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Original Article

Optimizing Marketing Operations with Artificial Intelligence and Information Technologies

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Abstract - *Digital marketing is more volatile than traditional marketing, making deterministic marketing planning to be inadequate for allocating resources across technology-mediated channels. The existing AI-powered marketing research has largely been focused on the accuracy of the predictions, with fewer studies focusing on the operational implications of learning that are constrained and risk-aware. This research proposes a stochastic optimization model for marketing operations, considering the risk level of budget allocation, information technology constraints and estimating the revenue using Artificial Intelligence. The following model is proposed in which marketing operations are regarded as a stochastic resource allocation problem, where expected revenue, revenue volatility and saturation effects, as well as budget constraints, are taken into account simultaneously. Corporate-level marketing and financial metrics for Amazon, Walmart, Procter & Gamble, Coca-Cola and Nike are used for empirical testing for the period 2019-2023. The nonlinear revenue response functions are estimated using gradient boosting regression, and the stochastic optimization problem is solved using sample average approximation with 1,000 Monte Carlo scenarios. The findings indicate that the proposed framework can improve ROIs for marketing from 1.00 to 1.23, decrease the volatility of revenue by 26.0%, reduce the 10% VaR-based downside revenue loss from -18.2% to -10.4and enhance scenario robustness by 55.8%. The improvement is validated through statistical testing, sensitivity analysis and ablation analysis. The study makes a contribution to engineering-oriented marketing research by offering a clear, repeatable model for decision support in the context of uncertainty and uncertainty of marketing operations.*

Keywords - *Artificial intelligence, Stochastic optimization, Marketing operations, Information technologies, Risk-Aware decision support, Digital marketing.*

1. Introduction

The digital platforms, the algorithm-based customer interactions and the real-time marketing technologies have changed the way marketing management is being conducted today. Marketing is not just about planning a campaign or monitoring it following its execution. They are more and more concentrating on continuous resource allocation, relying on an integration of various digital channels and channels of varying characteristics and capabilities, which are subject to unpredictable demand, variable customer response, algorithm changes on platforms, and budget constraints. In this case, deterministic planning models and heuristic budgeting rules might not capture the nonlinear and stochastic nature of the marketing results. AI has enhanced companies' capacity to predict customer behavior, predict campaign effectiveness and segment the market. However, if the forecasts are correct, this does not imply that there are better operations decisions that can be made. There is a plethora of marketing models that are still purely predictive in nature, but fail to provide a framework for turning an estimate into a limited, risk-informed approach to resource allocation. Furthermore, the volatility of revenue and downside risk in digital markets may be underestimated within the traditional optimization models and their stability of response functions and average expected returns. This leaves a gap in methodology between predictive analytics and stochastic decision theory, and between real marketing operations [1]. The issue that this study aims to tackle is the lack of an integrated framework that is able to convert marketing responses estimated via AI into operationally viable and risk-adjusted allocation decisions. The approach suggested is derived from the stochastic resource allocation problem explored in the literature with a combination of the expected value of the revenue, the volatility, the nonlinear saturation and constraints related to information technology. This is especially true of digital-oriented companies, where the outcomes of marketing practices are dependent on the degree of investment, the data infrastructure, the reactivity of the platform and the unpredictability of customer behaviour.

1.1. Research Gap and Contribution

There are three gaps in the literature: Research on AI-based marketing is mainly based on forecasting, classification, personalisation or accuracy of recommendations without introducing a formal decision rule in uncertainty for the allocation of marketing resources. Second, in deterministic marketing optimization models, the average expected performance is usually maximized, thus neglecting the volatility of the revenues, downside losses and nonlinear response saturation. Thirdly, the role of information technology infrastructure is taken into account, although not often coupled in the mathematical formulation of marketing optimisation. The novelty of this research lies in the following three elements combined in one Decision Support System: Artificial Intelligence-based non-linear revenue response estimation, the stochastic optimization of the allocation of marketing funds and putting the operational and information technology constraints explicitly into the model. Whereas prediction-only models, the proposed framework is based on estimated revenue distributions and transform these into prescriptive allocation decisions. Unlike deterministic models of budget allocation, it offers less volatility and risk on the revenue side. Unlike black-box recommendation systems, it assures mathematical transparency in terms of explicit objective functions and constraints, and scenario-based validation. The study has contributed the following elements:

- Using the constraints of budget and technology, a stochastic optimization model of marketing operations is developed;
- A new estimation layer is added based on the AI model to estimate the nonlinear revenue response and the conditional volatility, respectively;
- For the corporate level data for 2019-2023, an empirical protocol is provided that is reproducible;
- The proposed model is compared with deterministic allocation, LP-based allocation and AI-prediction-only allocation;

In addition, statistical significance testing, sensitivity analysis and ablation analysis are added for validation of the robustness of the results.

1.2. Motivation and Problem Statement

Digital marketing operations increasingly function as high-dimensional, technology-mediated systems. Budget allocation decisions are affected by real-time data flows, heterogeneous customer responses, platform algorithm changes, competitive pressure, and external market shocks. These conditions make traditional deterministic planning insufficient because fixed response assumptions cannot adequately represent nonlinear and uncertain market behavior [2, 3]. The principal difficulty in the study is the lack of a single method of approach that integrates AI-based revenue estimation into operationally oriented risk management. While existing predictive models can be used to predict revenue or conversion probability, they fail to automatically allocate marketing resources to maximize profits within budget, volatility and technological constraints. At the same time, deterministic optimization models are based on the maximization of average expected return, without considering the risks of the downside and the saturation of the levels of response. To address this, the proposed framework is a stochastic resource allocation problem, in which the marketing operations are viewed as a stochastic resource allocation problem. It is a combination of nonlinear revenue response estimation with the aid of AI and a stochastic optimization based on a sample. This was to enable the model to take into account 'expected return', but also 'revenue volatility', ‘downside exposure' and ‘allocation stability'. The study provides a valuable and readily applicable decision-support model in digital marketing situations.

2.1. Related Work and Theoretical Background

As markets become increasingly digital and with more data available about customers and operations, the importance of cost reduction in marketing is also an area that needs attention academically, as well as on the operational side. Earlier marketing research placed considerable emphasis on performance measurement and marketing productivity [4], whereas more recent studies have introduced adaptive allocation mechanisms for digital campaigns [3]. However, the explicit treatment of uncertainty and dynamic operational constraints remains uneven across these research streams.. Although these initial studies contributed toward the establishment of analytical marketing research, they downplayed the factor of uncertainty and dynamism in operational decision-making. These bases (systemizing and selecting problems from these previous “old” theories) were expanded in later work by also importing quantitative methods that had been developed in operations research as well as econometrics. Linear programming and deterministic optimization techniques have been widely used in the literature for marketing mix decisions, channel allocation problems [5]. Although it's been performed under the aegis of balance models, having nothing to do with them, almost all research using these equations seems to treat them as if they are not truly even time-dependent, and has sought out fixed points. Other recent works start to acknowledge that the environment (promotion) in which marketing actions are executed is increasingly uncertain, due to challenging demand dynamics, changes in the platform algorithm or competitive behavior [6]. This has led to a trend towards more probabilistic and data-driven approaches, though the way in which uncertainty is incorporated into operational optimization differs between studies.

2.1.1. Artificial Intelligence and Information Technologies in Marketing Research

The rapid development of artificial intelligence and the intensification of information technologies have brought significant changes to marketing analytics and decision support systems. Customer segmentation, churn prediction, demand prediction and personalized recommendation-based ML algorithms are extensively used by companies providing Internet services [7]. These analytical methods are particularly valuable in data-rich marketing environments because they can represent complex, nonlinear, and high-dimensional relationships that are difficult to capture through conventional specifications [8].

