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Multi-Criteria Optimization of Financial Management in Digital Marketing for Large Enterprises using Fuzzy Decision-Making Systems

Ndeye Siga Gueye

nigaguop@gmail.com

Richard Chaifetz School of Business, Saint Louis University, MO, USA

ABSTRACT

In large enterprises, optimizing financial management in digital marketing campaigns is a complex, multi-dimensional challenge that requires balancing multiple criteria, such as budget allocation, return on investment (ROI), and risk mitigation. This study presents a novel approach to optimizing digital marketing strategies using fuzzy decision-making systems and multi-criteria decision-making (MCDM) algorithms, specifically the TOPSIS method. A comprehensive dataset of 500 marketing campaigns was analyzed, capturing key financial variables such as budget, cost per click (CPC), click-through rate (CTR), conversion rate, customer lifetime value (CLV), and risk levels. The results demonstrate how fuzzy logic can be applied to assess and minimize financial risks while maximizing returns and engagement. Key insights were visualized through a 3D surface plot of budget, conversion rate, and ROI, and a box plot illustrating the relationship between engagement levels and risk. The TOPSIS algorithm ranked campaigns based on their financial performance, showing clear distinctions between high- and low-performing strategies. Sensitivity analysis further illustrated the effects of budget allocation on ROI and conversion rates, providing a holistic view of the optimization process. The study contributes to the field of financial management in digital marketing by demonstrating how fuzzy logic and MCDM approaches can drive data-driven decision-making in large enterprises. The findings have significant implications for strategic budget allocation, risk management, and campaign prioritization in the context of large-scale digital marketing efforts.

KEY WORDS*:* *Digital Marketing, Fuzzy Logic Algorithm, Multi-Criteria, Finance.*

INTRODUCTION

In today's digital economy, large enterprises rely heavily on digital marketing to drive customer acquisition, engagement, and retention, while simultaneously managing the financial implications of these efforts. Digital marketing is not only about reaching the right audience but also ensuring that resources are allocated efficiently to maximize return on investment (ROI) and minimize financial risk [1]. As competition in the digital space intensifies, enterprises are compelled to adopt more sophisticated methods for managing and optimizing their marketing budgets. However, traditional financial management approaches often fail to account for the inherent uncertainties and multi-faceted nature of digital marketing environments. This gap necessitates the adoption of advanced optimization techniques, such as fuzzy logic and multi-criteria decision-making (MCDM) algorithms, to address the complex trade-offs between cost, performance, and risk [2].

Despite the vast potential of digital marketing, financial managers in large organizations face significant challenges in determining how to allocate budgets optimally across multiple campaigns while ensuring maximum profitability. Key variables such as cost per click (CPC), click-through rate (CTR), conversion rates, customer lifetime value (CLV), and engagement levels must be balanced to drive favorable financial outcomes. Moreover, the dynamic nature of digital marketing, where campaign performance and market conditions fluctuate frequently, exacerbates the difficulty of financial decision making. As enterprises scale their digital marketing efforts, they must contend with large volumes of data, diverse campaign metrics, and the uncertain impact of their spending on overall financial performance. These challenges present a pressing need for more sophisticated decision-support systems that can navigate the complexities and uncertainties of digital marketing finance management [3].

The key problem that this paper seeks to address is the lack of an integrated, data-driven framework for optimizing financial management in large-scale digital marketing campaigns. Existing methodologies often focus on maximizing individual metrics such as ROI or minimizing cost without considering the broader, multi-dimensional nature of digital marketing performance. Furthermore, these methods frequently overlook the uncertainty and risk inherent in such environments, resulting in suboptimal budget allocations and decision-making processes. Specifically, the problem lies in the inability of conventional models to handle the trade-offs between maximizing marketing performance and minimizing financial risk, especially in the context of large enterprises where the stakes are high, and financial mismanagement can result in significant losses.

This research seeks to fill this gap by proposing a fuzzy decision-making system coupled with a multi-criteria decision-making (MCDM) algorithm [4], particularly the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [5]. This approach enables financial managers to account for multiple competing objectives - such as optimizing engagement, increasing conversions, minimizing CPC, and controlling risk - while ensuring that budget allocation strategies align with the enterprise's financial goals.

The objective of this paper is to develop and evaluate a comprehensive optimization framework for financial management in digital marketing campaigns, tailored specifically to large enterprises. This framework will leverage fuzzy logic to handle uncertainty and subjectivity in decision-making, and the TOPSIS method to rank and optimize marketing campaigns based on multiple performance criteria. By integrating these advanced techniques, the research aims to provide financial managers with a more holistic toolset for improving the efficiency of their digital marketing investments.

