

Optimizing Advertising Budget Allocation Across Traditional Marketing Channels Using Machine Learning: Evidence From Television, Radio, and Newspaper Advertising

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Abstract

This paper examined at how an advertising budget can be optimized using a machine learning architecture in the case of traditional advertising channels, i.e., television, radio, and newspaper advertising. The key task was to model and test a predictive model that could quantify the contribution of each channel to sales and thus help with more evidence-based budget allocations. It adopted a computational cross-sectional design that rested on secondary data analysis. In the study, a publicly available advertising dataset of 200 observations with four variables was used in the form of television advertising budget, radio advertising budget, newspaper advertising budget, and sales. Descriptive statistics, Pearson correlation, and multiple linear regression were employed to analyze the data.

The results had indicated that the general regression model was statistically significant, $F(3, 196) = 570.271$, $p < .001$, and explained 89.7% of the variance in sales ($R^2 = .897$; Adjusted $R^2 = .896$). Television advertising emerged as the strongest predictor of sales ($\beta = .753$, $p < .001$), followed by radio advertising ($\beta = .536$, $p < .001$), while newspaper advertising did not make a statistically significant independent contribution ($\beta = -.004$, $p = .860$). Such findings suggest that the traditional advertising mediums vary significantly in terms of their marginal performance and the analysis of budget allocation can be done based on machine learning as opposed to intuition-driven planning to offer a more dependable foundation of budget allocation.

The research adds to the literature in that machine learning-based allocation studies have been limited to digital advertising setting so far and cannot be extended to a traditional media setting. In practice, it provides managers with a clear system of priorities on the way to concentrate on high-impact channels and enhance accountability of marketing spending activities. The researchers state that information-grounded allocation has the potential to enhance the advertisement decision-making process and infers basis of future research based on richer, longitudinal, and multi-channel data sets.

INTRODUCTION

One of the hardest marketing decisions that a company makes is how much to spend on advertising since this requires that firms translate the strategy into specific spending decisions across different competing channels. In the traditional media settings, organizations have to make decisions concerning the allocation of the few resources between television, radio, and newspaper advertising without necessarily foregoing sales to gain. Theoretically, this decision ought to be rationalized, data-driven, and performance-based. A company ought to be in a position to distinguish between channels that yield better returns and allocate funds to them, and make corresponding changes in allocations when performance is fluctuating. Practically, however, that scarcely goes so smoothly. Effect of advertising is not even distributed and channel responses are not linear, and managers in most cases make allocation decisions based on uncertainties. What is to be optimized tends to be something of discretion, custom and preliminary approximation.

ance and not just by feeling. Smith (2022) reviews contemporary marketing as a process that will rely not just on communication but also on planning, optimization, and integration. Similarly, Huang and Rust (2021) and Ziakis and Vlachopoulou (2023) believe that artificial intelligence is transforming marketing by enhancing firms' predictability, personalization of communication, and resource allocation. This is particularly appealing regarding machine learning, as it can reveal patterns that are not necessarily apparent in traditional statistical summaries. That promise has spurred increasing curiosity about the potential of machine learning to enhance advertising decision-making, particularly when two or more channels are vying for the same limited budget.

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The issue, though, is that actual allocation of ad budgets does not always measure up to this optimal. In an ideal system, budget decisions ought to capture how much contribution each channel makes to the business results, and ought to aid in the effective use of resources. However, most companies continue to use past spending patterns, managerial judgment, or generalized rules of allocation that do not reflect the evolving performance patterns. What seems to be a working channel might just be getting a larger budgetary allocation because it has always been given the priority whereas a channel with higher marginal contribution may still not get allocated. This will lead to inefficiency both strategically and operationally. A poorly informed allocation decision in organizations may result in overspending on weak channels, under-spending on strong ones, and a decrease in the total payoff on the investment in advertising.

Some of the past researches have tried to address related issues of this problem. The academic literature on machine learning in advertising has mostly been on targeting, classification, recommendation, and personalization (Choi & Lim, 2020; Gao et al., 2023; Shah et al., 2020). These papers are significant since they present the way algorithmic systems can enhance marketing accuracy. Nonetheless, they do not specifically answer the question of how the total budgets need to be distributed between channels. Yet another set of studies, however, approached the issue more closely by studying reinforcement learning and ad budgeting optimization in advertising, specifically in the context of digital, or cross-channel advertisements (Li et al., 2024, 2025; Patella, 2024; Zhao et al., 2023). The dynamic budget allocation in social media and online campaign systems is also worked on (Luzon et al., 2022; Nuara et al., 2022). These papers have a significant contribution, although the bulk of them are modeled on the basis of digital advertising eco-mediacy, bidding settings, and extremely granular platform data.

That poses a definite constraint in the literature. More conventional marketing channels are still the relevant ones in various business environments, although they are not as actively targeted in the machine learning studies of budget optimization. Simultaneously, most of the currently available research relies on proprietary datasets or more sophisticated digital infrastructures that are hard to reach by researchers and small companies. Therefore, missing evidence on how machine learning might

be applied to more easily understood advertising data that is public and made through traditional channels is still limited. The problem is not that there is no research in optimization. Instead, a good part of it has evolved in situations that are not readily translatable to lower multi-channel advertisement environments like television, radio, and newspaper spending.

The costs of such a breach do not run slight. At the operational level, poor decisions on budget allocations may result to wastage of money, under-sell and inefficient investment. Such impacts may grow cumulative, writing false perceptions of which media is useful and reinvesting ineffective expenditure habits. At the organizational level, the lack of good allocation also contributes to a lack of confidence in marketing analytics and discourages the use of more formal decision-support tools. Academically, the difference decreases our knowledge of the ways in which machine learning can aid in marketing resource distribution, in case the data are lower-order, transparent, and limited. This is a significant concern since not every company works in the solid digital ecosystems of plentiful user-level data in real-time.

This paper fills that gap through the formulation of a machine learning model to maximize the allocation of advertising budget in the traditional marketing channels on the basis of an openly available dataset of television, radio, and newspaper advertising and sales expenditure and sales results. The study takes a deliberately focused approach. Instead of performing simulations of extremely dynamic online bidding systems, it explores the possibility of machine learning to produce useful information about allotment in a more traditional and explainable advertising setting. It thus extends previous optimization-based studies in advertising (Li et al., 2024, 2025; Vahabi et al., 2024), but contrasts with much of this literature in context and accessibility. The broader strategy is also relevant to AI in marketing, which dictates that AI needs to predict as well as aid better managerial decisions (Campbell et al., 2020; Huang & Rust, 2021).

The theoretical reasoning that informs the research is predictive-prescriptive. The model based on machine learning is first applied to estimate the correlation between sales performance and advertising expenditure. Second, predictive insights are interpreted to make decisions on budget allocation decisions across the three channels. In this respect, the research exceeds the question of whether sales can be predicted based on spending data. It raises the question on whether this type of forecasting may serve to inform an operative system of improved allocation. Such reasoning is validated by studies that have associated machine learning with decision support and optimization, subject to resource limitations (Adekunle et al., 2021; Wilder et al., 2019).

There are four objectives of the study. First, it aims at investigating the connection between the advertising spend on the television, radio, and newspaper channels and the sales performance. Second, it seeks to build a machine learning system that can model these relationships in a manner that can enable allocation analysis. Third, it will evaluate how the framework can be useful in predicting channel contributions to sales. Fourth, it will attempt to come up with evidence-based findings on how advertising budgets can be allocated more effectively through the traditional marketing channels.