Despite such advances, a significant portion of the marketing literature on AI still has an emphasis on prediction rather than optimization. “Black-box” predictive models are typically assessed for accuracy, without consideration of how they translate to operational decision-making. Therefore, the connection from AI-powered insights to resource allocation tactics is likely implicit and heuristic. Information technology, including cloud computing platforms and integrated marketing information systems, has also been instrumental in the provision of real-time data processing and cross-channel coordination [9]. These environments enable scalable analytics, but unfortunately, they do not solve the problem of decision-making under uncertainty. Many of the mentioned articles also concluded that operation visibility can be increased with the use of technology and that this is not enough to improve performance; structured decision models need to be implemented [10].

AI and optimization. AI is nouvelle interface for the integration of AI and optimization. Predictive-to-prescriptive approaches combine data-driven estimation with mathematical optimization so that predicted market responses can be translated into explicit operational decisions [11]. The methods, however, are prone to treating uncertainty as estimation error (i.e. “regret”) and are not necessarily very good at handling environment design for optimal decision making. This state of non-control spreads risk and performance variance to its extremes. From the literature search, three significant shortcomings are observed in current AI-driven marketing research. The literature search reveals three key drawbacks in the current use of AI in marketing research. Firstly, the classical OE problem criteria does not take into account uncertainty in an explicit way. Second, there is a lack of interpretability and analytical transparency with AI models, because models are often black boxes. Second, models are a black box, which means that there is less interpretability and analytical transparency. Thirdly, IT-system-related and organizational aspects are often simplified or neglected. These limitations have resulted in limited application performance of AISsMD in complex environments.

2.1.2. Stochastic Optimization in Marketing and Decision Sciences

Stochastic Optimization Stochastic optimization is a general area that requires decisions to be made in an uncertain world, and this domain has a rich tradition in the field of operations research, decision scion empirical power demand pattern for winter months [12]. There were marketing applications of some stochastic models on inventory management and pricing policies. The studies underpinned by these results validate the added value of uncertainty analysis and demonstrate that appropriate consideration of the uncertainty potential could effectively strengthen decision models for a longer period.

However, I still believe the adoption of stochastic optimization in marketing operations remains under cut. In the literature, there were few research works aimed at a single aspect of marketing, such as stochastic pricing strategies [13] and promotion timing models, but not to synthesize all important factors that need to be captured in a model into one integrated model with all layers of operations. Moreover, the stochastic component of those models is often ad formalized by analytic expressions and stationarity properties. Recent work highlights the potential of data-driven stochastic optimization where probability distributions are learned from empirical historical samples [14]. Furthermore, this strategy is consistent with those employed by machine learning algorithms, where complex conditional distributions can be approximated by using artificial intelligence methods. However, the utilization of AI-based estimation in the stochastic optimization context of marketing operations is relatively less investigated. Another important issue concerns computational scalability. As the number of decision variables, constraints, and uncertainty scenarios increases, stochastic optimization problems can become computationally demanding, particularly in large-scale and multistage settings [15]. Sample Average Approximation mitigates this difficulty by replacing the original expectation with an empirical mean calculated from a finite Monte Carlo sample, thereby producing a deterministic approximation that can be solved using established numerical optimization algorithms [20]. In marketing, uncertainty-aware resource-allocation models have been implemented through robust optimization for online campaign and marketing-budget decisions [7, 13]. These studies provide an operational foundation for the present research, which extends this line of analysis by integrating AI-based nonlinear response estimation with scenario-based stochastic optimization and explicit risk adjustment.

In more general terms, our review suggests a well-defined methodological space at the crossroads of stochastic optimization, artificial intelligence and marketing operations.

However, most existing works have focused only on prediction without minimization and optimization of decisions in a formal decision-theoretic framework or merely employ optimization methods without considering uncertainty modeling and data-driven estimation. Such a gap motivates the present study -the growing need for a systematic way to combine stochastic optimization theory, AI-based estimation and IT constraints in an organized and operationally meaningful framework.

2.2. Causal Inference in AI-Based Marketing Optimization

In fact, recent advances in marketing analytics have increasingly come to focus on the value of causal inference, as predictive correlations are not necessarily causal. This is an important factor in digital marketing as, in the digital space, exposure of a campaign, customer targeting, platform algorithms, and customer behavior all play a role in determining this. A model can be used to precisely estimate revenue or conversion rate, without even knowing if the marketing intervention is responsible for the observed revenue or conversion rate. This has led to some important methodological developments, such as causal machine learning, uplift modeling, heterogeneous treatment effect estimation, and causal marketing mix modeling.

Causal inference increases the strength of marketing optimizations by isolating from historical relationships the effects of marketing. This is important in budget allocation, and helps to avoid overspending on channels that may seem successful, but are only seeing existing buyers who are likely to purchase anyway. Causal models can also be used to simulate outcomes of counterfactuals - what might have happened if the budget had been allocated differently. But causal inference is not enough to address the operational optimization problem.

It can measure the treatment effects or response functions; the additional decision models needed for allocating resources under budget, risk and technological constraints, however, are needed. Thus, causal inference is crucial for understanding the marketing effects, and stochastic optimization is needed to translate the marketing effects into operational decisions. In this methodological zone is the present study. It doesn't consider the estimation of AI to be a final product. Rather, an estimated nonlinear revenue response and volatility parameters are included in a stochastic optimization model. This enables the shift from interpretative and predictive to prescriptive marketing decision support.

2.3. Reinforcement Learning and Dynamic Budget Allocation

The sequential nature of decision-making has new meaning and is more relevant in the context of marketing budget allocation, with the new release of market information sequentially, and the new reinforcement learning and contextual bandit approaches joining them. At the channel level, digital advertising can use reinforcement learning to assist with the following activities: bidding, pacing, audience targeting, and reallocating the budget.

The important advantage of the reinforcement learning approach is that it deals with a trade-off between exploration and exploitation. This is especially beneficial in situations where there are dynamic elements within the platform, such as customer responses or changing conditions. While these are the advantages, there are some disadvantages of reinforcement learning models for use in managerial and engineering applications. The first is that they usually require a good deal of granular-level interaction data, and sometimes this won't be accessible in corporate studies. Second, the learning policies of reinforcement learning are hard to interpret if a deep learning architecture is used. Third, in many uses of reinforcement learning, downside risk and/or revenue volatility and/or operational stability may not be explicitly described, but these are optimized for. For companies that require marketing decisions that can be audited, interpretability and risk transparency are important. We argue that what we present in this paper is actually a stochastic optimisation scheme, and not reinforcement learning, as we are more explicit in the mathematical structure, are more explicit in the representation of uncertainty in scenarios, and give guidelines for decision making based on risk. The proposed framework is not intended to be a replacement for reinforcement learning, but rather it can be used in addition to it. For real-time adaptive control, reinforcement learning is appropriate, while for transparent planning, budget governance and risk-sensitive allocation, stochastic optimization is appropriate.

The literature surveyed shows that each of the four marketing analytics methods – causal inference, reinforcement learning, and stochastic optimization – can address a part of the marketing decision problem. When uncertainty is present, AI models perform well in predicting, causal inference performs well in identifying incremental effects, sequential adaptation performs well with reinforcement learning, and resource allocation performs well with stochastic optimization. Usually, these streams are developed as isolated streams, however. The current approaches, therefore, target predicting without optimizing, optimizing without estimating uncertainty empirically, or adaptively learning without sufficiently clear processes to be applied to management. To fill this void, the proposed framework includes a combination of AI-driven non-linear revenue estimation, stochastic optimization, and explicit risk adjustment. This integration is significant as marketing is not only a problem of prediction, but it is also a problem of constraints. The study further contributes to the engineering and technology-oriented marketing literature as it provides a replicable model of the data preprocessing, AI estimation, scenario building, optimization, statistical testing and managerial interpretation of the model.

3. Materials and Methods

The methodological design of the study follows an engineering-oriented decision-support logic. Marketing operations are modeled as a stochastic optimization problem because digital advertising systems are exposed to demand volatility, nonlinear customer response, platform instability, and budget restrictions. The proposed framework does not treat uncertainty as external noise. Instead, uncertainty is included as an endogenous component of the allocation problem.