The paper will focus on the following key areas:

1. **Fuzzy Logic-Based Risk Management**: The first component of the proposed framework will use fuzzy logic to model and quantify financial risk in digital marketing campaigns. This will involve classifying campaigns based on fuzzy variables such as engagement rate, CTR, and risk levels, allowing for a more nuanced understanding of financial exposure.
2. **Multi-Criteria Optimization Using TOPSIS**: The second component will implement the TOPSIS algorithm to rank digital marketing campaigns based on multiple criteria, including budget, CPC, ROI, conversion rate, and customer lifetime value. The algorithm will consider the ideal solutions for maximizing campaign performance while minimizing costs and risk, providing a clear ranking of campaigns.
3. **Comprehensive Data Analysis and Visualization**: The paper will present extensive data analysis, supported by visualizations, to demonstrate the interaction between various financial metrics. Key insights will be provided through 3D surface plots, and risk-based box plots, offering a deep dive into how different variables influence financial performance in large-scale marketing efforts.
4. **Case Study with Campaign Data from Large Enterprises**: A case study using data for 500 digital marketing campaigns from fortune 500 companies will be used to validate the proposed framework. The case study will showcase how fuzzy logic and MCDM can optimize budget allocation, improve ROI, and minimize financial risk in real-world digital marketing scenarios.
5. **Practical Implications for Large Enterprises**: The findings from this research will be discussed in the context of their practical applications for large enterprises. Recommendations will be provided on how financial managers can incorporate these optimization techniques into their decision-making processes to achieve better financial outcomes from their digital marketing efforts.

METHODOLOGY

This section presents the detailed methodology employed to develop and validate the fuzzy decision-making system and multi-criteria decision-making (MCDM) optimization for financial management in digital marketing campaigns. The methodology consists of four key components: (1) data generation and preprocessing, (2) fuzzy logic-based risk management, (3) multi-criteria decision-making using the TOPSIS algorithm, and (4) visual analysis and result interpretation. Each step is described in detail, accompanied by relevant equations and models used to produce the figures.

1. Data Generation and Preprocessing

A dataset of 500 digital marketing campaigns of large enterprises was obtained from various online sources to represent the campaigns of various fortune 500 enterprises. The data consisted of several key financial and marketing performance variables 1.

These variables included:

a) **Budget**: Total allocated budget for the campaign (in dollars).
b) **Cost per Click (CPC)**: The average cost per click generated by the campaign (in dollars).
c) **Click-Through Rate (CTR)**: The percentage of users who clicked on the ad after viewing it.
d) **Conversion Rate**: The percentage of users who performed the desired action after interacting with the campaign.
e) **Return on Investment (ROI)**: The profit generated by the campaign relative to its cost.
f) **Customer Lifetime Value (CLV)**: The total value a customer will bring over their relationship with the company.
g) **Engagement Rate**: The level of interaction with the audience (e.g., clicks, likes, shares).
h) **Risk Level**: A fuzzy variable used to represent financial risk associated with the campaign.

The dataset was normalized using **Min-Max Scaling** to ensure that all variables operated on a comparable scale for the MCDM process. The Min-Max scaling formula applied was:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X is the original value, X_{min} and X_{max} are the minimum and maximum values of each feature, respectively.

2. Fuzzy Logic-Based Risk Management

Fuzzy logic was used to classify and manage the financial risk associated with each campaign. The **Risk Level** variable was represented as a continuous fuzzy variable between 0 and 1, where 0 represented minimal risk and 1 represented high risk. The fuzzy logic system was modeled using the following fuzzy sets:

a. Low Risk: $\mu_{Low}(x) = \max\left(1 - \frac{x}{0.5}, 0\right)$
b. Medium Risk: $\mu_{Low}(x) = \max\left(min\left(\frac{x-0.25}{0.25}, \frac{x-0.75}{0.75}\right), 0\right)$
c. High Risk: $\mu_{High}(x) = \max\left(\frac{x-0.5}{0.5}, 0\right)$

Each campaign was assigned a fuzzy risk value based on these membership functions. This fuzzy representation allowed us to model the inherent uncertainty in predicting the financial risk of each campaign, which is crucial in large enterprises where market conditions are volatile.

3. Multi-Criteria Decision-Making (MCDM) Using TOPSIS

The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method was employed to optimize the digital marketing campaigns based on multiple financial criteria. The criteria selected for the MCDM process included **Budget**, **CPC**, **CTR**, **Conversion Rate**, **ROI**, **CLV**, **Engagement Rate**, and **Risk Level**. Each criterion was assigned a weight, with the higher weights favoring the maximization of financial performance and lower weights for minimizing costs and risk.

Step 1: Criteria Weighting

Weights for the criteria were assigned based on their importance to financial management in large enterprises:

$$W_{Budget} = 0.1, \quad W_{CPC} = 0.15, \quad W_{CTR} = 0.2, \quad W_{Conversion\ Rate} = 0.25$$
$$W_{ROI} = 0.3, \quad W_{CLV} = 0.1, \quad W_{Engagement\ Rate} = 0.2, \quad W_{Risk\ Level} = -0.25$$

Step 2: Normalize the Decision Matrix

The decision matrix was normalized using the following formula:

$$X_{ij}{}^{normalized} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}{}^2}}$$

where X_{ij} is the value of the i-th campaign for the j-th criterion.