These are the goals that indicate the larger aim of the study to investigate whether machine learning can offer a more solid analytical foundation of budget allocation than traditional decision-making methods in a traditional advertising environment. The research is significant in a number of ways. It contributes to existing discussions on AI in marketing by addressing a more limited, although understudied, problem of allocation. Practically, it offers a framework which can assist firms having modest data infrastructure to make transparent and evidence based spending choices. This is an indication of the increasing pressure on organizations to ensure that marketing spending is more accountable and efficient in policy and professional terms.

The paper is based on the logic of the CARS model. It initially delineates the ground by indicating why the allocation of advertising budget and machine learning are important in modern marketing research and practice. It then pinpoints the niche by showing that current work has been focused on digital advertising settings, rather than on interpretable machine learning applications on conventional channels. And lastly, it fills that niche by introducing a machine learning framework on a conventional advertising dataset.

LITERATURE REVIEW

The allocation of advertising budget has always been at the heart of marketing since it has been associated with the strategic intent and quantifiable performance in the market. The simplest variant of the problem will involve how a company should allocate scarce resources to the channels at its disposal in order to achieve the maximum results, i.e. sales, visibility or return on investment. This seemingly simple question, however, gets complicated when one takes into consideration the fact that the channels vary in terms of reach, cost structure, pattern of response, and marginal effect. Even in the traditional media setting where television, radio, and newspaper still serve as viable advertising media, the budget allocation is often influenced by judgment and historical expenditure patterns of the managers and not by logical predictive indicators. This renders this a particularly important topic. As long as channel expenditure is modeled better, then planning about allocation could shift to an evidence-based optimization, rather than one that is based on intuition. And that is where machine learning can come in handy. Its usefulness, however, is not just in prediction, but in the fact that it can be used to put predictive insight into action in supporting decisions that are aimed at allocating resources.

This shift has the intellectual basis of the greater literature on artificial intelligence in marketing. The strategic framework created by Huang and Rust (2021) demonstrates that AI is becoming more and more integrated into marketing activities, which demand prediction, personalization, and decision support. Their input is significant as it puts machine learning in a managerial, as opposed to a technical, situation. Nevertheless, it is a conceptual framework. It gives a reason as to why AI is important yet fails to demonstrate how particular issues in marketing allocation need to be modelled in an empirical way. The same tendency can be observed in the review by Ziakis and Vlachopoulou (2023), who compile the application of artificial intelligence to digital marketing and pinpoint the aspect of optimization as one of its fundamental applications. The scope of the influence of AI is witnessed in their work, but the focus is mostly on digital ecosystems, and the allocation of channels in the traditional channel is not developed.

Gao et al. (2023) also focus on the issue of AI in advertising, paying their attention to the personalization, targeting, content creation, and optimization. They discuss analytically will be useful in that they introduce ethical and operational issues, but once again, budget allocation is not addressed as an empirical issue but a subset of a bigger AI advertising picture.

Another literature corpus focuses on the application of machine learning in advertising activities, including targeting and classification. As an example, Choi and Lim (2020) analyze the applications of machine learning to classify target advertising and conclude that algorithmic methods should be able to enhance the accuracy of advertising. The research has a methodological value in that it reveals the ability of machine learning to be superior to more traditional methods of a classification problem. But, it is indirectly relevant to the current study. The definition of target advertising is different to the budget distribution among the channels. The contribution is more about demonstrating the appropriateness of machine learning in marketing decision situations than on the optimal spending. Shah et al. (2020) also conducted a review of the trend in the use of machine learning and artificial intelligence in advertising. Their publication is field mapping, confirming a rising interest in the field, yet is general in nature. It does not put the managerial question of the allocation of expenditure among channels towards better sales results on its own. These studies thus justify the methodological validity of machine learning in advertising, although they do not entirely align with the goal of developing a budget allocation framework.

More pertinent are those studies that apply the reinforcement learning and optimization technique to the budget allocation in advertising. Li et al. (2024) suggest using a multi-channel advertising budget allocation model that incorporates the reinforcement learning approach with a better differential evolution algorithm. The research is very relevant in the sense that it clearly takes budget allocation as an optimization problem and demonstrates how the advanced learning systems can evolve to the dynamics of the channels. Its key advantage is the inclusion of machine learning with optimization logic that makes it very relevant to the aim of the current research. But there are restrictions. The model is technically advanced and probably presupposes a more enriched decision environment than most of the traditional media environments. This renders transferability to be a problem particularly when researchers or companies are using relatively small datasets which are transparent instead of intricate campaign structures. Li et al. (2025) build upon this idea by using Q-learning and a better algorithm to allocate advertising budgets in a multi-channel environment with an artificial bee colony. Once again, the contribution has a high algorithmic quality, but is focused on novelty of optimization as opposed to interpretability or accessibility. These works are helpful templates, but not comprehensive, to the current study.

Patella (2024) studies the use of reinforcement learning in cross-channel budget optimization of digital advertising, as well. This study is useful as it validates the fact that adaptive learning models have the potential to perform better in comparison to the non-adaptive allocation logic in dynamic advertising scenarios. Nevertheless, the emphasis on digital cross-channel advertising brings about a mismatch in context. Digital ecosystems produce real-time interaction data, auction data, and user-level data that is

not easily found in most traditional media datasets. Therefore, although the research gives solid arguments in support of the allocation made by machine learning, it does not answer the question of how these approaches can be applied to television, radio, and newspaper spending data. The study by Zhao et al. (2023) is also aimed at constrained deep reinforcement learning to allocate marketing budget. Their input is significant in demonstrating that allocation could be optimum given operational constraints, which are real-world conditions of budget decisions. Even the study is still geared towards more advanced computational environments, leaving a gap for more comprehensible, traditional-channel implementations.

The existing literature in the field of dynamic budget allocation beyond the conventional reinforcement learning is beneficial. According to Luzon et al. (2022), the dynamic budget allocation of social media advertising campaigns is studied, and the authors conclude that adaptive decision rules, as opposed to the traditional ones, are beneficial in deciding on the budget optimization. Their results are informative in that they point out the lack of soundness of the assumption of the fixed budget allocation. Nevertheless, the channel environment is not a traditional medium, but a social medium, and the logic of operations of social campaigns is quite different compared to broadcasting and print advertising. Nuara et al. (2022) studied online joint optimization of bids and daily budget of internet advertising campaigns that unite bidding behavior and spending control. This work is analytically deep and is indicative of commercial reality, and yet even more detached than the conventional media apportionment since it is highly situated within the internet advertising process. These studies all suggest the following: much of the best empirical research on budget allocation has been created in digital settings, rather than in conventional channel settings.

The wider investigation of AI-based optimization in business can also be used to contextualize the present investigation. Adekunle et al. (2021) demonstrate that predictive modeling can be used to enhance operational efficiency, whereas Wilder et al. (2019) suggest decision-oriented learning methods that relate prediction to optimization. They are not studies of advertisement per se, but offer a valuable conceptual bridge. They recommend that the machine learning can be most helpful when it does not halt at forecasting but rather, it helps make improved decisions under constraints. That rationale is quite valid to the objective of the current study to proceed with the prediction of sales outcomes to optimization of channel allocation. Similar statements are made by Campbell et al. (2020), who believe that marketers must shift their data to action, and that the true worth of AI is in its managerial application. This correlates well with the current research aim though their discussion is strategic as opposed to their discussion being empirically oriented towards traditional media expenditure.