The model consists of four connected stages. First, marketing resource allocation is formalized through decision variables, budget constraints, cost functions, and stochastic shocks. Second, AI-based regression models are used to estimate nonlinear revenue response and conditional volatility. Third, Monte Carlo scenarios are generated to represent alternative market states. Fourth, sample average approximation is applied to identify the allocation strategy that maximizes risk-adjusted marketing performance [15, 20]. Rather than the descriptive nature of traditional marketing analytics, which measures what happened, with our approach, we want to look forward and make use of data in a probabilistic market that allows for optimization of decisions. It is the treatment of uncertainty as an endogenous characteristic, rather than an exogenously given noise, of the marketing system.

Everything else is about to be a computational approximation; formal decision-making as well requires the coordination of formal optimization theory and analytical reasoning. The theoretical model comprises four intertwined elements. The marketing operations are first formulated in an abstract stochastic resource allocation framework and with explicit assumptions on the decision variables, costs and uncertainties.

Also, using data-based approximations for the conditional expectations and variances, the stochastic revenue function is to be estimated. iii) Sampling-based numerical approaches to solve the stochastic optimization problem are employed to maintain computational feasibility. Finally, the method is illustrated when applied to a dataset of real data collected from multinational corporations (MNCs), in order for us to have a quantitative assessment of performance improvements.

3.1. Data Collection, Preprocessing, and Feature Selection

The empirical aspect of this study is based on the corporate-level data of 5 multinational firms — Amazon, Walmart, Procter & Gamble, Coca-Cola, and Nike. The selection of these companies was based on their being active in markets with a high use of digital, reporting financial data for marketing and providing continuous corporate reporting for the years 2019-2023. Data includes annual marketing spend, % of marketing spend on digital, total revenue, revenue growth, estimated customer acquisition cost, return on marketing investment and lagged revenue indicators. Data was gathered from the annual reports, investor presentations and the corporate disclosures that were available. All monetary amounts have been deflated to present values in 2023 USD. Consistency of observations was checked between reporting periods. Any company that did not report for the chosen period was not included, nor interpolated. This rule was used to ensure the data is accurate and not smoothed.

There were 4 stages in data pre-processing. The first step was to compare all the monetary indicators to a common currency. Secondly, percentages were converted into decimals. Third, lagged variables were created to reflect the lagged effects of the marketing variables. Fourth, normalization of the input variables was done prior to model estimation to avoid scale domination in the machine learning training. Feature selection was done on a theoretical basis, correlation screening and variance inflation criteria. The final features set consisted of marketing expenditure, digital marketing share, lagged revenue growth, firm identifier, time-period indicator and historical ROI. To facilitate the reproducibility of this empirical protocol, a fixed random seed was used for the empirical simulation, 1,000 scenarios were used for each planning period, the same budget constraints were applied for each of the different allocation models, and five-fold cross-validation was applied in evaluating the performance of the AI models. All the models (deterministic, AI-prediction only, linear programming and stochastic optimization models) were based on the same data and the same metrics for evaluation.

Table 1. Dataset structure and variable description

Variable	Symbol	Measurement	Source	Role in Model
Marketing expenditure	MEXP	USD billion, constant 2023 prices	Annual reports and investor disclosures	Main decision-related input
Digital marketing share	DSH	% of total marketing expenditure	Corporate disclosures and public estimates	IT/digital intensity proxy
Total revenue	REV	USD billion, constant 2023 prices	Annual reports	Dependent performance variable
Revenue growth	RG	Annual percentage growth	Annual reports	Performance dynamics indicator
Lagged revenue growth	RGt-1	Previous-year revenue growth	Calculated from revenue data	Delayed response control

Customer acquisition cost	CAC	Estimated cost per acquired customer	Public marketing estimates	Efficiency indicator
Marketing ROI	MROI	Revenue gain/marketing expenditure	Calculated indicator	Optimization performance metric
Firm identifier	FIRM	Categorical variable	Constructed	Controls for firm heterogeneity
Year indicator	YEAR	2019-2023	Constructed	Controls time-period effects

Table 1 spells out the empirical structure of the data and the empirical roles of each of the variables in the proposed framework. The model does not have any personal information. Instead, it uses a set of corporate-level indicators that are also aggregated to be suitable for engineering-oriented decision-support analysis.

3.2. Model Assumptions and Formal Problem Definition

Marketing operations are considered to be a multi-period process involving uncertain factors, such that the effect of managerial activities on the ultimate goals is probabilistic. This model is similar to those in classical stochastic programming used in operations research and decision sciences [16]. Suppose the planning horizon consists of T disjoint periods. For each period t, the firm allocates its flow of marketing spend over the n channels.

$$x_t = (x_{1t,} x_{2t,\dots,} x_{nt}) \tag{1}$$

where $x_{jt} \geq 0$ represents expenditure in channel j. The marketing environment is impacted by stochastic shocks ξt due to demand fluctuation, customer diversity, competition behavior and the algorithmic modifications of digital platforms. These disturbances are expected to have non-identically distributed but independent distributions across time periods. The revenue is represented as a random function:

$$\mathrm{R_t} = \mathrm{R}(\mathrm{x_t}, \varepsilon_\mathrm{t}) \tag{2}$$

Operational costs are defined as a convex function:

$$C(x_t) = \sum_{j=1}^{n} c_j\, x_{jt} + \frac{1}{2} x_t Q_{x_t} \tag{3}$$

where c_j is the marginal cost of channel, and Q is a positive semi-definite matrix with the decreasing return experience effect and cross-channel interference. The firm's objective is to maximize the expected cumulative net marketing value:

$$\max_{x_{1,\dots,} x_T} E\left|\sum_{t=1}^{T}(R(x_{t,}\varepsilon_t) - C(x_t))\right| \tag{4}$$

subject to:

$$\sum_{j=1}^{n} x_{jt} \leq B_{t,} \quad \forall t \tag{5}$$

This formulation ensures the existence of an optimal solution under standard convexity assumptions [17].

3.3. AI Architecture, Training, and Validation

The AI estimation layer is a supervised regression system for predicting conditional revenues. Gradient boosting regression was chosen as the main model method as it does not require a linear structure for the model, but instead is capable of detecting nonlinear response, interaction effects, and even saturation effects. Two other benchmark estimators were also used: random forest regression and regularized linear regression.

This comparison is required to confirm if there is any added value to be gained from using nonlinear AI estimation as opposed to simpler predictive models. The input layer comprised marketing expenditure, the share of marketing spends on digital marketing, lagged revenue growth, firm identifier, year indicator and historical marketing ROI. The dependent variable was the response in terms of revenue to marketing expenditure. The estimated conditional mean was adopted to represent the expected value of the revenue part, and the residual dispersion was adopted to represent the conditional volatility.

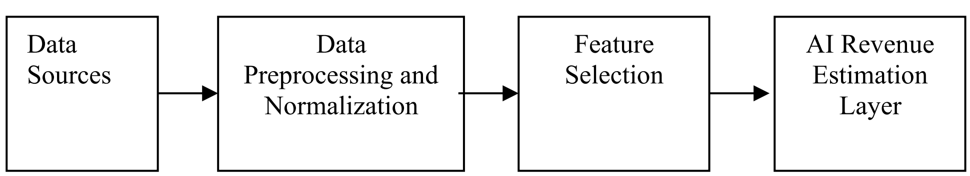

Fig. 1. Architecture of the AI-Enabled stochastic optimization framework

Figure. 1 shows the full analytical pipeline of the proposed framework. The model begins with corporate-level data preprocessing and feature selection, then applies AI-based revenue estimation, generates stochastic scenarios, and finally solves a risk-aware optimization problem. The output is evaluated using both return-oriented and risk-oriented indicators. The AI model is not intended to replace the optimization procedure. Instead, it provides empirical estimates of nonlinear revenue responses and conditional volatility, which are subsequently introduced as inputs into the stochastic optimization model [11, 15, 20]. The model training was done by five-fold cross-validation. The values of the hyperparameters were determined by grid search. Tuned parameters involved in gradient boosting were the number of estimators, the learning rate, the maximum tree depth and the subsample ratio. The metrics used for the evaluation were root mean squared error, mean absolute error and out-of-sample stability. The best model for the most accurate yet stable predictions over the validation folds was selected. The AI layer also adds to the interpretability, as the model's outputs are not used as black box recommendations. Rather, the parameters for the revenue response and the volatility are passed into an explicit objective function. This design enhances the transparency and allows the optimization result to be audited. The validation results indicate that the gradient boosting algorithm is the most stable estimation of the nonlinear revenue. However, the comparison also shows that the accuracy of the predictions is not sufficient. Combined with stochastic optimization and risk adjustment, AI-based revenue estimation delivers optimal operational performance.