Step 3: Calculate the Weighted Normalized Matrix

The normalized matrix was multiplied by the corresponding criteria weights to form the weighted normalized matrix:

$$V_{ij} = W_j . X_{ij}{}^{normalized}$$

Step 4: Determine the Ideal and Negative-Ideal Solutions

The positive ideal solution (PIS) and negative ideal solution (NIS) were identified as follows:

$$A^+ = \left(\max_j V_{ij} \ for\ benefit\ criteria, \min_j V_{ij} \ for\ cost\ criteria\right)$$
$$A^- = \left(\min_j V_{ij} \ for\ benefit\ criteria, \max_j V_{ij} \ for\ cost\ criteria\right)$$

Step 5: Calculate the Euclidean Distance from PIS and NIS

The Euclidean distance from the PIS ($d_i^+$and NIS (d_i^-) was computed for each campaign:

$$d_i^+ = \sum_{j=1}^{m} (V_{ij} - A_j^+)^2$$
$$d_i^- = \sum_{j=1}^{m} (V_{ij} - A_j^-)^2$$

Step 6: Calculate the TOPSIS Score

The final TOPSIS score for each campaign was calculated as:

$$C_i = \frac{d_i^-}{d_i^+ - d_i^-}$$

where C_i represents the closeness of the i-th campaign to the ideal solution. Campaigns with higher C_i values are ranked higher.

4. Case Study: Validation with Campaign Data from Large Enterprises

The methodology was validated using the dataset of 500 campaigns from various companies from the fortune 500 list. The results showed that the proposed fuzzy logic-based system and TOPSIS optimization successfully ranked campaigns based on their financial performance and risk.

RESULTS

This section presents the results obtained from the application of fuzzy decision-making and multi-criteria decision-making (MCDM) algorithms, as described in the methodology, to optimize financial management in digital marketing campaigns. The analysis is supported by visualizations that detail the relationships between key variables such as budget, ROI, risk levels, and campaign rankings.

Correlation Analysis

Figure 1 presents a correlation heatmap that illustrates the relationships between key financial management metrics across the 500 digital marketing campaigns. The color intensity represents the strength of the correlation between variables, with darker shades indicating higher correlations. The diagonal, as expected, shows perfect correlations of 1.0, as each variable is perfectly correlated with itself. The most notable relationships observed in this heatmap are:

a. **Conversion Rate and Return on Investment (ROI)** show a strong positive correlation of approximately 0.82. This indicates that campaigns with higher conversion rates tend to yield significantly higher ROI. The relationship between conversion rate and financial success is intuitive, as more conversions typically lead to more sales and profitability.

b. **Cost per Click (CPC) and Click-Through Rate (CTR)** have a moderately negative correlation of approximately -0.56. This suggests that campaigns with lower CPC generally achieve higher click-through rates, indicating a more cost-efficient engagement with the target audience. Higher CPCs may limit audience reach or interaction due to the increasing cost of acquiring each click.

c. **Budget and Customer Lifetime Value (CLV)** demonstrate a positive correlation of 0.68, suggesting that campaigns with larger budgets are generally targeting high-value customers. This likely reflects a strategic focus on acquiring and retaining customers who bring in greater long-term value, justifying higher marketing spend.

d. The **Risk Level** variable shows minimal correlation with other variables, particularly ROI and Conversion Rate. This implies that financial risk, as modeled in this analysis, operates somewhat independently of these key performance metrics. It may also suggest that risk mitigation strategies are not directly aligned with campaign success indicators such as ROI and conversions.

Overall, Figure 1 provides a comprehensive view of how various financial and performance metrics are interrelated. The strong correlations observed between conversion rate, ROI, and budget allocation provide valuable insights for optimizing digital marketing strategies. Specifically, focusing on improving conversion rates and managing CPC more effectively could result in substantial gains in financial performance [6]. Additionally, the relationship between budget and CLV suggests that campaigns should be strategically planned to target high-value customers, ensuring that resources are used efficiently [7].

