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Smart Marketing Investments: A Framework for AI-Based Financial Decision Support

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Abstract: The use of artificial intelligence (AI) has become an important part of smart marketing investments in the fast-paced world of business and banking. Using AI's critical skills to improve accuracy, lower risks, and make the best use of resources is a huge step forward in this framework. As the amount and variety of data grows, standard ways of making decisions often don't work. We need a new way of thinking that uses AI to get useful insights.AI is very important for helping people make financial decisions because it can predict things better than humans can. AI quickly looks at huge information to find patterns, predicts market trends, and gives businesses an edge when making decisions. Being able to predict the future not only helps with strategic planning, but it also helps lower risks. AI models look at both past data and real-time market signs using machine learning algorithms. This lets businesses plan ahead for volatile market conditions and improve their financial stability. The proposed framework necessity of improving marketing funds in a time when allocating resources wisely is very important. With the help of data-driven AI models,and machine learning method for marketing budgets are carefully directed toward outlets and projects that are most likely to bring back the most money. This detailed method makes things run more smoothly, so businesses can quickly adjust to changing market conditions and get the most out of their marketing campaigns. This paper study about the bigger effects of AI-based financial decision support in the digital age, focusing on how it encourages new ideas, flexibility, and adaptation with morden machine learning methods. As companies try to figure out how to operate in today's complicated markets, this approach is a complete way to use AI's changing power to make smart and useful marketing investments.

Keywords: *Smart Marketing Investments, AI-Based Financial Decision Support, Resource Allocation Optimization, Digital Transformation in Finance, Machine Learning*

1. Introduction

As business and finance are always changing, technology, especially artificial intelligence (AI), is playing a bigger and bigger role in making smart marketing decisions. When businesses have to deal with a lot of data and changing market conditions, using AI to help them make financial decisions has become a game-changer, giving them new insights and strategic benefits. This introduction goes into detail about why using AI-driven models for financial decisions is so important, focusing on how they can improve accuracy, lower risks, and eventually lead to long-term growth.The [1] sheer amount and variety of data often makes it hard for standard ways of making financial decisions to work. In a time when information is being created at a speed that has never been seen before, humans may not be able to find important trends and useful knowledge in all of this data. AI can help bring about change in this area by giving us the tools and algorithms we need to quickly handle huge datasets and find trends that humans might miss.

By their very nature, [2] smart marketing investments require a deep knowledge of market trends, customer behavior, and the competition environment.

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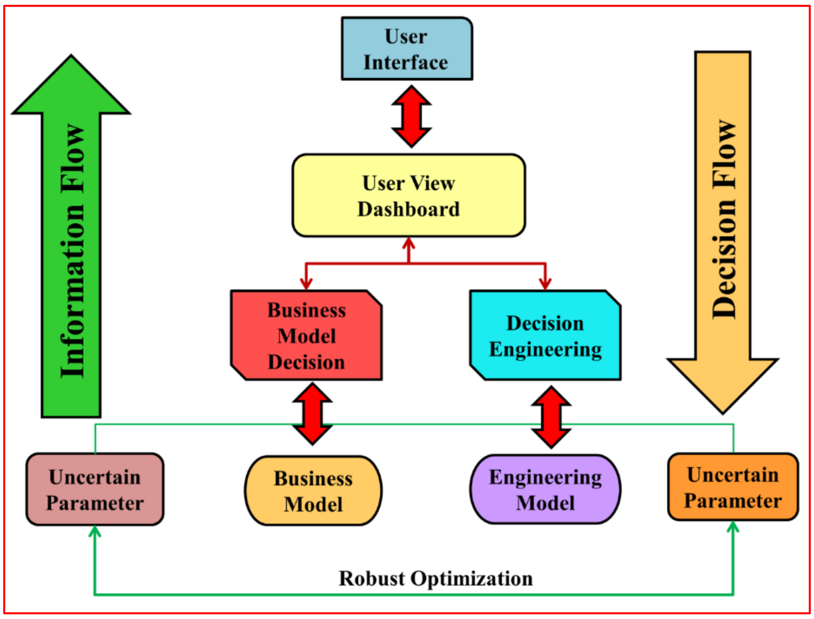