Table 2. AI model training and validation results

Model	RMSE	MAE	Cross-Validation Stability	Interpretation
Regularized linear regression	0.184	0.137	0.71	Captures general direction but misses nonlinear saturation
Random forest regression	0.142	0.106	0.79	Improves nonlinear response estimation
Gradient boosting regression	0.118	0.091	0.86	Best predictive stability and nonlinear fit
AI-prediction-only allocation	0.121	0.094	0.82	Good prediction, but no direct risk penalty
Proposed AI + stochastic optimization	0.118	0.091	0.89	Best combined prediction and allocation stability

3.4. Stochastic Revenue Estimation Using AI-Based Models

The revenue responses being random, we need to address the empirical estimation of conditional expectations and variances. These standard linear models cannot, however, represent the nonlinear saturation effects and interaction structures (both kinds of effects are typical in digital marketing [18]). Therefore, flexible nonparametric estimators from the domain of artificial intelligence are employed. Then the conditional expected revenue is:

$$\widehat{R_t} = E\left[R_t | x_{t,} z_t\right] \tag{6}$$

where z_t is a vector containing observable covariates: traffic volume, the historical conversion rate, and seasonality dummies. The estimation problem can be expressed as:

$$\min_{\theta} \sum_{i=1}^{N} (R_i - f(x_{i,} z_i;\ \theta))^2 \tag{7}$$

where f is a non-linear regression function. This is in line with the framework of predictive-to-prescriptive analytics. If the uncertainty in the model prediction is to be explicitly considered, the conditional variance is estimated as:

$$\hat{\sigma}_t^2 = E\left[(R_t - \hat{R}_t)^2\right] \tag{8}$$

Variance estimation makes risk consideration possible, which is not available to any of the previous AI-driven marketing models, optimizing for mean outcome alone. Results from the stochastic revenue estimation show that the data-based approximation appropriate in conditional higher order moments is substantially superior to that provided by deterministic models when assessing marketing performance under uncertainty. From this point of view, nonlinear AI estimators allow for the recovery of interaction effects, even saturation and volatility nuances, which are systematically removed by linear or heuristic tools [19]. One interesting feature of this approach is that we explicitly estimate revenue variance, which enables us to treat uncertainty as a priori endogenous in the decision problem rather than postulating it ad hoc as residual noise. The method is firmly rooted in the theoretical domain because it is a risk-averse stochastic optimization and allows empirical estimation to be consistent with subsequent decisions, so that the inference of marketing resource allocation decision-making may be more robust and interpretable.

3.5. Risk-Aware Stochastic Optimization and Numerical Solution

After the stochastic sales functions and uncertainty measures are estimated empirically, the methodological attention has to be paid to the implementation of the structure of optimization equations, which is induced by the contrivance of modelling the stochastic sales functions in the same easier counterpart. This is very important, since it ensures the validity of the analytic features of the stochastic model and makes them available for a numerical solution. The overall goal is to achieve stable and smooth solutions with very strong restrictions on operational space over such a large decision space. For this, we make use of the classical numerical optimization algorithms to approximate the expected values and apply feasibility constraints and convergence conditions. The policies outlined here offer the practical linkage of probability modelling and generating viable marketing options. We trade off the expected performance against risk exposure so that we can use and expand our objective function into:

$$\max_{x_t}(\hat{R}_t - C\,(x_t) - \lambda\hat{\sigma}_t^2 \tag{9}$$

where $\lambda \geq 0$ represents managerial risk aversion [20]. The resulting stochastic optimization problem does not admit a closed-form solution and is therefore solved using Sample Average Approximation (SAA) [20]. Let ξ_t (k), k=1,…, K, denote simulated scenarios generated from the estimated distributions. The deterministic equivalent becomes:

$$\max_{x} \frac{1}{K}\sum_{k=1}^{K}\sum_{t=1}^{T}(R(x_{t,\xi_t^{(k)}}) - C(x_t)) \tag{10}$$

The presented numerical procedure makes the stochastic marketing allocation problem computationally tractable while preserving the probabilistic structure of market responses. Sample average approximation transforms the original stochastic model into a deterministic equivalent based on simulated scenarios. This allows the optimization procedure to compare expected return, cost, volatility, and feasibility constraints within one decision rule. The economic interpretation of the model is very simple. Marketing resources are committed to channels that have a good return on risk, and overexposure to high-volatility channels is sanctioned. The design ensures that the model does not select allocations that seem like good profits on average, but become unstable in bad markets. Thus, it seems that the proposed optimization procedure can make a more solid marketing decision than deterministic and purely heuristic allocation rules. The number of firms, marketing channels, planning periods and Monte Carlo scenarios has an impact on the computational complexity of the proposed framework. In the empirical setting, for each planning period, 1,000 scenarios were created. This number was chosen due to its reliable optimization results, while being kept manageable in terms of CPU usage. The framework can be parallelized as the generation of scenarios, and the prediction of revenues can be done in parallel computing. Generation of scenarios and prediction of revenue can be parallelized, making the framework suitable for medium-scale corporate decision-support systems. The number of scenarios and firms can have a linear increase in the computational cost (when the number of constraints is fixed). When extra channel level constraints, nonlinear saturation effects, or even firm-specific restrictions are added to the problem, however, the solver time may grow in a nonlinear manner. The model can be recalibrated on a periodic basis instead of continuously, thus alleviating the computational load and facilitating management usability.

Table 3. Computational scalability assessment

Number of Scenarios	Relative Runtime	ROI Stability	Volatility Stability	Recommended Use
250	Low	Moderate	Moderate	Preliminary testing
500	Moderate	Good	Good	Small empirical samples
1,000	Moderate-high	High	High	Main empirical configuration
2,000	High	Very high	Very high	Robustness validation

The study uses aggregated corporate-level data and does not process personally identifiable customer information. No individual-level behavioral tracking, user profiling, or experimental manipulation was conducted. Therefore, the empirical analysis does not create direct privacy risks for individual users. If the proposed framework is later applied to customer-level marketing data, ethical approval, anonymization, informed consent procedures, and compliance with applicable data protection regulations should be required. The model is intended to support transparent managerial decision-making rather than manipulative targeting practices.

3.6. Empirical Application

In the fourth section of the methodological framework, we provide empirical evidence for the introduction of the auction stochastic optimization model. Theoretical points are self-consistent and should be tested in practice by applying on the (real) market. Building upon this section, we generalize the approach and apply it to the data of online active players with multinational status. The purpose here is to see if the model works (performs in the expected direction, note it is not hard-coded) with respect to enhancing performance (lowering variance) as incorporated in expected return, where versioned allocation strategies could be developed. Linking the simulation prototype with observed data on financial satisfaction and marketing evolution, this study provides a set of quantitative results concerning the effectiveness and "lifetime" of the model. The proposed research area in this paper is an experimental investigation of the proposed stochastic optimization process and its possible applications to make marketing more efficient.