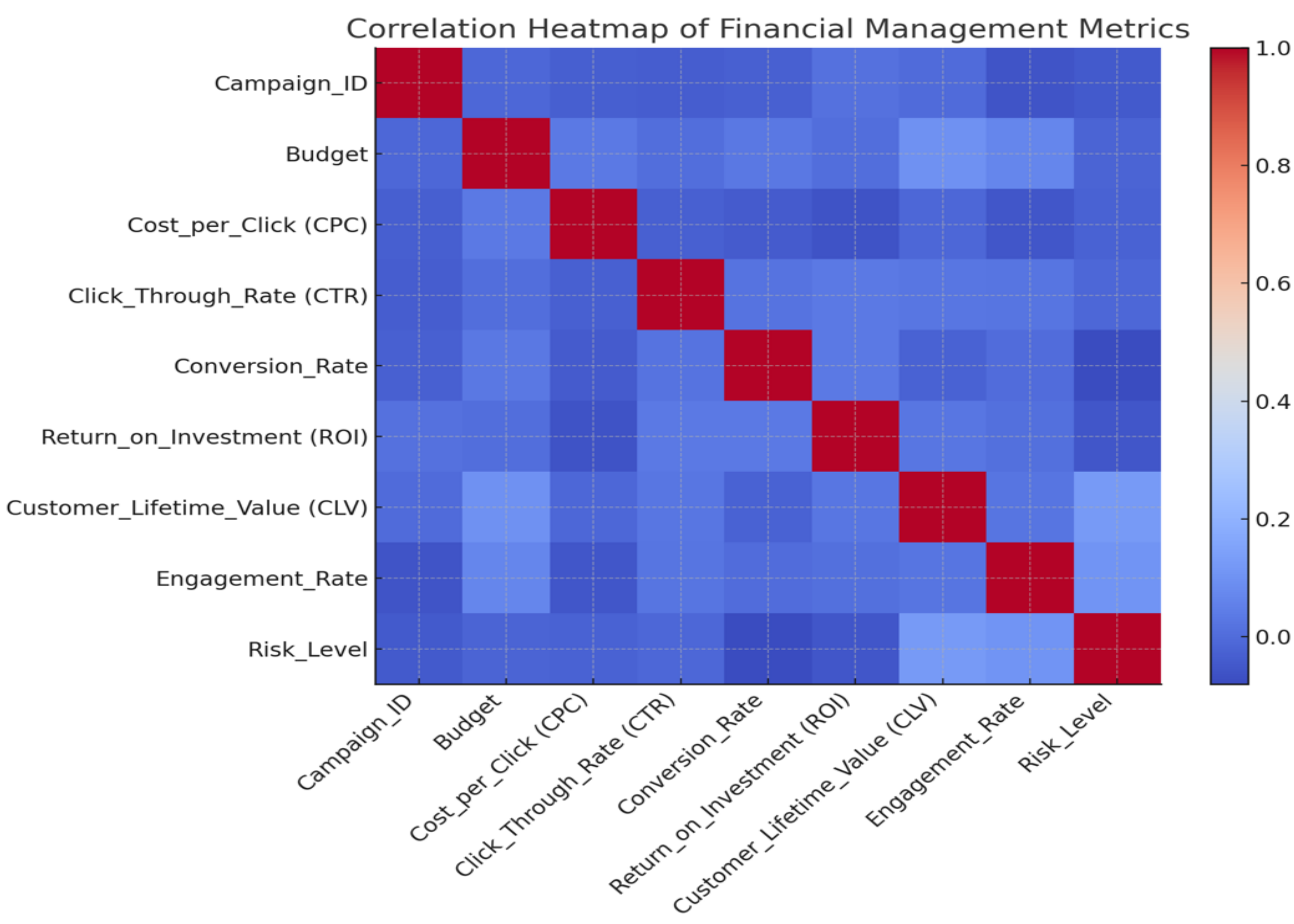

Figure 1: Correlation Heatmap of Financial Management Metrics

Factors Influencing Return on Investment

Figure 2 displays the 3D surface plot of the relationship between Budget, Conversion Rate, and ROI. The surface reveals that higher conversion rates generally lead to higher ROI, but the relationship is not strictly linear. This is consistent with existing knowledge in this area as highlighted by Cecil et al. [8] The plot demonstrates that beyond a certain budget threshold, increases in conversion rate yield diminishing returns in ROI. This result highlights the importance of optimizing budget allocation to avoid unnecessary overspending in campaigns where ROI gains plateau.