A sort of commonality is thus evident in the literature. To begin with, it is universally accepted that AI and machine learning can enhance marketing decisions. Second, there are more specific studies which indicate that reinforcement learning and optimization techniques can be used to make advertising budget allocation. Third, but the majority of the most robust empirical research is amassed in digital, online or highly prolific advertising settings. This puts a contradiction in the literature. On the one hand, researchers believe that machine learning is widely applicable to allocate marketing resources. The

factual empirical displays on the other hand, are usually located in settings that are quite different to the traditional channels that are still in use by many businesses. Consequently, the literature promotes the concept of optimization but is yet to develop properly how a machine learning system is to be developed and assessed regarding the allocation of budgets to television, radio, and newspapers based on transparent and publicly available data.

This gap cannot be undermined particularly given the objective of the current study: to develop and test a machine learning model that can be used to optimize advertising funds allocation on television, radio, and newspaper media to achieve better sales results. The reason is that the existing studies are incomplete to this goal in three ways. To start with, a lot of them are centered on digital or cross-platform settings, instead of traditional channels. Second, a number of them put an emphasis on algorithmic technicality rather than interpretable practicality. Third, a great deal of the empirical research is based on proprietary or very fine-grained data that cannot be replicated in more general scholarly work. The next idea that is still under-researched is the creation of a machine learning design that is analytically sound, empirically open, and straight-forward to use on conventional data of advertising spending.

Altogether, the literature is robust in showing a potential of machine learning in advertisement and optimizing resources, yet it is not as comprehensive to solve the issue of accessible, traditional-channel allocation. The current paper overcomes this drawback by applying the machine learning not to the prediction of the outcomes only but also to the justification of the practical decision-making in budget allocation by using a traditional advertising dataset of variables including television, radio, newspaper and sales. In that regard, the study is based on the logic of optimization developed in the recent studies but moves the empirical context towards a more simplified, interpretable, and yet highly relevant marketing context. That is a small contribution, that, but it is needed. It bridges the gap between the dream of AI-driven optimization of advertising and the realities of the traditional channel decision-making process.

METHODOLOGY

Study Design

This research was done as a computational, cross-sectional secondary data analysis aimed at creating and testing a machine learning model to optimize advertising budgetary allocation in the traditional marketing channels. This design was suitable since the study did not aim to quantify attitudes, track the participants over a period of time or provide an intervention. Rather it concentrated on establishing relationships between the amount of advertising and the sales results and subsequently applied those established relationships in making decisions pertaining to the budget allocation. In that regard, the research was a combination of predictive analysis and prescriptive interpretation. This strategy complemented previous claims that machine learning can be most useful when prediction is linked with the decision support and optimization, but not an independent technical task (Wilder et al., 2019). The

study environment was the classic advertising environment, particularly the television, radio and newspaper media. The dataset used was publicly available and comprised of 200 observations and four substantive variables which include television advertising budget, radio advertising budget, newspaper advertising budget and sales. analyse

Ethics statement

No primary data or human or animal interaction was utilized in the study, as they used only anonymized, publicly available secondary data. That is why, informed consent could not be used. No individual names, business secret documents and sensitive human information was involved in the analysis. The study was considered as low-risk secondary research since the data used was publicly available and de-identified. The research was performed following the general principles of ethical conduct such as transparency, responsible use of data and reproducibility in computational research. As no new data about humans were gathered, and no experimental intervention was conducted, there were no official participant-based ethical procedures needed.

Participants

The units of analysis in this research were not human beings but observations of advertisement that were included in the dataset. All the observations were case-based on levels of expenditure through the three conventional marketing channels and the resultant level of sales. The research involved total population sampling, that is, all the records contained in the data were analyzed instead of a sample being chosen. This choice could be explained by the fact that the size of the data was not very large and the necessity to consider the entire spectrum of possible expenditure-sales associations. The records were deemed to be eligible when they had full values of television, radio, newspaper and sales variables. Cases that were missed, or had invalid values would have been filtered out during screening, but the data were checked prior to analysis to ensure structural consistency. Since the study involved observational records of advertising as opposed to human subjects, demographic features like age, sex or occupation could not be used.

Equipment and Materials

The main dataset of the study consisted of the actual public advertising data. Python was used to perform computational analysis in a Jupyter Notebook. There were a number of libraries of analyses that were employed to assist various workflow phases. Data cleaning and management were performed using Pandas, numerical operations were done using NumPy and performance evaluation of the model was done using scikit-learn. Exploratory visualization and diagnostic inspection were done with Matplotlib and seaborn. The tools were chosen due to the fact that they are common in the field of machine learning research, they are adequate in the process of predictive modeling which is regression based and they are simple to replicate by other researchers. No physical laboratory equipment, calibrated devices, interview devices, questionnaires or experimental materials were necessary since the study was purely computational.

Study Procedures

The processes were in an orderly manner. First, the data set was imported and filtered to check the names of the variables, data type, completeness and consistency. The index column which is not substantive was deleted since it was not useful in terms of prediction and budget allocation analysis. Then, exploratory data analysis was performed to get the idea of the overall distribution of the variables and the relationships at the beginning between advertising expenditure and sales. The stage involved descriptive summaries and distribution checks and visual inspections of possible outliers and channel level trends.

The data went through initial examination and were modeled. The advertising budgets of television, radio and newspaper were used as the independent variables whereas sales were the dependent variable. The data was then divided into a training and testing data set to allow out-of-sample validation. This had to be done to minimize the chances of overfitting and evaluate whether the chosen models would be able to generalize to other data.

The development of models started with linear regression as a reference point since it provided clarity and a known reference point in analyzing advertising responses. Subsequently, additional more flexible machine learning models were fitted such as decision tree regression, and random forest regression to identify potential nonlinear and interaction effects across channels. Gradient-boosting based models were also taken into account in case of better predictive performance, where applicable. The hyper parameter was tuned by using cross validation on the training data in order to enhance robustness of the models. The predictive relationships obtained by the final models were then explained in terms of budget allocation with specific focus on the potential impact of the relative contribution of each channel to make more efficient decisions on spending. This was selected as this process aligned with the objective of the study to go beyond mere prediction to a model that could be used to aid in practical allocation decisions.

Outcome Measures

The sales were the main outcome measure. The key outcome chosen was sales since the aim of the study was to plan the advertising budget better in order to enhance commercial performance. It gave a direct indication on the usefulness of advertising spending on the traditional channels looked at in the dataset. The independent measures of input were the budgets of television, radio and newspaper advertising.

Secondary outcome measures were model evaluation measures that served to measure the predictive adequacy. These were the mean absolute error, root mean squared error and the coefficient of determination. Such measures were suitable since they represented various aspects of model quality such as average prediction error, how sensitive the model is to larger errors and the amount of variance that it can explain. Furthermore, model-specific indicators like variable importance were applied where

possible to explain the relative impact of each channel of advertisement to sales prediction and budget allocation argument.

Statistical Analysis

The statistical computation was done in Python with the Jupyter Notebook and the corresponding machine learning libraries. The initial step was to create descriptive statistics to summarize the central tendency and variability of all the variables. An initial step followed by correlation analysis was then utilized to analyze the linear relationships between the variables television, radio, newspaper and sales. After this, regression-based and machine learning analyses were conducted as the study comprised of a continuous dependent variable and compared methods of predictive analysis.