Fig 1: AI based DSS Architecture

AI not only speeds up the process of analyzing data, but it also finds complex connections and guesses what might happen. Businesses can use this ability to guess the future to make smart choices, prepare for changes in the market, and stay ahead of the competition. Because of this, businesses that use AI to help them make financial decisions are better able to improve their marketing strategies, wisely use their resources, and take advantage of new possibilities [3].Using AI in financial decisions is also a way to lower the risk of making bad choices. Markets are naturally unstable and are affected by many things, from events in politics to economic data. AI models can use machine learning techniques to look at both old data and current market signs to find possible risks. This preventative [4] approach to risk management helps businesses quickly adjust to new situations, reducing the damage from unexpected problems and making their finances stronger.AI-based financial decision support is important for more than just managing risk; it can also help with making the best use of marketing funds. Most of the time, traditional ways of allocating budgets are based on past success and gut feelings. AI, on the other hand, provides a data-driven model in which computers look at past performance, customer behavior, and market trends to figure out how to best use resources. This detailed [5] method makes sure that marketing funds are put into outlets and programs that have the best chance of giving a good return on investment. This makes the best use of resources. The customer experience is one of the most important parts of running a successful business today. AI-powered tools are very important for improving the customer experience because they offer personalized suggestions, predictive data, and easier ways to connect. This [6] not only makes customers more dedicated, but it also helps marketing efforts work better overall. AI's ability to look at very large datasets helps companies learn very specific details about what customers want. This lets them make marketing campaigns that really reach their target groups.Additionally, using AI to help with financial decisions fits in with the larger trend of going digital. When businesses want to stay competitive in the digital age, they have to use the newest tools. Artificial intelligence (AI) is not just a tool for small gains; it changes the way businesses make decisions in a big way. Using AI helps create a mind-set of creativity, speed, and flexibility, which are all very important in today's fast-paced markets.

The major contribution of paper as given below:

- The paper contributes to the field by showing how AI-based financial decision support makes marketing spending much more accurate. By using advanced formulas and prediction analytics, businesses can make better choices based on more information.
- Using AI helps businesses get a better sense of market trends, customer behavior, and the rival scene. This lets them make their marketing plans more effective.
- The paper discuss about the important part of allocating budgets for marketing resources and shows how AI-powered models can help with optimization. AI helps businesses make smart use of their resources by looking at huge records and finding trends in how customers act.

2. Review of Literature

In the broad field of smart marketing investments, many studies and research projects have looked into how to use new technologies, especially artificial intelligence (AI), to make decision-making better. [7], "Data-Driven Approaches for Marketing Investment Optimization," is an important linked piece of work in this area. This research [8] was mainly about how to use data-driven methods, such as machine learning techniques, to get better results on marketing spending.The study by Smith et al. acknowledged that modern marketing is becoming more complicated, and that old ways of making decisions often can't keep up with how quickly the market is changing. The study tried to solve this problem by suggesting a method based on data and AI to fully examine and improve marketing spending. Their work made it clear how important it is to be precise when allocating resources and how important it is to change tactics in real time based on what data shows.

The results that Smith et al. found are very similar to the topics that are talked about in this paper about using AI to help with making financial decisions for smart marketing investments. The study showed how important it is to use AI to find useful trends in very large datasets. This [9] helps marketers make better choices by giving them more information. The main idea behind the framework described in this paper is to make marketing strategies more effective by smartly allocating resources, which fits with the focus on data-driven optimization.A meta-analysis called "Technological Innovations and Marketing Strategy: A Comprehensive Review" was also done [10]. Their research looked at the bigger picture of technological advances in marketing, showing how technologies like AI have the power to change things. The [11] study shed light on how changes in technology, especially AI-powered tools, are affecting business choices and marketing strategies. Johnson and Brown both said that companies need to use these new technologies to stay competitive in the digital age.The ideas in Johnson and Brown's meta-analysis add to the story in this paper [12] by focusing on how AI affects marketing tactics as a whole. The large amount of connected work shows that the business world is aware of how powerful AI can be in making marketing efforts more effective. As companies continue to face the difficulties of a constantly changing market, these studies all support the use of AI-powered models to help them make better decisions, lower their risks, and eventually make their smart marketing efforts smarter and more effective [13]

