lower average profits [35]. These differences indicate it is important for resource-constrained businesses to consider which platform to use, but it is important to note that the averages shown in this platform are not necessarily indicative of one platform being inherently better when looking at different campaigns, audience types, creative strategies and the industry context that could impact profitability [36]. The budget tier analysis also showed medium budget campaigns had the highest average ROAS, and an average ROAS of less than a medium budget campaign was seen with high-budget campaigns pointing to a slight loss of efficiency when spend is increased [37]. This discovery reinforces the main idea of the study, which is that allocation in marketing should not only be geared towards greater expenditure; it should instead be directed towards optimizing resources [38]. This was confirmed by the campaign-objective analysis, which found that campaign profits for conversion campaigns and for lead generation campaigns were significantly higher than those for engagement and brand awareness campaigns [39]. For small businesses with limited resources, it could then be prudent to allocate a larger percentage of budgets to goals that are tied to quantifiable economic returns, and still invest the proper amount of strategic spending in awareness-building activities, for the business' expected profitability may be enhanced [40]. The predictive-model comparison shows that the Random Forest model outperforms the linear regression model in terms of the R^2 (0.3735) and RMSE, suggesting that machine-learning approaches that can consider the relationship between profitability and the other variables are potentially more suitable for capturing the patterns of profitability that are not captured by the linear regression approach [41]. Yet, the moderate R^2 also highlights that there is still a significant amount of variance in profitability not captured, thus underscoring the need to view the predictions of AI as evidence for making decisions, not as certainties. In addition, the SHAP analysis validated the framework by pinpointing influential predictors of the model such as impressions, desktop targeting, bounce rate, creative format, industry, quality score, and retargeting [42]. Importantly, these explanations provide transparency by providing the manager with insight to which variables are associated with predictions, but SHAP associations are not causal effects. The greatest evidence for bridging the gap between AI and action

is the resource-allocation analysis [43]. The AI-optimized approach yielded around $25,223 in average predicted profit, while the equal allocation approach yielded around $24,520 in average predicted profit and the historical-spend allocation approach yielded around $24,493 in average predicted profit. It's a rather small improvement, but it is a proof of how predictive insights can be used in the context of budgetary limitations to make allocation decisions [44]. The results validate this framework's core concept of adopting AI in small-business marketing that is more than just predictive, and must be accompanied by explanation, constraint awareness, actionable recommendations, and human oversight [45]. This framework then defines AI as a support tool to augment the manager's decision-making, not as a replacement for them [46].The framework thus makes AI an advisory tool to support managerial decisions, not automating them.

Ethical Concerned and Limitation

The proposed framework poses some methodological concerns and ethical issues which are worth being noted during the interpretation of results. Ethically, AI marketing recommendations can have an impact on financial choices, so it's critical for companies to be transparent, accountable, and have a human touch [47]. By using Explainable AI, and specifically SHAP, managers can gain insight into the factors that are driving their predictions of profitability and minimize reliance on black box algorithmic suggestions [48]. But, an explanation should not be seen as proof of cause, and managers need to be able to accept, adapt, or reject the AI's suggestions [49]. Marketing models are also likely to carry biases if the patterns of past campaigns exhibit systematic disparities in the representation of audience, device, platform or demographically [50]. Fairness and responsible feature usage should be considered when implementing marketing models, as historical campaign patterns are likely to carry biases, and there may be systematic disparities in the representation of audience, device, platform, or demographically [51]. One of the weaknesses of this research is that the Digital Advertising Campaign Performance Dataset is synthetic, which means that the relationships may not be representative of real U.S. small-business marketing contexts [52]. Therefore, it is not possible to directly conclude that the results of this study apply to all small businesses. The medium prediction ability also suggests that there are key profitability drivers that are not explained [53]. The budget constraint is a limited indicator of resource limitations since it only reflects cash-flow constraints but not managerial knowledge, workforce capacity or strategic priorities. Last, the allocation analysis assumes future results, rather than actual outcomes [54]. Further studies should test the framework with real world longitudinal data and experiments designed by managers that incorporate decisions.