The statistical model that was used as the baseline was linear regression because it is interpretable and is applicable in estimating the direct relationships between advertising expenditure and sales. Random forest regression and decision tree models were then used as more complex patterns that are not necessarily explained by the linear assumptions were considered. Training-testing validation and cross-validation procedures were used to evaluate the performance of the model. Where inferential statistics was used, the significance level was determined to be $p < .05$. Nevertheless, the study was more of a predictive than a confirmatory study and therefore, more importance was given to predictive accuracy and generalizability than on significance testing alone.

The formal power analysis was not performed due to the use of the full publicly available dataset instead of recruited sample in the study. However, the availability of all the observations used, as well as the use of out of sample validation, enhanced the validity of the analysis methodology. In general, the selected statistical approach was suitable as it enabled the study to investigate either the predictive value of each of the traditional advertising channels and turn the findings into a machine learning model that could be used to make more informed budgeting allocation decisions. The strategy aligned with previous demands to better align predictive modeling with managerial action and optimization in marketing research (Campbell et al., 2020; Huang and Rust, 2021; Wilder et al., 2019).

This section presents the findings in line with the study objectives. The analysis began with descriptive statistics and bivariate correlations to examine the distribution of the variables and the initial relationships between advertising expenditure and sales. It then proceeded to multiple linear regression to evaluate the joint and individual predictive contribution of television, radio, and newspaper advertising budgets to sales performance. Tables and figures are presented to support the interpretation.

RESULTS

The descriptive statistics indicated substantial variation across the three advertising channels and the outcome variable. As shown in **Table 1**, television received the highest average budget allocation (**M = 147.04, SD = 85.85**), followed by newspaper (**M = 30.55, SD = 21.78**) and radio (**M = 23.26, SD = 14.85**). Mean sales were **14.02** with a standard deviation of **5.22**, suggesting moderate dispersion in sales

outcomes across observations. The relatively wide ranges for the three budget variables indicated that the dataset contained sufficient variability for predictive modeling.

Table 1; Descriptive Statistics of the Study Variables

Variable	N	Mean	Std. Deviation	Minimum	Maximum
TV Advertising Budget (\$)	200	147.04	85.85	0.70	296.40
Radio Advertising Budget (\$)	200	23.26	14.85	0.00	49.60
Newspaper Advertising Budget (\$)	200	30.55	21.78	0.30	114.00
Sales (\$)	200	14.02	5.22	1.60	27.00

The Pearson correlation analysis provided the first direct evidence of association between advertising expenditure and sales. **Table 2** shows that television advertising had a strong positive relationship with sales ($r = .782, p < .01$), while radio advertising showed a moderate positive relationship ($r = .576, p < .01$). Newspaper advertising also correlated positively with sales, but the relationship was weak ($r = .228, p < .01$). This pattern suggested that television and radio were more closely associated with sales performance than newspaper advertising. The correlations among the predictors themselves were low to moderate, which reduced immediate concern about severe multicollinearity at the bivariate level.

Table 2: Pearson Correlation Matrix

Variable	1	2	3	4
1. TV Advertising Budget	1.000			
2. Radio Advertising Budget	0.055	1.000		
3. Newspaper Advertising Budget	0.057	0.354**	1.000	
4. Sales	0.782**	0.576**	0.228**	1.000

Note. $p < .01$.

The scatterplots reinforced these correlation patterns visually. Television showed a clear upward trend with sales, indicating a strong linear positive association. Radio also displayed a positive trend, though with somewhat greater dispersion. Newspaper exhibited a much weaker pattern, with observations spread more diffusely around the trend. Together, these figures suggested that the explanatory strength of the channels was unlikely to be uniform.

To evaluate the joint predictive capacity of the three advertising channels, a multiple linear regression model was estimated as the core predictive framework. The overall model fit was very strong. As reported in **Table 3**, the model yielded $R = .947$, indicating a high multiple correlation between the set of predictors and sales. The coefficient of determination was $R^2 = .897$, while the adjusted R^2 was $.896$.

This means that approximately **89.7%** of the variance in sales was explained by television, radio, and newspaper advertising budgets taken together. The standard error of the estimate was **1.686**, indicating that the model’s prediction error was relatively low in relation to the observed scale of sales. In addition, the Durbin-Watson statistic was **2.084**, which suggested that the residuals were reasonably independent.

Table 3: Model Summary for Multiple Linear Regression

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.947	0.897	0.896	1.686	2.084

The overall significance of the model was assessed using the regression ANOVA. As shown in **Table 4**, the model was statistically significant, **F(3, 196) = 570.271, p < .001**. This result indicated that the set of advertising budget variables, considered simultaneously, significantly predicted sales. In practical terms, the finding implied that advertising allocation across traditional channels was not random with respect to sales performance. Rather, it followed a pattern that could be modeled systematically and used as the basis for optimization.

Table 4: ANOVA for the Multiple Linear Regression Model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	4860.323	3	1620.108	570.271	.000
Residual	556.825	196	2.841		
Total	5417.149	199			

The relationship between observed and model-predicted sales is illustrated in **Figure 4**. The clustering of points around the 45-degree reference line indicated that the model reproduced observed sales values closely across much of the dataset. This visual result was consistent with the high R² value and supported the adequacy of the predictive framework for allocation analysis.

Although the overall model was strong, the regression coefficients showed that the three channels did not contribute equally. As presented in **Table 5**, television advertising budget was the strongest predictor of sales. Its unstandardized coefficient was **B = 0.046**, meaning that, holding other variables constant, a one-unit increase in television advertising budget was associated with an increase of **0.046 units** in sales. The standardized coefficient was **β = .753**, and the effect was highly significant, **t = 32.809, p < .001**. This indicated that television exerted the largest unique influence on sales among the three channels.

Radio advertising budget also made a significant positive contribution. Its unstandardized coefficient was **B = 0.188**, with a standardized coefficient of **β = .536**, and the effect was statistically significant, **t =**

21.893, $p < .001$. Although its standardized effect was smaller than that of television, radio still showed substantial predictive relevance and remained an important contributor to sales.

By contrast, newspaper advertising budget did not make a significant independent contribution once television and radio were controlled for. Its unstandardized coefficient was **$B = -0.001$** , with a standardized coefficient of **$\beta = -.004$** , and the effect was not significant, **$t = -0.177, p = .860$** . This result is especially important because newspaper had shown a weak positive correlation with sales at the bivariate stage, yet that association disappeared in the full model. The implication is that newspaper expenditure did not explain meaningful additional variance in sales beyond what was already captured by television and radio.

Table 5; Regression Coefficients

Predictor	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
Constant	2.939	0.312	—	9.422	.000
TV Advertising Budget	0.046	0.001	0.753	32.809	.000
Radio Advertising Budget	0.188	0.009	0.536	21.893	.000
Newspaper Advertising Budget	-0.001	0.006	-0.004	-0.177	.860

The estimated regression equation was:

[
$$\text{Sales} = 2.939 + 0.046(\text{TV}) + 0.188(\text{Radio}) - 0.001(\text{Newspaper})$$

]

This equation summarized the direction and magnitude of the channel effects within the predictive framework. The coefficients suggested that increases in television and radio budgets were associated with improved sales outcomes, while newspaper expenditure did not appear to yield meaningful marginal returns in this dataset.