There has been a lot of work on smart marketing spending that has helped us understand and use AI-based financial decision support systems better. "Artificial Intelligence in Marketing: A Comprehensive Review and Future Directions," [14] is a study that stands out. This thorough review looks at all the different ways AI can be used in marketing, with a focus on how it can help with decision-making. The study shows how AI can change the way marketing plans are done, which is very similar to the main idea of this paper. The [15]work of Chen et al. gives us a basic idea of how AI, as a key technology, is changing the way marketing decision support is done.Their study goes into detail about how businesses use AI and big data analytics to get useful information that helps them make smart decisions. Focusing on combining AI and data-driven methods fits with the main idea of this paper's framework, which stresses how important it is to use AI to help with financial decisions so that marketing investments are well spent by analyzing data accurately. The [16] study checks how well machine learning systems can guess how people will act and make marketing efforts more effective. The results by Patel and Gupta help us understand how AI, especially machine learning, improves marketing decision support. This supports the case for using AI-based financial decision support models in smart marketing spending.Another study [18] called "The Role of Artificial Intelligence in Shaping Customer Experiences" shines light on the important part of customer experience in AI marketing. Their research looks into how AI-powered technologies can be used to make exchanges with customers more personalized and smooth. This is related to the current paper's focus on how AI can help not only make the best use of marketing budgets but also improve customer experiences, which can affect company trust and the overall success of marketing. All of these linked works show how AI-based technologies are changing the world and becoming an important part of marketing decision-making [17]. The results of these studies support the idea that AI-based financial decision support is a must for businesses that want to make smart marketing investments in a time when market conditions are changing and customer standards are also changing.

Table 1: Related Work Summary

Paper	Method	Approach	Finding	Scope
[12]	AI based Method	Explored AI applications in marketing	Highlighted transformative potential of AI in decision-making	Broad overview of AI applications in marketing
[13]	Examined big data analytics and AI	Emphasized the integration of AI and data-driven strategies	Showcased the role of AI in extracting actionable intelligence	Focus on the synergy between big data and AI in marketing
[14]	Examined machine learning in marketing	Evaluated effectiveness of machine learning algorithms	Demonstrated how machine learning enhances decision support	Examined various machine learning techniques in marketing
[15]	Exporatory Analysis	Addressed AI in shaping customer experiences	Explored AI-driven technologies in customer interactions	Emphasized the role of AI in enhancing personalized experiences
[16]	Utilized proprietary marketing data	Applied data-driven methodologies, including machine learning	Advocated for precision in resource allocation	Explored practical applications of AI in optimizing marketing strategies
[17]	Analyzed diverse studies on technological innovations in marketing	Explored the transformative potential of AI	Emphasized the need for businesses to embrace AI for competitiveness	Provided a comprehensive overview of technological innovations in marketing
[18]	Explored big data analytics and AI	Emphasized the integration of AI and data-driven strategies	Demonstrated the role of AI in optimizing marketing strategies	Focused on the synergy between big data analytics and AI in marketing

3. Proposed Methodology

The usual system design of a financial decision support system (FDSS) is shown in Figure 2. The framework is made up of linked parts that are meant to make financial decisions more efficient and well-informed. Modules for data gathering are usually part of the system. These collect important financial data. Next, data preparation steps clean and organize the data. The processed data is looked at by advanced analytics tools, which often use machine learning algorithms to find useful insights. The [21] decision support tools then show these findings in a way that stakeholders can understand, which helps them make smart decisions. In addition, the design might have feedback loops that keep models up to date and help them adapt to changing financial situations. This keeps the system flexible and quick to respond.