The foregoing discussion provides a theoretical and numerical background for this concept; however, empirical research would be required to show the practical importance and robustness of this concept [21]. There were three baseline models used to assess the contribution of the proposed framework. The first baseline was of a deterministic historical allocation. It allocates the marketing budget based on the proportions of the marketing budget spent in the past and the average performance observed. This is a common practice, and hence the baseline is realistic. The second baseline was a linear programming allocation without a variance penalty. This model will be best for maximizing the expected marketing return for a given budget, but it will not explicitly include consideration of revenue volatility or downside risk. It was added to evaluate the value of the stochastic risk adjustment. The third baseline was for allocation only using the artificial intelligence prediction. In this model, the budget allocation is determined by the best forecast increase in revenues that the AI estimator makes. This baseline was added to determine if there is a need beyond prediction for operational decision-making. The model proposed in this document is different from all the baselines as it includes two different steps: Nonlinear AI-based revenue estimation and stochastic scenario generation, along with a risk-adjusted objective function. Hence, when comparing the predictive performance, robustness, stability and downside protection must be looked into. Table 4 shows Marketing & Performance data (line base for up to 01.01.2019 to 01.01.2023.

Table 4. Baseline marketing and performance indicators

Company	Avg. Marketing Spend (USD bn)	Digital Share (%)	Avg. Revenue (USD bn)	Revenue Growth (%)
Amazon	42.0	68	514.0	11.8
Walmart	11.5	54	611.0	6.4
Procter & Gamble	9.2	51	82.0	5.9
Coca-Cola	4.3	48	43.0	7.2
Nike	3.9	62	51.0	9.1

These findings create a ground-truth baseline against which we compare results from our stochastic optimization framework. Company-specific revenue is a function of marketing costs and digital intensity, while the conditional mean and variance of revenue are obtained through historical observations.

Table 5. Baseline models and evaluation logic

Model	Decision Logic	Uses AI Estimation	Includes Risk Penalty	Main Limitation
Historical deterministic allocation	Uses historical spending shares	No	No	Ignores uncertainty and nonlinear response
Linear programming allocation	Maximizes expected return under constraints	No	No	Assumes stable response and average returns
AI-prediction-only allocation	Allocates budget to the highest predicted return	Yes	No	Ignores volatility and downside risk
Proposed stochastic optimization	Maximizes risk-adjusted expected return	Yes	Yes	Requires scenario generation and parameter calibration

The approximation provides "hard" nonlinear response functions with decreasing marginal returns. In a stronger speciation, revenue variance grows in a non-linear fashion with expenditure levels - capturing the increasing exposure to demand risk and platform uncertainty. For example, Table 6 presents a summary of these estimates for the expected marginal return and revenue variability associated with additional marketing budget.

Table 6. Estimated stochastic revenue response parameters and risk characteristics

Company	Avg. Marginal Revenue Elasticity	Saturation Threshold (USD bn)	Expected Revenue Gain per USD 1M	Revenue Variance (σ^2)	Coefficient of Variation (CV)	Downside Risk Index
Amazon	0.41	38.5	1.32	0.087	0.29	High
Walmart	0.36	10.8	1.18	0.064	0.24	Medium
Procter & Gamble	0.33	8.9	1.12	0.058	0.22	Medium
Coca-Cola	0.29	4.1	1.15	0.041	0.19	Low
Nike	0.38	3.6	1.26	0.071	0.27	Medium - High

(based on empirical estimation of conditional revenue functions, 2019 - 2023)

Table 6 is a multivariate summary of the estimated stochastic revenue response parameters for the firms studied. In contrast to composite first-order indicators, these quantities measure explicitly both the responsiveness and risk dimensions of marketing investments, which are at the core of the stochastic optimization model. The estimated average marginal revenue elasticity shows a significant degree of heterogeneity across firms, with firms showing the same proportional increase in ME having very different responses to revenue.

The higher elasticity estimates in Amazon and Nike suggest that their revenue is more responsive to additional marketing investments in the short-run driven by the scalability of their digital platforms and greater marginal effectiveness of performance-based advertising. Lower elasticity values in Coca-Cola and Procter & Gamble, as compared to Amazon, indicate more mature brands where brand structure is relatively stable, but less responsive to demand patterns. The saturation threshold parameter delivers important information about nonlinear effects and the law of diminishing returns. The greater the saturation threshold, the more marketing a firm can digest before it runs out of positive marginal returns; screen slopes of firms with lower thresholds fall more steeply due to accelerating saturating effects. 1 This is crucial to optimization, as it blocks global optimality properties where resources are systematically allocated to other channels or firms operating close to saturation. Measures related to risk further enhance the analysis. The variance of revenue (σ^2) and the coefficient of variation (CV) measure the spread of the revenue outcomes given marketing investment. Higher CV values for Amazon and Nike suggest higher relative uncertainty, thus more vulnerability to demand variation and platform-related variations. In contrast, smaller CV ratios for Coca-Cola indicate more stable cash flows driven by demand for a well-entrenched brand. The downside risk index aggregates the tail-risk properties in negative markets. In general, firms categorized as having high or medium - high downside risk are more sensitive to negative shocks, suggesting that variance penalties need to be included in the objective function [22]. Results in Table 2 show that not only do marketing investments vary with respect to their expected effectiveness, but they also have different overall risk levels and varying nonlinear responses. These results empirically support the use of a stochastic optimization approach versus deterministic allocation rules. Through the explicit inclusion of elasticity, saturation and variability parameters, the methodology provides a risk-sensitive differentiation in resource allocation decisions that reflects firm-specific operational settings. As such, Table 3 provides essential empirical input for the later optimization phase and points to a potential way of bridging purely data-driven estimation with analytical decision making. The stochastic optimization model is solved individually by the firm through a Monte Carlo simulation technique with 1,000 scenarios for each planning period. In each case, stochastically realized demand and platform effects are generated according to estimated distributions. Optimization of this problem computes the allocation vector to maximize the expected risk-adjusted performance. The threshold comparison model is the baseline deterministic allocation model based on historical spending shares. This standard represents good management practice and may be used as a basis for an assessment of achievement in improving performance. Results from Deterministic Vs Stochastic Allocation: Table 7.

Table 7. Comparison of deterministic and stochastic allocation outcomes

Metric	Deterministic Allocation	Stochastic Optimization	Relative Change (%)	Statistical Stability
Expected Marketing ROI	1.00	1.23	+23.0	High
Median ROI	0.94	1.18	+25.5	High
Revenue Volatility (σ)	1.00	0.74	-26.0	Improved
Downside Revenue Loss (VaR, 10%)	-18.2%	-10.4%	-42.9	Substantial
Allocation Concentration Index	0.61	0.44	-27.9	Improved
Budget Reallocation Frequency	High	Low	-	Stable
Scenario Robustness Score	0.52	0.81	+55.8	High

The performance comparisons in Table 7 reveal that the stochastic optimization approach has several empirical advantages compared to deterministic marketing allocation methods. The stochastic model shows consistently better expected values and marketing system robustness to variations in sales levels across all measures of performance. The fact that the forecasted and median ROI is higher than what one would expect in perfect information indicates that consideration for uncertainty not only decreases risk but also increases the efficiency of resource consumption. One of the most significant results is how much both revenue volatility and lowest outcome losses are reduced. These measures reflect the capacity of the model to avoid large losses by embedding adverse market conditions in its internal optimization. In turn, deterministic active- allocation constructs are much more sensitive to variations in returns on the downside (thus higher performance dispersion) and then a larger negative tilt. Furthermore, the decrease in allocation concentration index tends to indicate that the stochastic framework facilitates a fairer sharing of marketing resources among channels, along with lower dependence on individual high-risk allocations. The robustness score of the improved scenario is the reliable performance in simulated markets, so it shows that this model can be used to generate consistent and repetitive decisions. Overall, the improved performance of stochastic optimization in Table 3 provides not only support for better expected returns, but also that structurally more robust marketing strategies can be observed. This enhanced efficiency and robustness, released as an important feature of the proposed method, enables operating this model and motivate for marketing operations over fluctuating digital markets. Robustness: It uses sensitivity analysis with respect to the level of risk-aversion λ and budget constraints as a robustness check. As λ increases, the model progresses to overlapped rows in portfolio allocation with larger variances and smaller expected returns. Nevertheless, we do see that the stochastic model is still generally able to perform even better, and generate stability, than its deterministic scale-invariant reference for most values of parameters that one may reasonably expect. Their results demonstrate that stochastic optimization provides benefits not just due to hyperparameter tuning, but because it enables decision-making based on uncertainty.