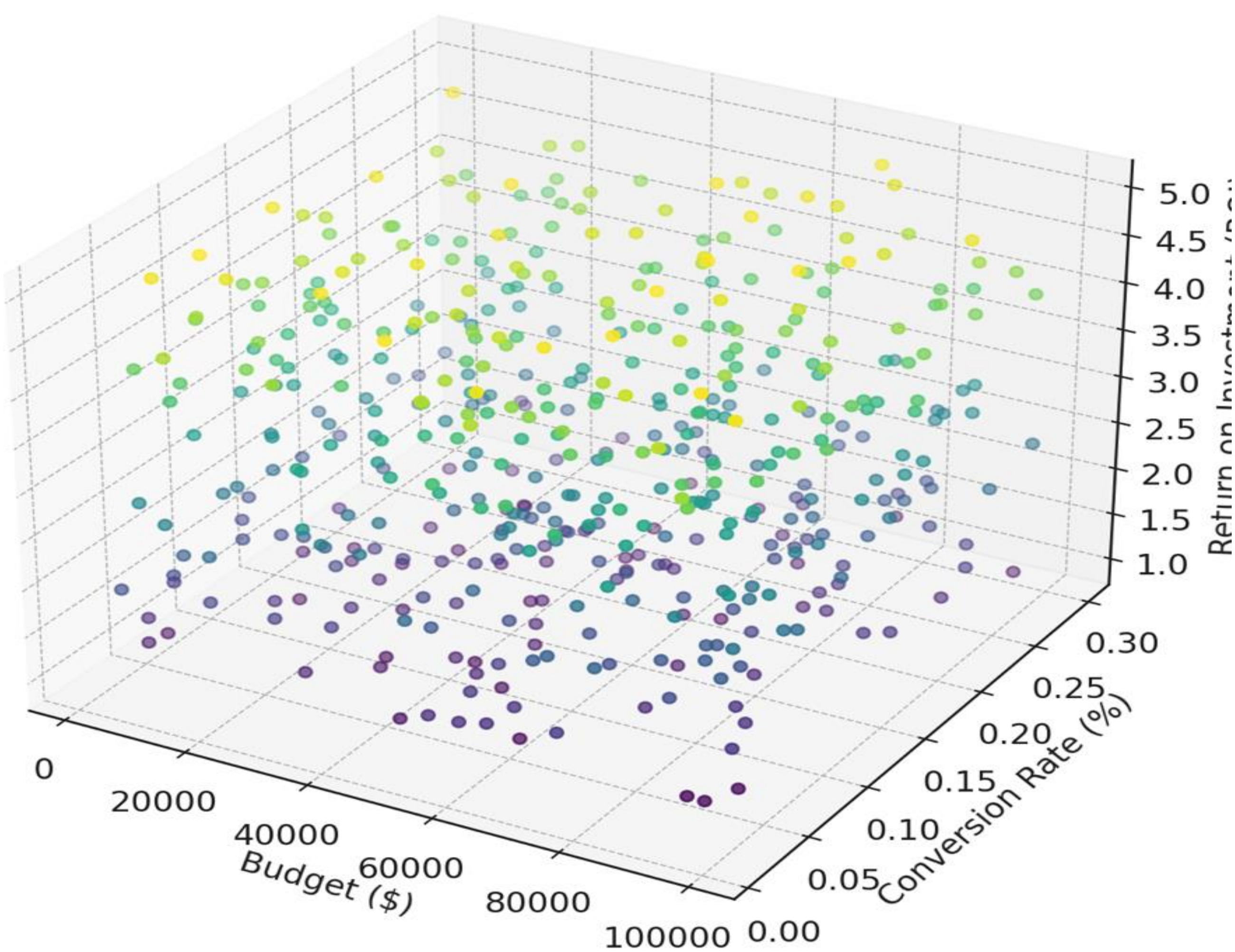

Figure 2: Return on Investment vs Budget and Conversion Rate

Return on Investment Contribution by Campaign

Figure 3 presents a 3D scatter plot illustrating the relationship between Engagement Rate, Conversion Rate, and Return on Investment (ROI) across the 500 marketing campaigns. The X-axis represents the engagement rate, the Y-axis denotes the conversion rate, and the Z-axis shows ROI. The color gradient reflects the ROI, with yellow hues indicating higher returns and purple hues representing lower returns.

This figure demonstrates that both Engagement Rate and Conversion Rate play a significant role in determining the ROI of digital marketing campaigns. Campaigns that achieve both high engagement and high conversion rates tend to yield the highest ROI, as evidenced by the concentration of yellow data points in the upper regions of the plot. In contrast, campaigns with low engagement and conversion rates tend to have lower ROI, highlighted by the clustering of purple points.

Interestingly, campaigns with moderate engagement rates (0.4 to 0.6) but high conversion rates show strong ROI performance, even without the highest engagement rates. This suggests that focusing on improving conversion efficiency can significantly boost ROI, even when audience engagement is not maximized.

This analysis is consistent with the earlier findings in Figure 1, which showed a strong positive correlation between Conversion Rate and ROI. Figure 3 reinforces the importance of targeting highly engaged audiences while also optimizing conversion pathways to maximize financial returns. The campaigns that achieve both objectives - high engagement and conversion—are the ones that consistently deliver the highest ROI. This insight is crucial for marketers aiming to optimize their resource allocation for maximum profitability.