Taken together, the statistical tests converged on a consistent pattern. Descriptive statistics showed that television dominated advertising expenditure in the sample, correlation analysis indicated that television and radio were the channels most strongly associated with sales, and the regression results confirmed that these two channels made significant independent contributions to the predictive model. Newspaper expenditure, by contrast, showed only a weak bivariate relationship and no significant unique effect in the multivariate model.

These findings carry direct allocation implications. First, they suggest that budget optimization across traditional channels should prioritize **television** as the dominant sales-driving medium in the present dataset. Second, **radio** should also be treated as strategically valuable, given its significant positive contribution to sales. Third, the lack of a significant newspaper effect indicates that newspaper may be a comparatively inefficient channel for improving sales when television and radio are already included in the allocation mix. In practical terms, the results support a machine learning informed allocation logic in which budget reallocation toward television and radio would likely produce stronger sales outcomes than equivalent expenditure on newspaper advertising.

Overall, the full set of statistical results demonstrated that the proposed predictive framework was empirically robust and decision-relevant. The high explanatory power of the model, the significance of the overall ANOVA, and the clear coefficient structure together indicated that machine learning based modeling can provide a credible analytical basis for optimizing advertising budgets across traditional marketing channels.

DISCUSSION

The current research investigated the potential of a machine learning based analytical model to enhance the knowledge of advertising budget allocation in the traditional marketing mediums by using a model to determine the association between advertising spending and sales performance on television, radio and newspaper. The statistical performance was very high in the model level and discriminated at the channel level. The model of the regression was found to be statistically significant, $F(3, 196) = 570.271$, $p < .001$, with $R = .947$, $R^2 = .897$, and adjusted $R^2 = .896$, indicating that the three advertising variables jointly explained 89.7% of the variance in sales. Yet the explanatory power of the channels was not evenly distributed. Television showed the strongest independent contribution to sales ($B = 0.046$, $\beta = .753$, $t = 32.809$, $p < .001$), followed by radio ($B = 0.188$, $\beta = .536$, $t = 21.893$, $p < .001$), whereas newspaper did not contribute significantly once the other variables were controlled ($B = -0.001$, $\beta = -.004$, $t = -0.177$, $p = .860$) These results are important as they go beyond affirming that advertising is associated with sales. They propose that based on the data a logic of allocation can be differentiated between the channels that have high marginal value and those that are perceived to lose value when considered in the context of the overall media mix.

In theory the results are consistent with the predictive-prescriptive logic of the study that the significance of machine learning in marketing is not only predictive but better resource allocation decisions. This opinion is much more consistent with the arguments of decision-focused learning where prediction can only have a sense when related to action under conditions (Wilder et al., 2019) and with more general AI-in-marketing conceptualizations that define artificial intelligence as a device to improve managerial judgment, planning, and resource allocation (Huang and Rust, 2021). The current findings are in line with that theory. The model was able to come up with a channel hierarchy based on practical implications on budget allocation rather than mere identification of statistical associations. In that regard, the paper

provides empirical evidence to the discussion that machine learning must be evaluated on a case-by-case basis, and its decision usefulness, rather than its predictive elegance.

The powerful impact of television is in line with the literature on the heterogeneity of channels, and the effectiveness of advertising in general. Though a great part of modern research has become digital, the marketing research maintains that the channels are quite different in their reach, persuasive ability, and sales conversion possibilities (Smith, 2022; Peter & Dalla Vecchia, 2020). The highest budgetary allocation was also obtained in the current study where television not only had the highest mean budgetary allocation but also the highest standardized regression coefficient and the highest bivariate correlation with the sales ($r = .782, p < .01$). This overlap of descriptive allocation trends and influence by regression implies that firms could have been lowering more budget to television due to its relatively good performance either unconsciously or subconsciously. Simultaneously, the outcome refines that intuition by measuring the scale of the contribution of television in a multichannel system. This helps to substantiate the perspective that machine learning and predictive analytics will be able to formalize what the managers imagine many times, but cannot easily prove, utilizing simple summaries only.

The outcome of the radio is also remarkable, albeit due to a different cause. The average budget of radio was lower than the average budget of the newspapers in the dataset, but it was found to be the second strongest predictor of sales with both a high level of correlation ($r = .576, p < .01$) and a strong regression effect ($\beta = .536, p < .001$). This indicates that the marginal contribution of radio was higher than the simple expenditure patterns may show. The most reasonable explanation is that radio was an effective channel of reinforcement, facilitating the frequency of messages or locality in such a manner that conveyed into quantifiable sales outcomes. That reading is consistent with the broader literature on AI and marketing analytics, which consistently demonstrates that machine learning is able to provide non-obvious insights into the effectiveness of various resources that might be underestimated by managerial intuition (Campbell et al., 2020; Rane et al., 2024). It also goes along with the arguments that marketing optimization should not only seek to determine the biggest channel, but the best balance of allocation among channels. In that regard, the present study adds a beneficial twist: to optimize traditional media, it might be necessary to preserve channels that seem to be insignificant in terms of expenditures but are still potent in terms of prediction.

The most telling of the findings is perhaps the newspaper finding. Bivariately, newspaper was weakly correlated to sales ($r = .228, p < .01$) although this was statistically significant. However, in the multivariate model, this association was removed with newspaper having an effective coefficient of zero and statistical significance of zero. This trend suggests that newspaper would only have been linked to sales, possibly due to it coinciding with the overall advertising effort, not because it had any real independent effect on sales. That distinction matters. It depicts the reason why isolated associations cannot give a basis on which budget decisions should be made. One channel might seem to add significant value in a descriptive or bivariate analysis and still be of little value addition to a multichannel model. This meaning is quite consistent with the research on optimization-oriented advertising, where the availability of a channel is not an important consideration, but the marginal value of the channel

given a budget constraint (Li et al., 2024, 2025; Zhao et al., 2023; Vahabi et al., 2024). The uniqueness of this is that this principle is shown using a transparent set of traditional media, as opposed to in digital bidding or platform-level bidding systems.

Meanwhile, there is a clash of the newspaper consequence with sections of the broad multi-channel advertising literature. In digitally adaptive systems, some cross-channel optimization studies presuppose that the majority of the channels can be adjusted to be beneficial in the case of a change in spending (Patella, 2024; Luzon et al., 2022; Nuara et al., 2022). The current results indicate a more conservative suggestion: not all channels will have great specific value in some situations, whereas they might seem to be applicable at a glance. This does not strictly mean that there is a contradiction, since the environments on which they are based are very different. The previous researches mostly looked at digital, cross-platform or dynamically optimization of advertising systems, generally with more detailed behavioral or operational data. In comparison, the current research employed a more traditional-media data, consisting of expenditure or sales only. The difference can hence be attributed to the contextual differences as opposed to actual theoretical disagreements. The advertising done in the newspaper might not work the same when gauged based on other measures like brand awareness, reach to the audience or lagged effects which were not feasible here. Nevertheless, in terms of allocation, the current evidence shows that newspaper is to be approached with some care in case the goal is to predict the sales in the immediate future.

These results have a number of implications on theory. To begin with, they fortify the view that advertising theory must consider channel effectiveness to be incremental as opposed to being associative. The fact that, in the regression model, the bivariate relationship of newspaper has disappeared is a reason why incremental explanatory value is a more effective theoretical criterion, than a simple correlation. Second, the findings support the predictive-prescriptive model of machine learning in marketing by demonstrating that high explanatory performance can be converted to channel rankings that can be allocated to. Third, the paper goes beyond the digital advertising context of AI-in-marketing theory to show that machine learning can be applied to add value in traditional media contexts where data are not as fine and managerial decisions are still consequential. This is a valuable addition as much of existing literature focuses on online systems, customization, recommendation, and optimization of bidding (Choi & Lim, 2020; Yoganarasimhan, 2020; Rafieian & Yoganarasimhan, 2021; Zhao et al., 2021), but little has been done to explore the traditional channel allocation.