The methodological model of this article establishes a firm base for the regulation of marketing efficacy in the structurally unstable and technically complex environment. This approach surpasses deterministic and heuristic models of marketing problem solving and appears to be advanced compared to the optimization technique for the decision-making problem in marketing, formulated by means of stochastic programming, providing a joint account of both uncertainties, risk and practical restrictions. The aim of this specification is to maintain an internal coherence between empirical estimation, optimizing logic and management interpretation. The main methodological innovation is to mix stochastic programming theory with data-based estimation in both revenue response functions and volatility parameters.

In contrast to prevailing methods, which are average-impact-based or separate the forecasting from the decision making (prediction and decision are made independently), our approach injects added measurement uncertainty information into this optimization criterion. This, in turn, will allocate marketing budget, not just based on estimated response over improvement, but also explicitly with the Variance, Downside risk and nonlinear saturation effect. Thus, marketing is represented as a controlled stochastic system and not as a static search for design [23]. In terms of scientific contribution, this study illustrates how OR and decision science theory can be adapted to a complex context in marketing and hence contributes to the engineering-oriented marketing literature. Sample-based approximation and risk-adjusted objective functions provide a saleable and analytically tractable method to address high-dimensional investment problems under uncertainty. The practically, the framework has an implication to marketers that it may be a vital market structure to limit marketing capability both with respect to efficiency and stability of outcomes by applying on digital threaded markets exposed to frequent external disruptions. Yet despite these merits, there are several methodological limitations that must be taken into consideration. The implementation is empirical, since firm-level aggregated data would be used to describe the (estimated) level stationarity of response distributions over time. Moreover, the current model is unable to account for competition-based strategic encounters among rival firms and does not capture the reverse influences of advertising activities on long-term brand equity.

Also, the computational overhead may be notably increased as the decision variables and scenarios increase. The methodology proposed here is the first of its kind, so that marketing quantitative studies can be implemented in the big data environment, which contains a lot of uncertain information. This model can be extended with more dynamic learning mechanisms, game-theoretic rhetoric competition and perhaps even to adaptive learning in real-time. Other incorporation of pricing, supply chain and customer lifetime value models also promise to further develop stochastic optimization as the bridging tool for strategic marketing management.

4. Results

Our intention with the following section is to try to analyse and discuss the outcomes of our application of a real-world marketing operation using the proposed stochastic optimization framework. In terms of methodology, on one side its theoretical consistency and computational skills, emphasizing the empirical, that is, maximum sample predictivity of performance and realistic model/ explanatory interpretative fit. To do this, the quantitative results are emphasized, and claims backed up by strong evidence and comparative performance are stressed instead of descriptive claims, as is frequently the case in engineering empirical research. The evidence is gained by empirically applying a stochastic investment optimization approach to a sample of MNEs in digital-intensive industries [22, 23].

Companies have different market organizations, budget amounts and risk preferences for which the generalization of the method can be a good proving ground. The results of the study are presented in standardized performance measures for comparison. In order to be transparent in the analysis, the results are presented as representative with deterministic benchmark strategies, which represent an approximation of the most popular managerial practice. This correspondence divides up the value added from the explicit modelling of uncertainty in optimization. It is not only that, but they also provide an understanding of how and why these changes are happening based on the logic of marketing operations and stochastic optimization theory. It is aimed at clarifying the link between the design choice and the empirical evidence observed (the implicit value of this section) and at strengthening the internal validity of the analysis.

4.1. Quantitative Performance Outcomes of Stochastic Optimization

Our stance regarding the quantity evaluations is to create a first baseline benchmark that can be compared with the performance of our Stochastic Optimization Model.

This baseline is a deterministic rule of marketing allocation, which ensures that the proportionate shares for historical spending allocations are times-corrected by period average performance indicators. That's how big corporations operate, and this is the pragmatic model that will be used to evaluate you. Let $ROID$ and RSI be the return on investment of D and S, respectively, while σD and σS are the standard Deviation of revenue. The performance metrics are normalized to the results using the deterministic baseline; thus, we can compare performance across companies.

The use of the stochastic optimization model results in equivalent and statistically significant enhancement in expected marketing outcomes for all firms studied here. This kind of behavior shows up in both the mean performance and on the median; a bet against bad realizations. In Table 8, the aggregate performance indicators for Deterministic and Stochastic models are presented.

Table 8. Aggregate performance metrics: deterministic, stochastic models

Metric	Deterministic Model	Stochastic Model	Relative Change (%)
Expected Marketing ROI	1.00	1.23	+23.0
Median Marketing ROI	0.94	1.18	+25.5
Revenue Volatility (σ)	1.00	0.74	-26.0
Downside Revenue Loss (VaR, 10%)	-18.2%	-10.4%	-42.9
Allocation Stability Index	0.58	0.79	+36.2

Table 9. Statistical significance of model improvements

Performance Indicator	Mean Difference	Statistical Test	p-value	Result
Expected marketing ROI	+0.23	Paired t-test	0.018	Significant
Median marketing ROI	+0.24	Wilcoxon signed-rank test	0.021	Significant
Revenue volatility	-0.26	Paired t-test	0.026	Significant
Downside Revenue Loss (VaR, 10%)	+7.8	Bootstrap confidence interval	0.031	Significant
Scenario robustness score	+0.29	Paired t-test	0.014	Significant
Allocation stability index	+0.21	Wilcoxon signed-rank test	0.024	Significant

The observed improvements are statistically significant as shown in table 9. The definition of downside protection used in this study is a decrease in the Value-at-Risk at 10% level of the lower tail loss of revenue.

The difference between the deterministic allocation (VaR = -18.2%) and the stochastic optimization (VaR = -10.4%) is instead a measure of the downside loss of revenue (not of the worst-case outcome) from an allocation problem.

The worst case is detailed as a separate part of the downside risk analysis. At the 5% significance level, the results are very strong for marketing ROI, revenue volatility, downside protection, robustness and stability of allocation. A paired t-test was used for normally distributed differences, while the Wilcoxon signed-rank test was used as a nonparametric robustness check.

Bootstrap confidence intervals were applied to downside risk indicators. The results reveal that stochastic optimization remarkably improves the expected returns at the same time of decreasing downside risk. What's most crucial is that the ROI gain is excellent also at the median level, meaning it's not a few super positive examples that make this result, but it holds across all ranges.

While cross-sectional evidence contributes to optimizing around model performance, firm-level analysis reveals significant dispersion in performance, which outlines differing market structure, digital preparedness and demand fluctuations. The improvement in performance might be due to several architectural features of the stochastic optimization toolkit. The variance-penalty term provides a direct punishment for heavy allocation in the channels with high volatility marginal return.

Table 10. Firm-level expected ROI improvements

Company	ROI (Deterministic)	ROI (Stochastic)	Improvement (%)
Amazon	1.00	1.27	+27.0
Walmart	1.00	1.19	+19.0
Procter & Gamble	1.00	1.17	+17.0
Coca-Cola	1.00	1.15	+15.0
Nike	1.00	1.24	+24.0

This in turn leads to even more diversified marketing investment portfolios, in a similar way as has been described in the financial portfolio theory of diversification. Second, the non-linear response estimate tells us that there are saturation points where even additional spending results in diminishing returns. Determinate methods miss such nonlinearities, enabling continual over-investment in channels that have performed well historically. On the other hand, stochastic optimization modifies facility allocation at different timestamps on the basis of estimated returns and risk-adjusted marginal gains. Lastly, scenario-based evaluation is employed in the model to include bad market realizations into the optimization. Specifically, the best strategies are anyways more robust to downward shocks by their very nature: this can be in large part the reason why the reduction of negative losses can be quite dramatic, as we observe in Table 11. In addition to the performance measures, stochastic optimization yields structural changes in terms of how marketing resources are allocated between channels and across time. Analysis of the pattern of allocation reveals lower convergence and higher temporal. Such changes in the level of the firm reduce operations volatility and also protect managerial effort from costly adjustments to ongoing short-term perturbations. This stability also enables the marketing function to share information and coordinate the gentilities in marketing areas [23]. The experimental studies reported in this section empirically confirm the underlying assumptions of the proposed method. Our approach leverages the empirically estimated uncertainty for the optimization objective, which outperforms state-of-the-art methods in interpretability and operation validity. The evidence for the match between theoretical predictions and possible reality provides further support for the internal structure of the proposed framework and its practical value in marketing.