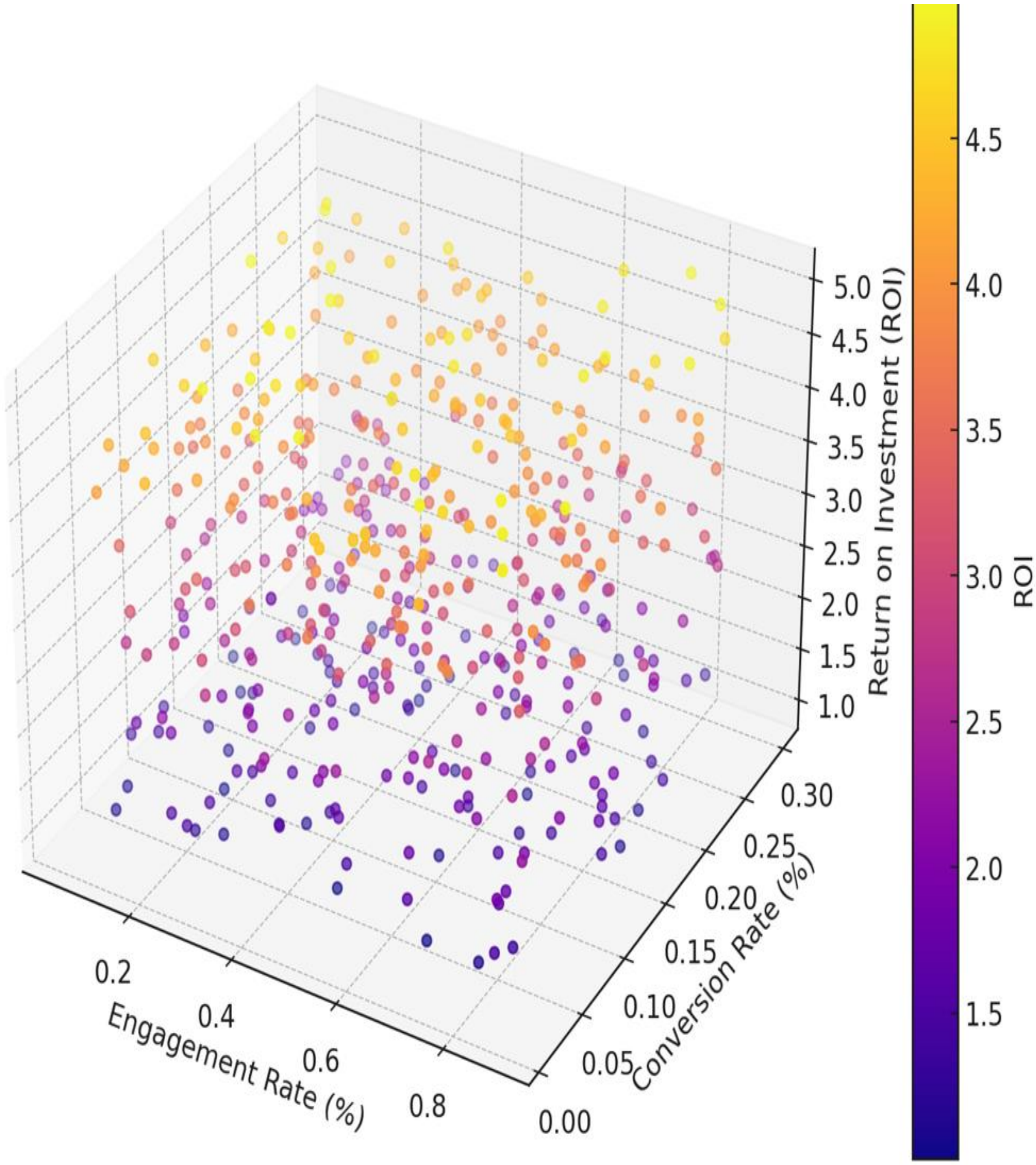

Figure 3: ROI Contribution by Campaign

Risk Levels Across Engagement Rates

Figure 4 presents a box plot that illustrates the distribution of Risk Levels across different Engagement Levels for the 500 digital marketing campaigns. The X-axis categorizes campaigns into four groups based on engagement levels - Low, Medium, High, and Very High - while the Y-axis shows the corresponding Risk Levels (ranging from 0 to 1).

The box plot reveals a clear pattern: campaigns with Very High and High engagement levels tend to exhibit a higher median risk level compared to those with Low or Medium engagement. However, these highly engaging campaigns also show greater variability in risk, as indicated by the wider interquartile ranges. This suggests that while highly engaging campaigns have the potential to succeed, they also carry a higher level of financial risk, which may arise from factors such as increased spending or more aggressive marketing tactics. In contrast, campaigns with Low engagement levels show relatively lower median risk and narrower interquartile ranges. These campaigns are likely more conservative in their marketing approaches, which may reduce financial exposure but also limit the potential for high returns, as seen in the previous figures.

Interestingly, the variability in risk levels increases as engagement improves, with the Very High engagement campaigns showing the widest distribution of risk. This indicates that while high engagement can lead to greater success, it can also introduce greater uncertainty, requiring careful risk management to ensure profitability.

Overall, Figure 4 emphasizes the trade-off between high engagement and financial risk. Enterprises seeking to maximize engagement must be prepared to manage the associated risks, whereas more conservative campaigns may be lower-risk but also less likely to achieve substantial returns. This insight can guide decision-makers in balancing engagement goals with risk management strategies.