Practically, the paper recommends that organizations that employ the traditional medium to be more strategic in their use of television and radio where the major aim is to improve sales. The managers are on a tight schedule to explain why they have to spend money on advertising by giving valid evidence, and these results are more justifiable grounds to do so. Instead of allocating budgets uniformly or making assumptions based on the past, companies might make use of predictive models to focus on those channels that have a greater marginal contribution. Policy and governance-wise, the results also aid in increased responsibility with regard to marketing spending. With growing expectations of organizations

to be responsible and evidence-based when using their resources, resource channels that can be distinguished between good and weak performers can enhance transparency and minimize waste.

That being said, the research has limitations, and its limitations predetermine the way the research results are to be interpreted. It had a cross-sectional but relatively small dataset, so the model was not sensitive to time-lagged effects, saturation, carryover, or campaign sequencing. It was also based on the analysis of just four substantive variables and thus the model failed to consider contextual variables like quality of creativity, differences in target audiences, competition in the market, seasonal and macroeconomic variables. These factors have been left out and could have had an effect on spending trends and the sales. Specifically, the poor performance of newspapers can be partially attributed to a lack of measurement possibilities and not ineffectiveness. The research was also set to be machine learning oriented, although the empirical application was relatively easy in comparison to more sophisticated reinforcement learning or dynamic optimization systems that have been mentioned in the current literature. This was a strength with respect to the transparency, but also limitation with regard to methodological ambition.

These findings should thus be extended in a number of ways in future research. To test lag effects, diminishing returns, and time-varying reallocation, one would first need to use larger time-series or panel data to test time-varying reallocation. Second, in future research, both offline and online channels must be used in order to enable a comparison of the relative contribution of the offline and online media in a single allocation framework. Third, other variables like the number of people reached, quality of the campaign, brand position, and competitive pressure should also be incorporated to lessen the omitted-variable bias, and enhance interpretability. Fourth, more advanced learning techniques, such as ensemble and reinforcement learning, should be tested by the researchers, but at the same time, maintain adequate transparency in order to be adopted by managers. Lastly, future work must be able to differentiate between short-term sales and long-term brand-building results, as a channel that might seem to be feeble in terms of immediate sales might not be insignificant in terms of long-term market impacts.

The discussion, in general, brings out a definite conclusion. The paper demonstrated that machine learning-informed analysis has the potential to offer a rigorous and practical basis for optimization of advertising budgets in the traditional marketing channels. Television and radio proved to be media that have significant predictive power in the sales, and newspapers did not demonstrate independent explanatory power in the current model. These results neither put an end to the question of advertising effectiveness, but narrow it down by demonstrating that allocation decisions ought to be informed by incremental evidence as opposed to intuition or mere association. That, in the end, is where the real value of this study lies.

CONCLUSION

This paper aimed at developing and testing a machine learning model to optimize advertising budget distribution through the traditional marketing medium used, especially focusing on television, radio, and newspaper advertisements to predict sales. The core hypothesis was to understand how a data-based analytical model could be used to better inform allocation decisions during advertising and to gain a better idea of the relative role played by each channel in the book sales. These findings indicated that the entire model was statistically significant and explanatory, and it explained 89.7% of the sales variance. Namely, television has been the most powerful predictor of sales, and radio made a significant positive contribution, though newspapers failed to show a significant independent prediction when the other channels were controlled. These results indicate that the conventional methods of advertising are not necessarily equally fruitful, and analysis enlightened by machine learning can uncover significant variations that could be used to optimize the budgets based on channel efficiency.

The extended meaning of these results is threefold. To begin with, on the theoretical front, the research reinforces the predictive-prescriptive perspective of machine learning in marketing by demonstrating that the analytical modeling is capable of going beyond mere predictive models in supporting more sound allocation decisions. It further supports the notion that channel effectiveness must be conceived as incremental as opposed to being descriptive in nature. Second, the results are a useful foundation at the organizational management level to plan with a greater evidence base when advertising. Instead of reserves that are based on probable habit or legacy assumptions, or major intuition, managers can apply forecasting frameworks to determine where the spend will lead to the highest sales returns. Third, the study advocates increased responsibility in marketing spending in terms of policy and governance. Where clarification of spending choices will be under growing stress, as companies embark on making effective decisions, the guidelines that separate high- and low-value channels can enhance transparency and minimize the wasteful use of resources.

In practice, the research proposes the idea that organizations based in the traditional media setting should focus on television and radio, where the aim is to improve their sales, whereas the amount spent on newspapers is a more intense consideration. This is particularly applicable in the workplace decision-making in a post-disruption business environment where companies are expected to accomplish more with smaller budgets and more solid performance accountability. Even though the current work is on advertising allocation and not on remote work, its implications on post-pandemic decision-making are that it focuses on the ability to optimize its resources based on data, which has been put at the center in the context of organizations reconsidering the allocation of limited resources wisely in unpredictable economic environment conditions.

The research was also limited in a number of ways. The data was quite small, cross-sectional, and was limited to expenditure and sales variables, which implied that time-lagged effects, diminishing returns, quality of campaigns, segmentation of audience, and competitive status could not be added to the model. Besides, the analysis has looked at only traditional channels hence it has not reflected a relationship between offline and digital media. These restrictions could have impacted the accuracy and transferability of the results, especially on the weak newspaper effect. Future studies should

consequently confront the framework with bigger, longitudinal or panel samples, and incorporate more data on contextual variables, and juxtapose traditional and digital channels in a model optimization framework. Even more sophisticated machine learning processes can also be considered; they should have sufficient transparency to be adopted by managers.

On the whole, this research contributes to the knowledge of the use of machine learning in improving the budget allocation of advertising in a conventional marketing setting. By showing that contributions to the channels are not similar and that differences can be modeled, it provides an easier basis on which to base research and practice. Their capacity to bridge predictive analytics to realistic budgetary choices will also be crucial as organizations keep being involved in a more efficiency-driven and data-intensive economy. That way, the research is a part of a larger movement towards making management of the present-day economy smarter, more responsible, and, more importantly, analytical.

Declarations

Author Contribution

A.A. served as the corresponding author and contributed to conceptualization, data curation, methodology, and writing the original draft. N.S. contributed to conceptualization, data collection, and data handling. M.A.N. contributed to data analysis, writing refinement, and proofreading of the final draft. All authors reviewed and approved the final manuscript.