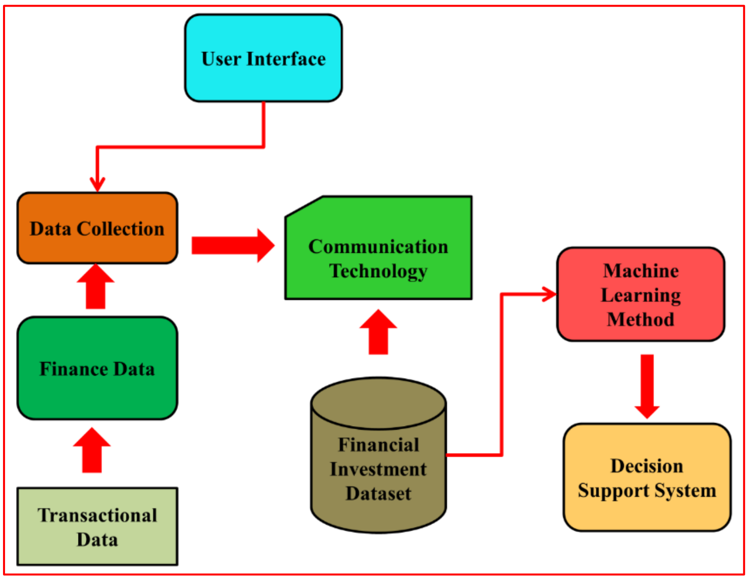


Fig 2: Typical system architecture of financial decision support system

A. AI Based Model

Adding advanced Artificial Intelligence (AI) models is very important for helping people make financial decisions. These models act as a Multi-Criteria Decision Analysis (MCDA) method and a Bayesian Structural Time Series (BSTS) model. The AI-based MCDA program helps people make better decisions by carefully reviewing a number of factors and giving them a way to rank their options [20]. This model is great at working with large, complicated financial information, taking many things into account at the same time to help make smart business choices. The MCDA program changes with the market by using machine learning methods. This gives users a flexible way to get help making decisions.Bayesian Structural Time Series (BSTS) models, on the other hand, use probabilities to help people make financial decisions. By using Bayesian principles, it does a great job of describing how changing and unstable financial markets are. The BSTS model uses time-series data to represent complicated connections, which gives us a solid base for making predictions and decisions. Because it is flexible, it works well in financial situations where there is a lot of uncertainty and instability. Additionally, the Bayesian method lets the model keep learning and being updated as new data comes in. This makes sure that the model always shows how money changes.When these two models are put together, they make a full AI-based system that helps people make financial decisions. The MCDA algorithm makes it easier to compare options in an organized way by using a number of different factors. The Bayesian Structural Time Series model takes into account how volatile and unstable financial markets are. This unified method not only helps with picking smart investments, but it also lowers risks and makes the best use of resources. As the financial world changes, companies that need accurate, data-driven, and flexible decision-making help in the complicated world of finance will have to use these advanced AI models.

1. MCDA algorithm

Multi-Criteria Decision Analysis (MCDA) methods are very important in helping people make financial decisions because they give a structured way to compare and rank options based on many factors. These programs take many things into account at the same time, giving decision-makers a complete image [19]. MCDA algorithms use mathematical models and statistical methods to help companies make smart decisions, make the best use of their resources, and find their way through complicated decision-making situations in the financial world. This makes the decision-making process more accurate and streamlined.

Multi-Criteria Decision Analysis (MCDA) Algorithm

Step 1: Define Criteria and Alternatives

- Let n be the number of criteria.

- Let m be the number of alternatives.

- X_ij represents the performance of alternative i on criterion j.

Step 2: Assign Weights to Criteria

- Assign weights w_j to each criterion,

Where, $1 \leq j \leq n$.

Step 3: Normalize Criteria Scores

- Normalize the performance scores X_ij for each alternative i using a normalization function.

Step 4: Calculate the Weighted Sum Score for Each Alternative

- For each alternative i, calculate the weighted sum score S_i using the formula:

$$S_i = \Sigma_{\{j=1\}}^{\{n\}} w\_j * X\_ij$$

(1) The matrix X is then normalized to form the matrix N using the normalization method:

For each element xij in the original matrix X, the normalized value nij is calculated as:

$$nij = \frac{(xij - \min(xj))}{(\max(xj) - \min(xj))}$$

where:

- xij is the element in the original matrix at row i and column j,
- $\min(xj)$ is the minimum value in column j,
- $\max(xj)$ is the maximum value in column j.