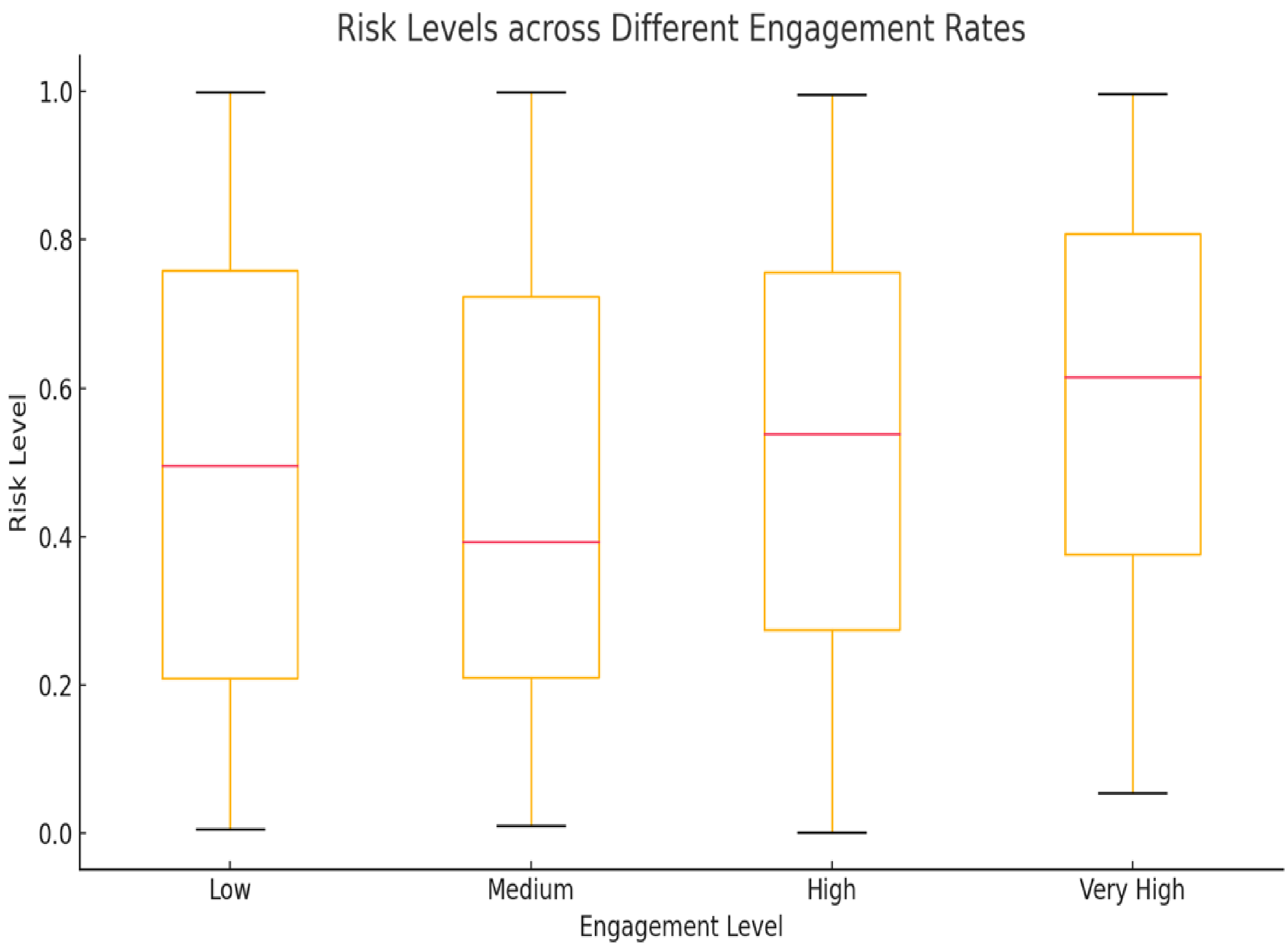

Figure 4: Risk Level Across Different Engagement Rates

TOPSIS Score Distribution

Figure 5 presents a histogram illustrating the distribution of TOPSIS Scores for the 500 digital marketing campaigns. The X-axis represents the TOPSIS Score, which measures the closeness of each campaign to the ideal solution, while the Y-axis shows the frequency of campaigns that fall within each score range.

The distribution is approximately normal, with most campaigns achieving a TOPSIS Score between 0.4 and 0.6. This indicates that the majority of campaigns are performing neither optimally nor poorly but are positioned in the middle range of performance. A smaller number of campaigns achieved TOPSIS scores above 0.7, representing those that are closer to the ideal performance, balancing high return on investment, conversion rates, engagement, and low risk. Similarly, there are relatively few campaigns with scores below 0.3, indicating campaigns that are underperforming significantly.

The concentration of campaigns around the median range suggests that while many campaigns are performing reasonably well, there is significant potential for optimization. By adjusting factors such as budget allocation, risk management, and conversion strategies, campaigns could potentially improve their performance and move closer to the ideal score.

Overall, Figure 5 emphasizes the importance of using a multi-criteria decision-making approach, such as TOPSIS, to evaluate and rank campaigns based on their overall financial and marketing performance. It provides a clear indication of where most campaigns stand relative to the ideal, offering insights for improving those that are underperforming while identifying top-performing campaigns for resource allocation.