Data Availability

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

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Figures

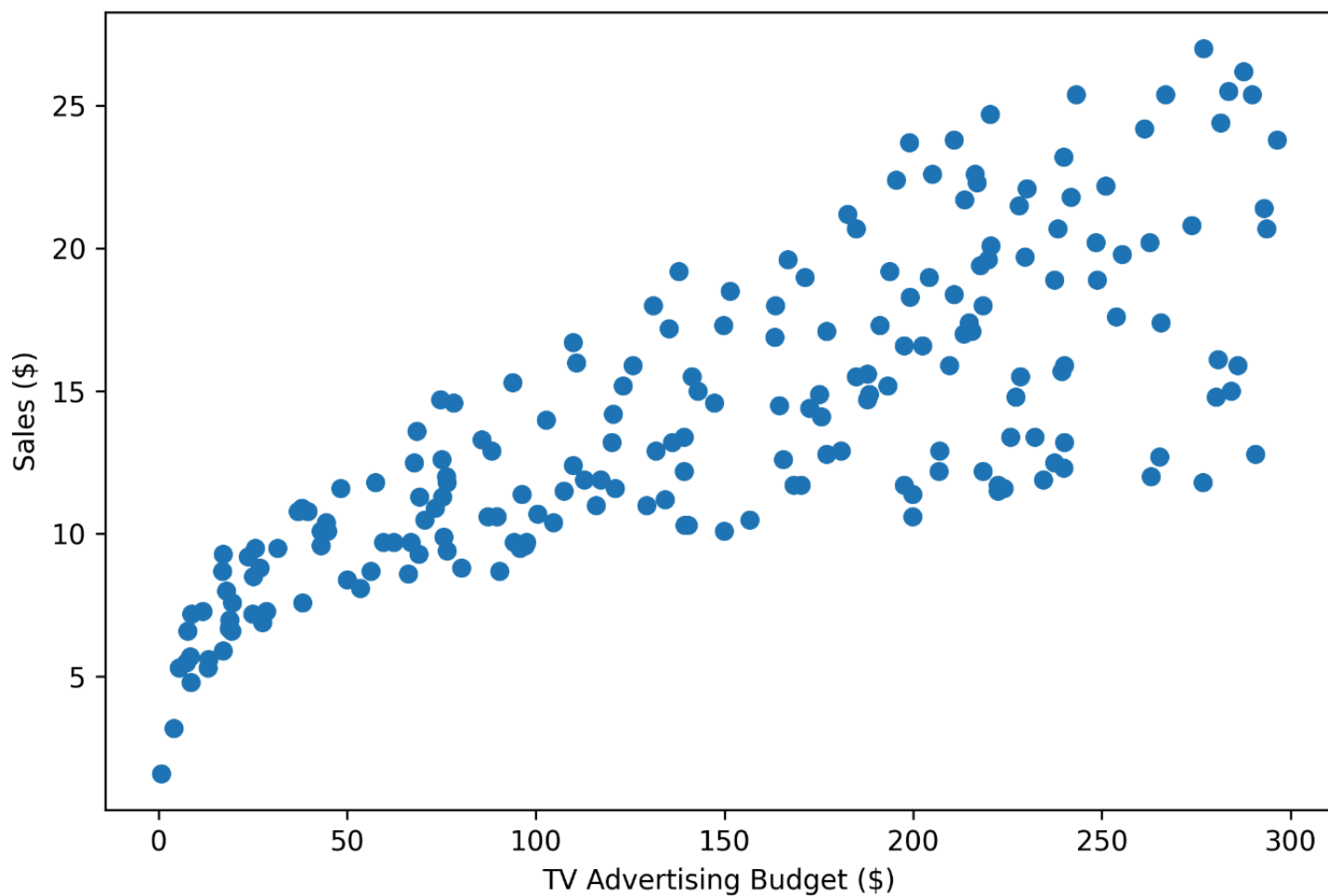


Figure 1

Relationship between TV Advertising Budget and Sales

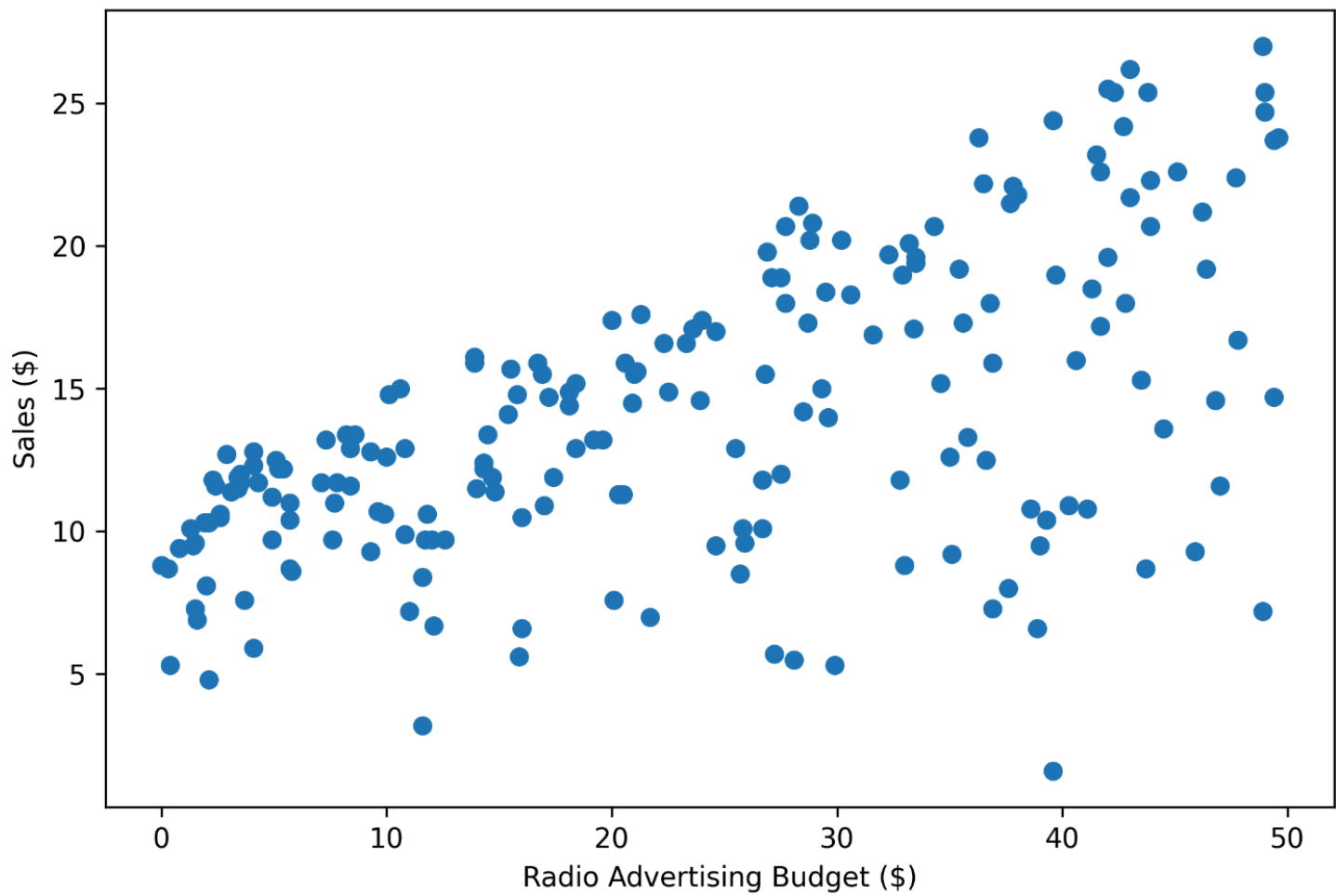