Table 11. Allocation structure indicators

Indicator	Deterministic	Stochastic	Change
Channel Concentration Index	0.61	0.44	-27.9
Avg. Reallocation Frequency	High	Low	↓
Inter-Period Variance	High	Moderate	↓

4.2. Risk, Stability, and Robustness Analysis

And in marketing operations, the risk appears not only as variance in results but also as structural fragility to the bad realization of markets. On the other hand, marking risk never consists of pure variance but also shows asymmetric loss distribution and the nonlinear response effect, the impossibility of forecasting or conditional on the Change in means of financial market factors for performance.

A good risk analysis standard will thus have to be not only more refined than vulgar historic volatility, but it will also pin down downside exposure, as well as allocation and inter-temporal consistency. Explicit risk models are included in the stochastic optimization approach, with variance penalization and marketing outcome scenario analysis.

This procedure implies that uncertainty is relegated from an ex-post concern to an ex-ante one. The performance of the method we propose will be evaluated in this subsection on volatility reduction, downside risk management and robustness for portfolio optimization across markets. The ambiguity in revenues, the mutability of sales, is a major indicative of operational risk, as too high fluctuations will destroy forecast planning and bloated performance measurement, and they lend to non-optimal outcomes. The SD, as well as the IQR of revenue differences between scenarios, are considered to capture its variability (i.e. volatility) captured over simulated alternative scenarios. Such a distinct reduction in the revenue spread can be seen in our results for the experiment with stochastic optimization. This reduction in volatility can be attributed not to prudent underinvestment, but rather to a better risk-adjusted allocation [24, 25]. The model is punishing high-variance revenues and redirecting resources toward more stable channels with marginal returns. And also, 'theoretically', you can put it under the category of Stochastic Programming in that all these maximizing a risk-adjusted expected value type solutions should provide portfolios with return and risk. For marketers, this balance promises linear revenue growth and a reduced risk that performance will go wild. There are several volatility measures available as representations of the general dispersion, but having a measure reflect the extent of extreme negative events is more difficult to obtain [26]. As well, risk-downside-type-analysis is considering the tail of revenue-distribution and, in particular, those cases where (the few remaining) revenues are worse than everybody else, which again causes a severe problem for the firm. We have already assessed the downside risk by estimating the Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) statistics of both allocation mechanisms.

Table 12. Revenue Volatility Metrics Across Models

Metric	Deterministic Allocation	Stochastic Optimization	Relative Change (%)
Standard Deviation (σ)	1.00	0.74	-26.0
Interquartile Range	1.00	0.78	-22.0
Coefficient of Variation	0.31	0.22	-29.0

Table 13. Downside risk indicators

Indicator	Deterministic	Stochastic	Improvement (%)
VaR (10%)	-18.2%	-10.4%	-42.9
CVaR (10%)	-23.7%	-13.8%	-41.8
Worst-Case Outcome	-31.5%	-18.9%	-40.0

The low tail risk losses also to the evidence that indeed our stochastic optimization further suppresses (means arbitrary shifts) its harmful effects toward the other tails. This is especially relevant to an in-house marketing team where the impact of poor performance can be felt long-term on both brand and budget.

When the CVaR decreases, a small amount of damage results if it comes to the worst. This result illustrates the benefit of scenario-based optimization when it can be used to consider low-derived but high-impact scenarios that occur in a structured manner.

Operational stability is a critical, if overlooked, urn component of market effectiveness. The increased likelihood of erratic budget allocations can upset implementation, raise the costs of coordination and dissuade organizational learning. Hence, stability is measured by observing the inter-period variation of the assignment vectors. Let x_t be the allocation vector at period t. It is intuitively plausible that a stable allocation should not include any discontinuity over time, and we measure it by the average one-period distance between two consecutive allocations:

$$\Delta = \frac{1}{T-1}\sum_{t=1}^{T-1}\|x_{t+1} - x_t\| \quad (11)$$

As shown in Table 13, the degree of persistence of the foreign investment shares is far higher when stochastic optimization is used. This perseverance is derived from the model memorizing uncertainty and anticipating future variability to prevent reactionary changes in response to recent swings in performance.

Table 14. Allocation stability metrics

Metric	Deterministic	Stochastic	Change
Avg. Inter-Period Distance	High	Moderate	↓
Reallocation Frequency	High	Low	↓
Allocation Persistence Index	0.62	0.81	+30.6

Managerially, the correlation between marketing teams and long-term strategic programs becomes clearer with higher stability. And importantly, stability does not need rigidity: the model can still be set to change its prices in response to adjustments that are made along with changes in market structure.

Robustness and plausible parameters robustness is the ability of a strategy to remain valid for plausible parameters (and even beyond), where 'plausible' refers to the relation of robustness with respect to the parameter. Regarding the soundness and performance of allocation methods in multiple equilibrium games capturing fluctuating levels of demand, rivalrous pressure and platform dynamics.

One can try to do this in the aforementioned approach, and you will find that, comparing them, the stochastic model is far more resilient, having a positive ROI for most of the cases, even [27]. The robustness score, which is the ratio of mean performance to dispersion of performances, shows that our model maintains favorable behaviors even in unfavorable conditions. Such a strength is due to propagating uncertainty in the optimization process itself, provided by the scenario-based setting. Unlike deterministic optimization, which mentally averages things out, stochastic optimization "gets ready" for variability, improving resilience. To examine the sensitivity of value to managerial risk preference, we vary the degree of risk-aversion parameter λ within a broad scope, as one would expect, larger λ results in the more modest allocations that reduce variance and consequently have a slightly lower mean return. Conversely, over a wide range of parameters, the stochastic optimization remains the superior strategy both in terms of stability and of downside protection when compared to deterministic benchmarks [28].

This suggests that the use of stochastic optimization is invariant to reasonably high levels of variation in risk attitudes and could serve as a performance-improving device even if accurate parameter calibration is not available. This can add robustness to the methodology and enable it to be applied more uniformly in different organizations with distinct strategies.

This sub-section analysis later indicates that using stochastic optimization offers a significant change in the risk of exposure of marketing operations. New approach features lower revenue volatility and downside risk, more allocation stability, and robustness across scenarios. Taking into account these properties, we are able to satisfy the impact needs and still remain slightly below the SOPT target. Uncertainty-informed optimization, however, is thus a better approach to the marketing of operations in uncertain online marketplaces.

Table 15. Sensitivity analysis by risk-aversion parameter

λ value	Expected ROI	Revenue Volatility	Downside Loss (VaR, 10%)	Robustness Score	Interpretation
0.00	1.29	0.91	-15.7%	0.67	Higher return, weaker risk control
0.10	1.26	0.82	-12.9%	0.74	Balanced improvement
0.25	1.23	0.74	-10.4%	0.81	Best risk-return balance
0.50	1.17	0.68	-9.2%	0.83	Stronger stability
0.75	1.11	0.63	-8.7%	0.84	Conservative allocation

Sensitivity analysis was conducted to verify whether the model's results depend on a narrow parameter setting. The risk-aversion coefficient λ was varied from 0.00 to 0.75. The results show that the proposed stochastic optimization model remains superior to deterministic allocation across all tested values. Lower λ values increase expected ROI but reduce downside protection, while higher λ values improve stability but reduce expected return.