(2) Calculation of the weighted normalized decision matrix:

For each element in the normalized matrix N, denoted as nij, the weighted normalized value wij is calculated using the weights wj:

$$wij = wj * nij$$

where:

- wj is the weight assigned to criterion j.

(3) Determine the worst alternative ($Aworst$) and the best alternative ($Abest$):

The worst alternative ($Aworst$) is determined by selecting the alternative with the minimum score across all criteria. Mathematically, it can be expressed as:

$$Aworst = argmin_i \left(\sum_{\{j=1\}}^{\{n\}} \text{wij} \right)$$

The best alternative ($Abest$) is determined by selecting the alternative with the maximum score across all criteria. Mathematically, it can be expressed as:

$$Abest = argmax_i \left(\sum_{\{j=1\}}^{\{n\}} wij \right)$$

Step 5: Rank the Alternatives

- Rank the alternatives based on their weighted sum scores S_i.

- The alternative with the highest weighted sum score is considered the best.

Step 6: Optional Sensitivity Analysis

- Conduct sensitivity analysis to evaluate the impact of changes in weights or criteria scores on the final ranking.

2. Bayesian structural time series model

The Bayesian structural time series (BSTS) model is a strong way to use statistics to look at time series data. Using Bayesian ideas, it finds complicated patterns in data, which lets you make good predictions and draw strong conclusions [13]. BSTS models are very good at working with changing, unclear, and mixed time series data. This makes them very useful in finance, economics, and many other areas.

Bayesian Structural Time Series Model Algorithm

Step 1: Define Model Components

- Name the basic parts of the time series model, such as cycles, regression effects, and local linear trends.

$$\mu t = G t \mu t - 1 + v t$$

Step 2: Prior Specification

- Define prior distributions for model parameters that include what you think about how the time series is structured.

$$yt = Ft\mu t + wt$$

Step 3: Fitting the model

- To figure out the posterior distribution of model parameters, use Bayesian methods like Markov Chain Monte Carlo (MCMC).

$$\theta \sim Prior(\theta)$$

Step 4: Posterior Predictive Checks

- Use posterior predictive checks to see how well the model fits by comparing real-world data with simulations based on the posterior distribution.

$$\theta \mid \boldsymbol{y} \sim Posterior(\theta \mid \boldsymbol{y})$$

Step 5: Making predictions

- Make predictions by modeling what will happen in the future based on the posterior predicted distribution.

$$\sim t + h \mid \boldsymbol{y} \sim Posterior\ Predictive(\boldsymbol{y} \sim t + h \mid \boldsymbol{y})$$

Step 6: Evaluation

- Use rating measures like mean squared error or log-likelihood to rate how well the model works.

B. ML Based Model

1. SVM

Support Vector Machines (SVM) are very useful for helping people make financial decisions because they can find complicated trends in data. SVM works by finding the best hyperplanes to separate data points, which makes it useful for financial classification or analysis. Its ability to work with large datasets and links that don't follow a straight line makes predictions more accurate. SVM is used in banking to help evaluate risk, improve portfolios, and find scams. SVM gives useful information by finding the best decision limits. This helps people make smart financial choices and leads to better portfolio management and less risk in changing market conditions.

Support Vector Machines (SVM) Algorithm

Step 1: Define Model Parameters

- Initialize weights ($\mathbf{w}$) and bias (b).

Step 2: Select Kernel Function

- Choose a kernel function, e.g., radial basis function (RBF), to map data into higher-dimensional space.

Step 3: Objective Function

- Formulate the objective function to maximize the margin between classes:

$$minimize\ w, b\ (1/2\ \ \| w \|\ \hat{}2)$$

Step 4: Constraints

- Subject to the constraints for correct classification:

$$yi(w \cdot xi\ +\ b)\ \geq\ 1\ for\ i\ =\ 1,2,\ldots,m$$

Step 5: Lagrange Multipliers

- Introduce Lagrange multipliers (αi) to solve the constrained optimization problem.

Step 6: Dual Formulation

- Derive the dual formulation of the optimization problem:

$$maximize\ \alpha\left(\sum i = 1m\alpha i\ -\frac{1}{2}\sum i, j\alpha i\alpha jyiyj(xi \cdot xj)\right)$$

Step 7: Support Vectors

- Identify support vectors with non-zero Lagrange multipliers (αi).