Future Work

Future studies should further expand the proposed framework to a broader real-world, longitudinal marketing context of U.S. small businesses [55]. In the future, we would like to see future studies also include real campaign-level data from small-business advertising accounts on Google, Meta, TikTok, LinkedIn, and other platforms to confirm that changes in profitability patterns and allocations seen in the current studies are also observed in real-world advertising environments [56]. Second, because of longitudinal datasets, researchers can analyze customer behavior over time, take into account seasonality, campaign fatigue, economic factors, and even changes in platforms and algorithms over time [57]. Third, further research is needed to explore more sophisticated prediction methods that are not only interpretable for managerial applications, but also include deep learning methods, ensemble stacking, Bayesian methods, and causal machine learning [58]. The resource allocation part can be extended from the static optimization to dynamic and multi-period budget optimization which will enable businesses to re-allocate resources based

on campaign performance [59]. Future research should consider other constraints that exist in the real world like the availability of cash flow, capacity of staff, limits of customer acquisition, minimum commitments of platforms, and strategic marketing goals [60]. The human-centered aspect must be assessed by experiments with real small business managers, to determine the level of trust, understanding, perceived usefulness, confidence in the decision made, and willingness to adhere or challenge the AI suggestions [61]. Future research could also explore issues of fairness and possible demographic and/or platform-specific biases in marketing recommendations, to make sure that optimization doesn't systematically disadvantage specific audience groups [62]. Another significant area is the creation of interactive dashboards that display predictions, SHAP explanations, budget scenarios and alternative allocation strategies in an easy-to-use interface [63]. Last but not least, future studies need to test the framework by looking at the actual marketing results of using AI-augmented choices versus the traditional marketing choices made by management, using controlled testing in the field [64]. This validation would offer greater reassurance on the effectiveness of the framework in bridging the gap between the use of AI and action, and in driving long-term profitability, resource efficiency, managerial confidence, and strategic marketing success.

5. Conclusion

This study proposed and tested an XAI framework geared toward a human-centered perspective to close the **AI-to-action gap** in marketing resource allocation for resource-constrained U.S. small businesses. The study, which was powered by the Digital Advertising Campaign Performance Dataset, showed the impact of scaling campaign level marketing data into explainable recommendations for allocation that are also efficient in their use of resources. The results showed that there are significant differences between the profit generated from each platform and each budget, and between each platform and campaign goal, as well as between traditional and uniform allocation strategies, supporting the notion that there is value in allocating limited marketing resources based on their likelihood of generating profit rather than based on the traditional or uniform allocation strategy. Random Forest outperformed all other evaluated predictive models which are Multiple Linear Regression (R^2=0.1923) and XGBoost (R^2=0.3552). The moderate predictive performance suggests that there are other factors that are not adequately represented by the variables included that still have an impact on profitability, but the results show the benefit of using nonlinear machine-learning techniques for marketing decision support. The framework was further reinforced by the findings of SHAP analysis which revealed some key profitability factors such as impressions, device type, bounce rate, creative format, industry, quality score, and retargeting. Such explainability is especially crucial because it helps managers comprehend why an AI system is making specific profitability predictions instead of merely being given recommendations without an explanation. The resource-allocation analysis also highlighted the practical utility of the framework with the AI optimized strategy reflecting an average of around $25,223 of predicted profits; whereas equal allocation and historical-spend allocation yielded around $24,520 and $24,493 of average predicted profit, respectively. The improvement was not very large, but it shows the potential gained by combining the power of predictive analytics, explainability, and budget constraints to optimize allocation choices. In conclusion, the study suggests that the successful application of AI in small business marketing should not just be about predicting the right outcome, but also providing clear explanations about the reasons behind the predictions, an awareness of resources and what is available, actionable recommendations, and

supervision by human managers. Thus, as part of the proposed framework, AI is designed as a tool for decision support and advice rather than a decision-making system. The study offers a systematic framework for future studies based on real-world, small-business marketing data and managerial decision experiments despite the limitations of the synthetic dataset and moderate predictive performance.

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