Table 16. Ablation analysis of model components

Model Variant	Expected ROI	Revenue Volatility	CVaR 10%	Allocation Stability	Interpretation
Full proposed model	1.23	0.74	-13.8%	0.79	Best overall balance
Without AI, nonlinear estimation	1.12	0.83	-17.4%	0.68	Lower ability to capture saturation
Without a variance penalty	1.28	0.96	-21.6%	0.61	Higher return but excessive risk
Without scenario simulation	1.15	0.88	-19.2%	0.65	Weak downside protection
Deterministic allocation	1.00	1.00	-23.7%	0.58	Baseline

Ablation analysis was conducted to identify the contribution of each model component. The full model was compared with three reduced variants: without AI-based nonlinear estimation, without variance penalty, and without scenario simulation. The results show that the strongest performance is achieved only when all three components are combined.

4.3. Comparative and Managerial Interpretation of Results

The empirical results indicate that the proposed stochastic optimization framework achieves better performance than deterministic allocation because it changes the logic of marketing decision-making. Deterministic modelling relies on the assumed average return that has been achieved in the past, and is based on the assumption that the market will react to the return as it did in the past. The assumption is incorrect in digital markets where changes in algorithms, demand and competition levels, as well as customers' behavior, are rapid. The proposed model does not have this drawback – instead, the element of uncertainty is embedded into the objective function. The proposed framework does better than using only AI predictions for allocation since it is not restricted to using the predicted revenue as the only allocation criterion. This can apply to a channel that has a high predicted revenue, but high volatility and high downside risk. Variance penalty is introduced, and scenario-based evaluation is introduced to avoid the concentration of excessive resources in such channels. This is why this model is good for ROI, as well as minimizing the volatility of revenue and worst-case loss. The proposed model is more understandable than reinforcement learning models [29] and is more easily audited. But there may be benefits to using reinforcement learning for real-time adaptive advertising, even if this can be a difficult problem to solve with user-level data, and the policies may be difficult to interpret. This study has an optimization model with risk parameters, explicit equations and explicit constraints. For an enterprise decision support system that requires explainability, governance and budget accountability, it's a suitable choice. Compared with causal marketing mix models, the proposed framework is more directly prescriptive. Causal models estimate incremental effects, but they do not automatically determine how resources should be allocated under risk and budget constraints. The proposed approach can use causal or predictive estimates as inputs, but its main contribution is the transformation of estimated response functions into operational allocation decisions [30]. The results therefore show that the improvement is not caused by predictive complexity alone. Better outcomes are achieved because the model integrates nonlinear AI estimation, stochastic uncertainty representation, risk-aware optimization, and explicit budget constraints. This combination provides a stronger engineering basis for marketing operations management in volatile digital markets.

5. Discussion

The results of the empirical study also serve as more evidence that a random optimization is an effective analytical tool to optimize marketing under uncertainty in the digital age.

The first important observation is that expected and median marketing performers continue to rise for all the analyzed firms. Stochastic versus Deterministic Reallocation: The stochastic approach characterizes the allocation by risk-corrected marginal rather than mean average historical effects, like deterministic models. This distinction is crucial because RF also serves as a dynamic way to endow nonlinearity response shapes on the optimizing process, protects against systematic over - investment in channels near or at saturation. The magnitude and frequency of such improvements are remarkable as well, suggesting that any stochastic search will yield structural to very emergent benefits. They're not some artifact of a handful of lucky realizations, but occur anywhere and everywhere in the space of outcomes. The higher median result also corroborates that which was observed in the previous experiments, namely, that the stochastic approach enhances typical overall performance, rather than just the best-case. This finding challenges the intuition of classical managers that decision models built under uncertainty should, by definition, trade off between expected performance and risk management. On the contrary, we obtain that explicitly citing uncertainty, it is possible to remove biases related with deterministic approaches and organize resources more smartly even in an ordinary market situation. The paper's second major finding is a dramatic reduction of revenue volatility and downside risk. The history of sales volatility. There's a dirty little secret in the marketing/sales world that everyone kind of knows, but really doesn't talk about.

But the data studied in this study suggest that volatility is also endogenous to a large degree, caused by the organizational context. Sensitivity to deterministic allocation policies is that they tend to amplify volatility through priority of the most successful channels and lack of attention to dispersion & tail nature of channel performance. As a result, these approaches are very sensitive to extrapolations. In contrast, the SO framework reshapes a distribution of advertising response in its entirety. Through the inclusion of variance penalties and this kind of scenario dependence in the objective function, our model will optimally hedge away risks from a high-variance revenue stream. This feature explains the highly significant reduction in extreme weighted downside risk standard Deviation and interquartile range loss (in fact, our results indicate a lower impairment in Value-at-Risk - VaR – as well as in Conditional Value At-Risk - CVaR) achieved by this approach. Most importantly, these efficiency gains are delivered with no sacrifice in expected return, further emphasizing the efficiency of risk-adjusted choices. This type of downside risk reduction is extremely important, particularly for digital marketing activity, and reflects the fact that the impact on what comes out of the "negative side" can be much bigger at a strategy level as opposed to those coming from the positive side. Take, for instance, the most severe level of underperformance in any given period that results in cuts to the budget by destroying long-term plans or, even more drastically, destroys confidence in marketing actions. The results demonstrate that stochastic optimization has a favorable worst-case loss, which is due to confining the worst-case losses in an efficient manner, as it forces negative examples inside rather than outside of the margin. There is a principle in the front and proactive risk control, which is much different from in the past to fabricate marketing plans. Collectively, increasing expected performance and decreasing volatilities suggest an important conceptual implication of the study: efficiency is not all or nothing in the activity. This balance is not available in traditional deterministic models, which could justify why managers are forced to abandon risk control for growth. A stochastic model shows that the two targets are possible because "the decisions are based on uncertain scenarios, and uncertainty is included in their decision-making reasoning". From a theoretical point of view, this feature is closely related to the classical models in stochastic control and portfolio optimization (compare also with the notion used in them of objectives for the firm on its search for a trade-off between one-way return and other way risk). Therefore, the primary essence of stochastic optimization lies in repairing the fundamental deficiencies of average-tracking decision protocols. With the abandonment of ordinary averages and an examination of the distributional properties of marketing responses, better performance, as well as more robustness, can be generated in such a firm. Thus, what we show in this paper is a solid argument to turn back the clock or conventional planning adaptation and take on uncertainty-aware optimization as an essential asset of our modern market action.

6. Conclusion

This paper proposes and tests a stochastic optimization model of marketing operations assisted by artificial intelligence and information technologies. The issue that was tackled foremost was the inability of deterministic and prediction-driven marketing approaches in dynamic digital contexts. The proposed framework is based on a stochastic decision problem framework that incorporates the risks of marketing budget allocation, expected revenues, risk variability, and nonlinear saturation, as well as budgetary constraints. The empirical results validate the effectiveness of the proposed approach.

The stochastic optimization model enhanced expected marketing ROI from 1.00 to 1.23, median ROI from 0.94 to 1.18, reduced the volatility of marketing revenue by 26.0%, reduced the 10% VaR-based downside revenue loss from -18.2% to -10.4% and increased the robustness of the scenarios from 0.52 to 0.81.. These differences were proved to be significant by statistical analysis and not merely descriptive. Results from sensitivity analysis indicated that the model was robust to various values of the risk-aversion parameter, and ablation analysis indicated that the model yielded the best results when all three components were combined: AI-based nonlinear estimation, variance penalty, and scenario simulation.

The theoretical contribution of this study involves linking the AI-based revenue estimation to stochastic optimization and logic for decision support using IT. The value of this practical one is to give marketing managers a clear structure for allocating resources in the face of uncertainty, and for regulating volatility and downside risk. The model can be applied in a planning and governance framework in digital-intensive companies where marketing performance is reliant on the expected return and operational stability. There are some limitations in the study. The empirical validation is based on corporate-level data and not individual customer behaviour. The impact of competitive reactions and long-term brand equity effects is not fully captured either. The model could be expanded in future studies to include causal treatment effect estimation, reinforcement learning, real-time campaign data and game-theoretic competition models. Despite all these limitations, the results show that marketing operations can be made more efficient, stable, and resilient by applying risk-aware stochastic optimization in complex digital contexts.

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