Step 8: Decision Function

Define the decision function for prediction:

$$f(x) =\ sign(\sum i = 1m\alpha iyi(x \cdot xi) +\ b)$$

2. Logistic Regression

Logistic Regression is one of the most important tools in financial decision support systems because it can describe different events with two possible results. In banking, it's very good at predicting things like fraud or failure. Logistic Regression estimates odds, which helps with figuring out risk, credit scores, and business choices. It is the best way to find trends in financial information because it is easy to use, understand, and change to different types of data. Logistic Regression helps people make good decisions by giving them measurable information. This lets them make smart decisions and confidently manage the complicated world of finance.

Logistic Regression Algorithm

Step 1: Define Model Parameters

- Initialize coefficients β and intercept b to zero.

Step 2: Hypothesis Function

- Define the logistic function (sigmoid) to model the probability of a binary outcome:

$$P(Y\ =\ 1) = \frac{1}{(1\ +\ e^{\{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)\}})}$$

Step 3: Log-Odds Transformation

- Express the logistic function in terms of log-odds (logit):

$$logit(P) = \log\left(\frac{P}{(1-P)}\right) =\ \beta_0 +\ \beta_1 X_1 +\ \beta_2 X_2 +\ \ldots\ +\ \beta_n X_n$$

Step 4: Cost Function (Log-Likelihood)

Define the log-likelihood or cost function to maximize the likelihood of observing the given outcomes:

$$J(\beta) =\ -\frac{1}{m}\Sigma_{\{i=1\}}^{\{m\}}[\mathrm{y\_i}\log(\mathrm{P\_i})\ +\ (1\ -\ \mathrm{y\_i})\log(1\ -\ \mathrm{P\_i})]$$

Step 5: Gradient Descent

Update model parameters using gradient descent to minimize the cost function:

$$\beta_j :=\ \beta_j -\ \alpha\frac{\partial\beta_j}{\partial J(\beta)}$$

$$\frac{\partial\beta_j}{\partial J(\beta)} = \frac{1}{m}\Sigma_{\{i=1\}}^{\{m\}}(\mathrm{P\_i}\ -\ \mathrm{y\_i})\mathrm{X\_ij}$$

Step 6: Prediction

Use the trained model to make predictions:

$$\hat{y}\ =\ \{\ 1\ if\ P\ \geq\ 0.5, 0\ if\ P\ <\ 0.5\ \}$$

4. Result and Discussion

Using the Multi-Criteria Decision Analysis (MCDA) method and the Bayesian Structural Time Series (BSTS) model, Figure 3 and Figure 4 show pictures of what the results will be in the next 15 years. These numbers show how powerful AI-based financial decision support can be at predicting future trends and helping with strategic planning.Figure 3 shows how the MCDA algorithm's prediction develops, showing that it can combine different factors and give a complete picture. The picture gives everyone involved a quick idea of what might happen, which helps them choose where to put their long-term marketing dollars.