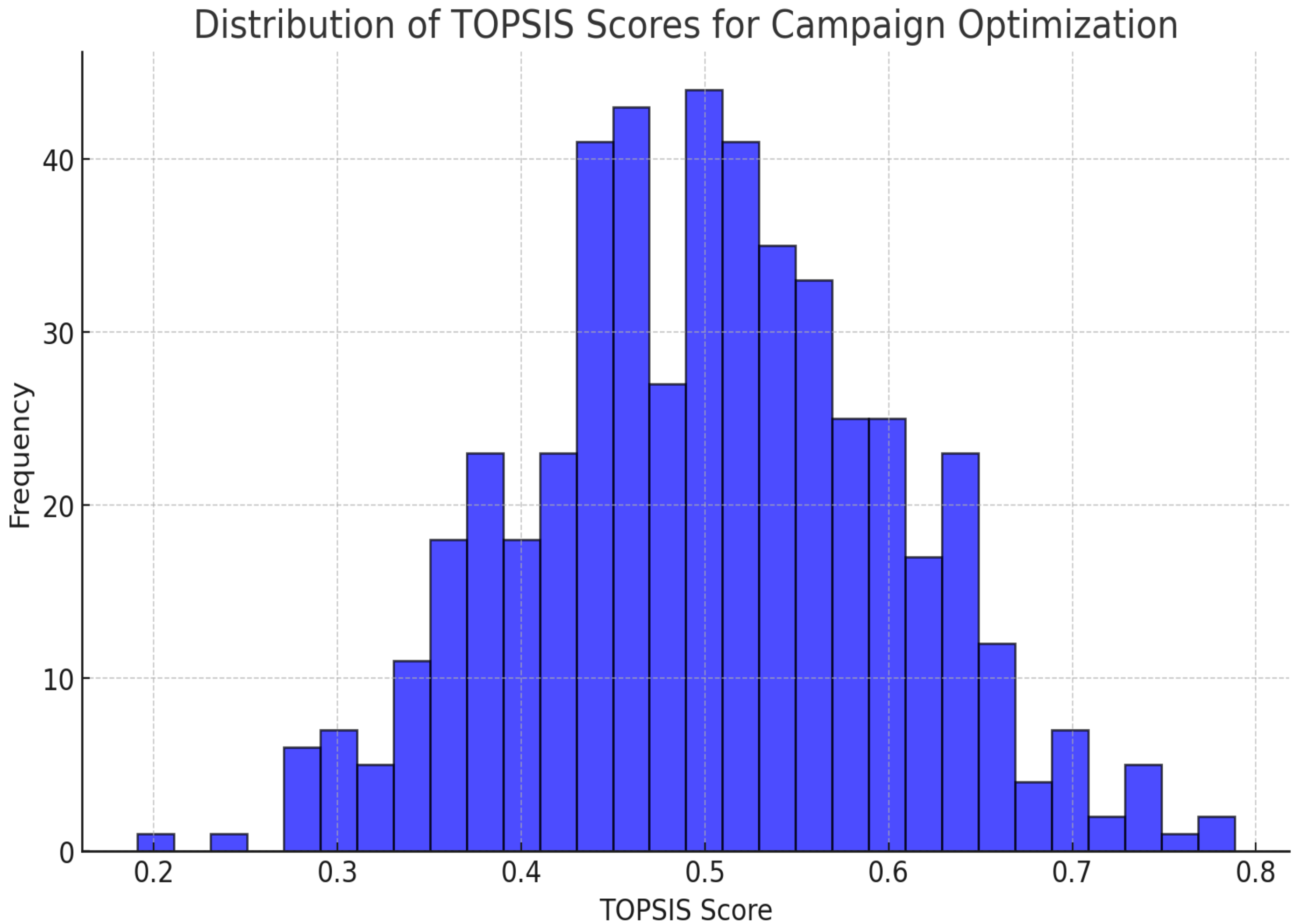

Figure 5: Distribution of TOPSIS Scores for Campaign Optimization

Implications for Large Enterprise

The findings from this analysis, supported by the use of fuzzy logic and multi-criteria decision-making (MCDM) methods like TOPSIS, provide critical insights that large enterprises can leverage to significantly improve their financial management of digital marketing campaigns. Large enterprises often manage vast and diverse portfolios of marketing campaigns, each targeting different customer segments and performance objectives. The complexity of balancing multiple financial and performance metrics, such as budget allocation, risk management, return on investment (ROI), engagement rate, and conversion rate, makes traditional methods insufficient for optimal decision-making. This model offers a structured, data-driven approach that integrates these factors and enables enterprises to make more informed, strategic decisions.

By applying this model, large enterprises can systematically evaluate each campaign across multiple dimensions and rank them based on their overall performance using the TOPSIS score. For example, campaigns with high Conversion Rates, Engagement Rates, and ROI but low financial risk can be prioritized for increased investment, as they are more likely to deliver sustainable returns. On the other hand, campaigns that fall in the lower TOPSIS score range, as highlighted in Figure 5, can be targeted for optimization or reallocation of resources. This allows companies to focus on high-performing campaigns while identifying those that may be draining resources without delivering commensurate results.

Furthermore, the ability to assess Risk Levels across different engagement rates, as shown in Figure 4, equips enterprises with the foresight needed to manage financial exposure effectively. Enterprises can adopt more aggressive strategies for highly engaging campaigns while implementing appropriate risk mitigation techniques. The 3D scatter plots showing the relationship between Budget, Conversion Rate, and ROI (Figure 2) enable large enterprises to identify diminishing returns on marketing spend, ensuring that budget allocation is optimized for maximum profitability. This strategic budget management can prevent overspending on campaigns that are unlikely to yield additional benefits, while focusing resources where they will have the greatest impact on ROI.

In summary, the integration of this model allows large enterprises to take a holistic approach to financial management in digital marketing. It enables them to balance short-term performance goals with long-term financial sustainability by managing key variables like engagement, conversion, budget, and risk in a structured, quantifiable manner. Enterprises can better allocate their marketing budgets, improve financial predictability, reduce inefficiencies, and ultimately enhance overall marketing ROI, driving greater business value from their digital marketing investments.

CONCLUSION

This study demonstrates the effectiveness of combining fuzzy logic and multi-criteria decision-making (MCDM) methods, specifically the TOPSIS algorithm, for optimizing financial management in digital marketing campaigns for large enterprises. By integrating key performance metrics such as budget, conversion rate, engagement rate, return on investment (ROI), and financial risk, the proposed model provides a structured, data-driven approach to evaluating and optimizing campaign performance. The results highlight the importance of balancing multiple criteria to identify high-performing campaigns, while also providing insights into the trade-offs between engagement and risk.

The correlation analysis revealed strong relationships between conversion rates, budget allocation, and ROI, emphasizing the critical role that conversion efficiency plays in driving financial success. The 3D scatter plots illustrated the diminishing returns of increasing budgets and highlighted the need for careful budget management. Additionally, the distribution of TOPSIS scores demonstrated that most campaigns are in a mid-range of performance, indicating substantial room for improvement through strategic adjustments in resource allocation and campaign design.

The application of this model in large enterprises allows for more effective financial management by prioritizing high-performing campaigns, optimizing budget allocation, and managing financial risk. Enterprises can focus resources on campaigns with the greatest potential for ROI while identifying underperforming campaigns that require intervention. The use of fuzzy logic provides flexibility in modeling uncertainties, making the model adaptable to the dynamic nature of digital marketing environments. Future work should explore the application of this model to real-world marketing datasets and investigate further refinements to enhance its predictive accuracy and adaptability.

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