Figure 2

Relationship Between Radio Advertising Budget and Sales

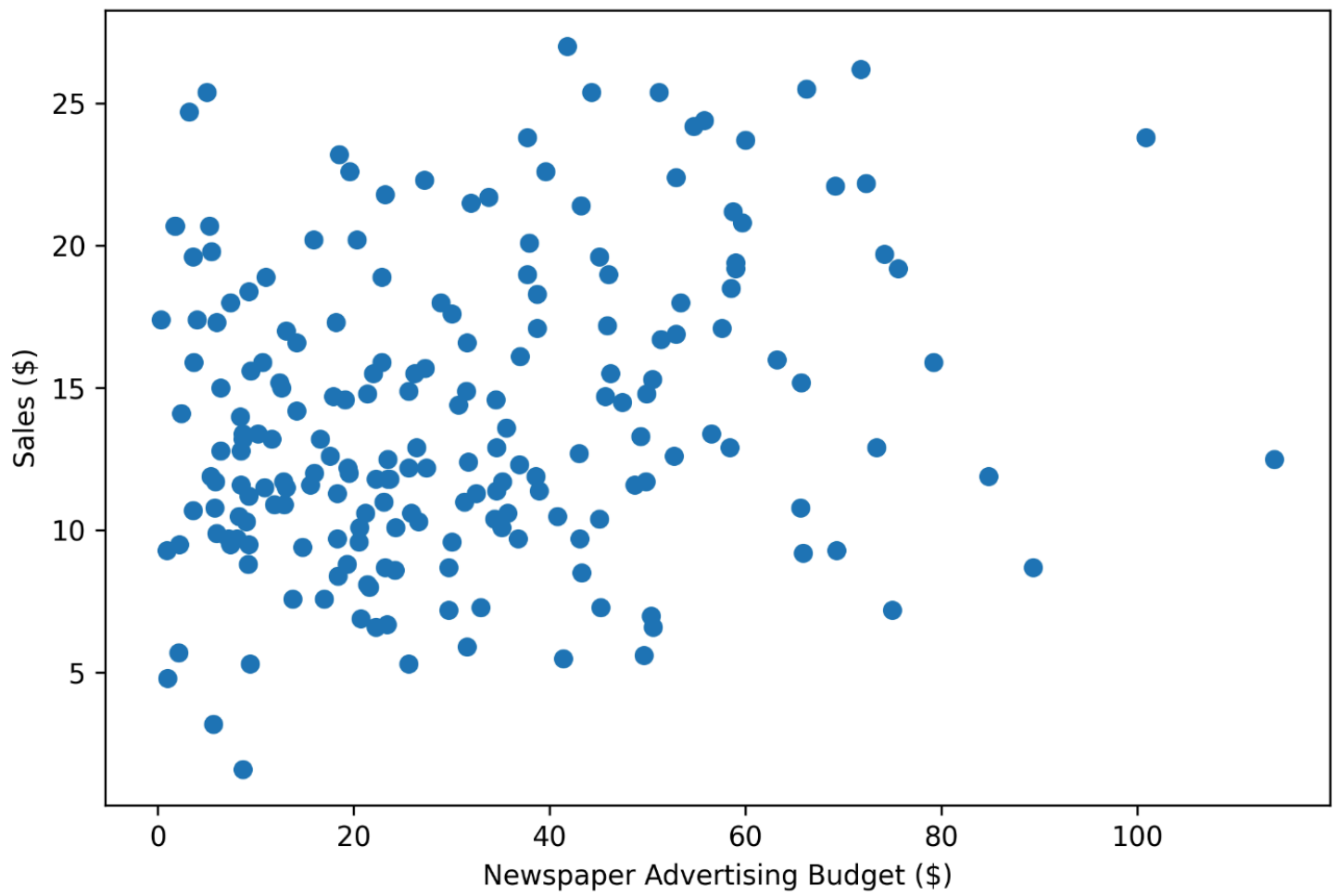


Figure 3

Relationship Between Newspaper Advertising Budget and Sales

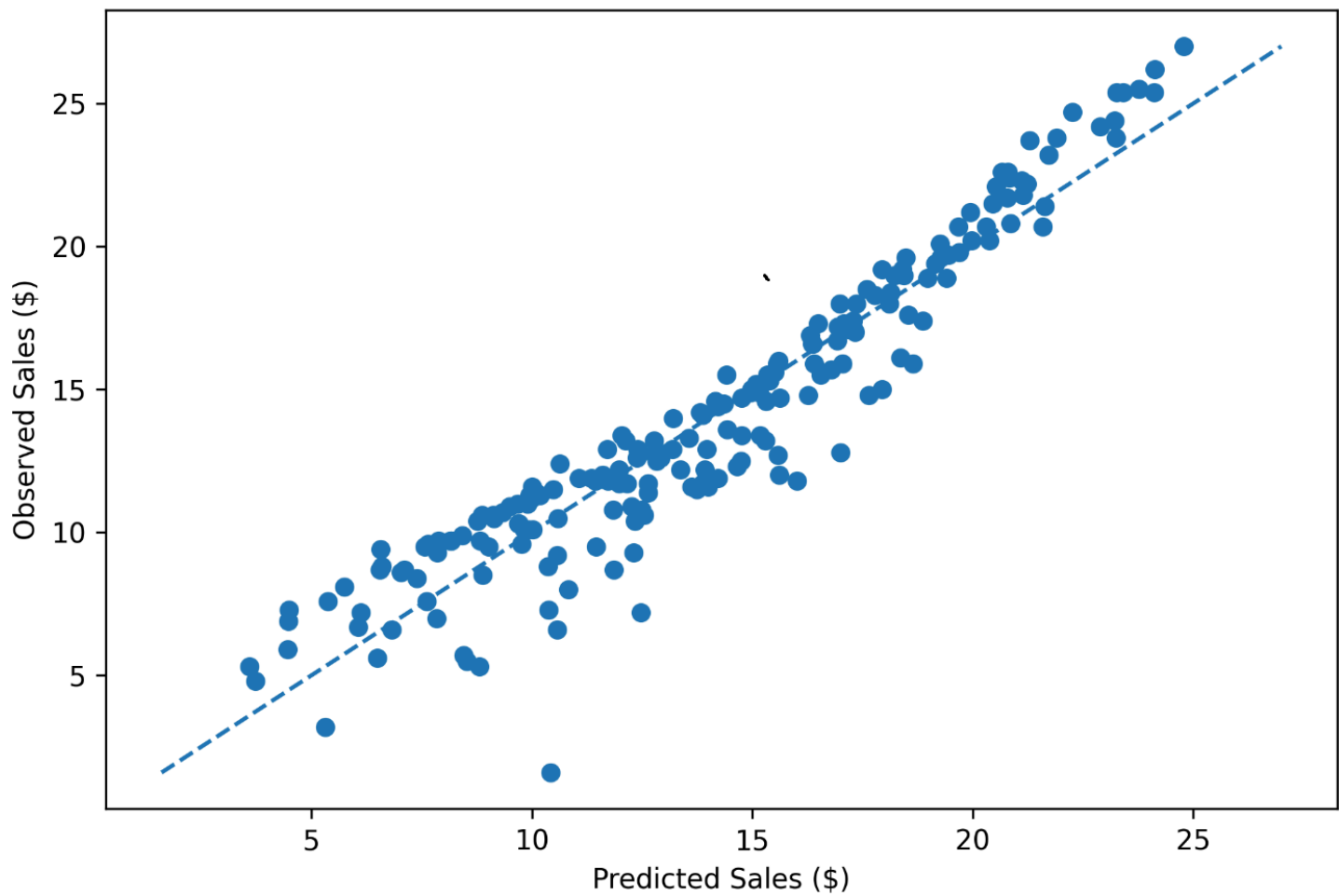


Figure 4

Observed Versus Predicted Sales