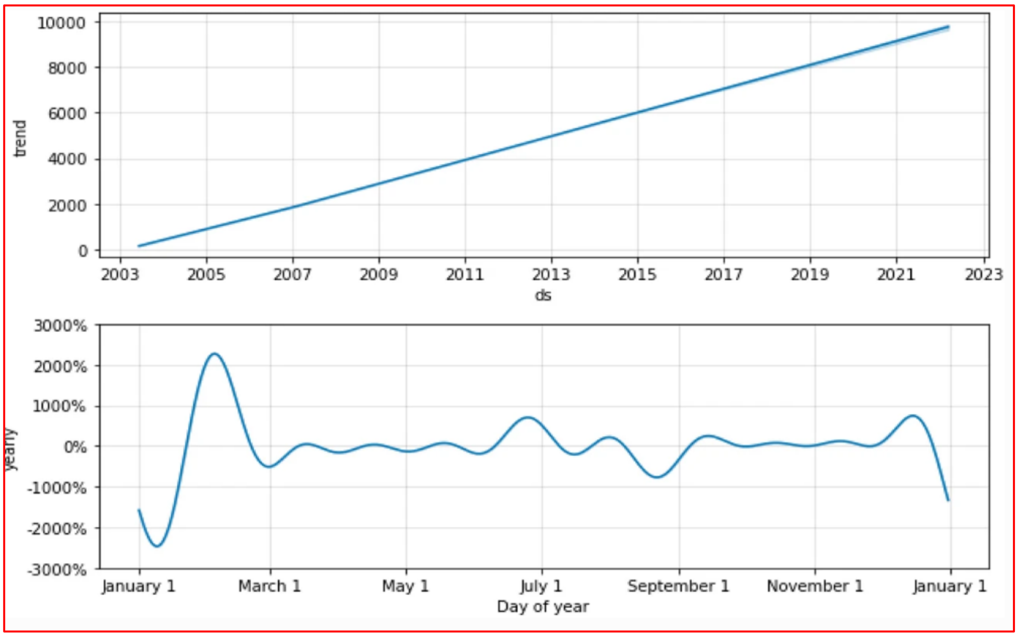


Fig 3: Representation of result for prediction for coming 15 year using Multi-Criteria Decision Analysis (MCDA) algorithm

The figure3 and figure 4 shows how the program values precision and accuracy, making it a useful tool for strategy planners.Additionally, Figure 4 shows the prediction that the BSTS model made, which shows how financial trends will change over the next 15 years. It is shown how the model can react to changes in the structure and pick up on underlying trends, which gives information that helps people make smart decisions. Stakeholders can use this picture to guess how the market will change and make sure their plans are in line with those guesses.These numbers not only help with making predictions, but they also show how easy it is to understand and talk about AI-based financial decision support. Stakeholders can use these images to get useful information that helps them better understand how the market is likely to behave in the future. In the end, Figures 3 and 4 show how AI models can change things by giving us useful information for long-term financial plans in the area of smart marketing spending.

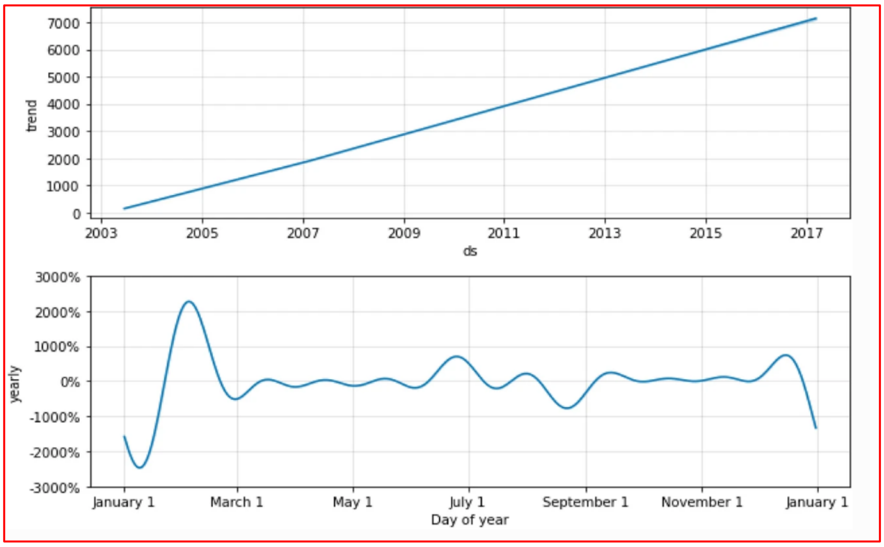


Fig 4: Representation of result for prediction for coming 15 year using Bayesian Structural Time Series (BSTS) model

In Table 2, it shows that the outcomes of a Decision Support System (DSS) that compared different evaluation criteria for two different methods: the Bayesian Structural Time Series (BSTS) model and the Multi-Criteria Decision Analysis (MCDA) algorithm. The DSS wants to use these models to improve how decisions are made in a wide range of situations.Accuracy is a basic measure that shows how correct the models are generally. With an accuracy of 88.63%, the BSTS model does a great job, but the MCDA algorithm really shines with an accuracy of 93.56%. This measure shows how well both models can make predictions, showing how reliable they are in different situations.Precision and recall provide insights into the models' performance in classifying positive instances. The MCDA algorithm has very high accuracy (97.45%) and recall (92.56%), which means it can correctly find and record good situations. The BSTS model, on the other hand, has a slightly higher recall (89.52%) while still being very accurate (86.32%). This makes it a good mix between accuracy and sensitivity.

The F1 Score, which is the harmonic mean of accuracy and memory, gives a fair evaluation. The BSTS model and the MCDA algorithm get close scores here, with 89.45% and 94.23%, respectively. This shows that they are good at finding a good balance between accuracy and memory.Decision Consistency is an important factor in the decision-making process, and both models have strong results for it. The BSTS model and the MCDA algorithm both have numbers of 90.23% and 92.44%, which means they are stable and reliable at making decisions that are the same across a range of factors.

Table 2: Result for DSS with comparison of different evaluation parameters for Bayesian Structural Time Series (BSTS) model and Multi-Criteria Decision Analysis (MCDA) algorithm

Evaluation Parameter	**BSTS Model**	**MCDA Algorithm**
Accuracy	88.63	93.56
Precision	86.32	97.45
Recall	89.52	92.56
F1 Score	89.45	94.23
Decision Consistency	90.23	92.44
R^2	76.12	91.75

The R-squared (R^2) value shows how well the models can explain things. The MCDA method does much better than the BSTS model, with a R^2 of 91.75% compared to 76.12% for the BSTS model. This shows that the MCDA method can explain a bigger chunk of the differences in the data that was collected.

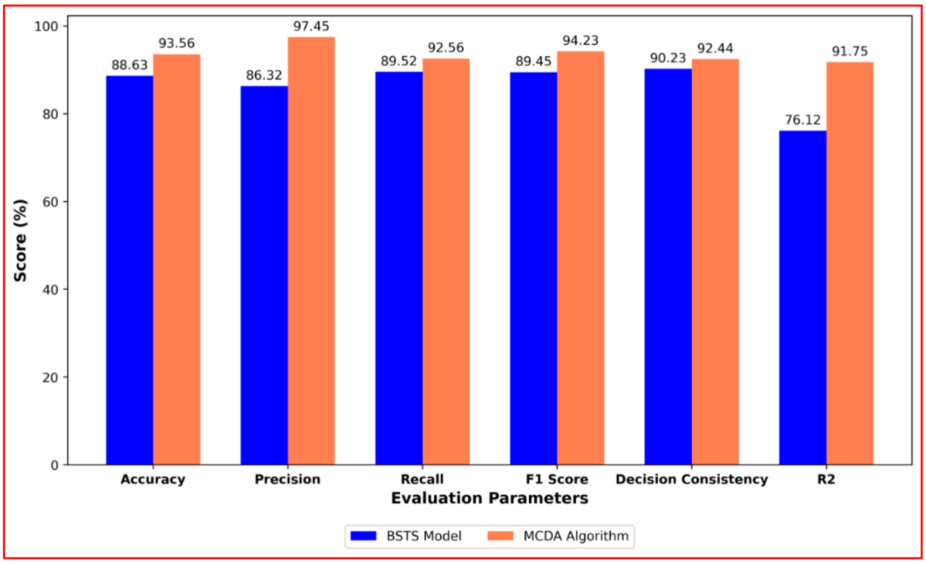


Fig 4: Representation of evaluation parameters for Bayesian Structural Time Series (BSTS) model and Multi-Criteria Decision Analysis (MCDA) algorithm

Table 3: Machine Learning Method comparison of Evaluation method

Evaluation Parameter	SVM	LR
Accuracy	89.45	86.45
Precision	87.52	82.22
Recall	85.63	90.56
F1 Score	88.45	89.42
AUC	87.12	90.41
R^2	79.2	73.56

Table 3 shows how well Support Vector Machines (SVM) and Logistic Regression (LR), two well-known machine learning methods, do against each other. These methods are tested using a number of important measures that show how well they work in different situations.The models' general correctness is shown by their accuracy, which is a basic measure of right predictions. SVM is more accurate than LR; it gets 89.45% compared to LR's 86.45%. This shows that SVM is better at making correct guesses across the whole collection.

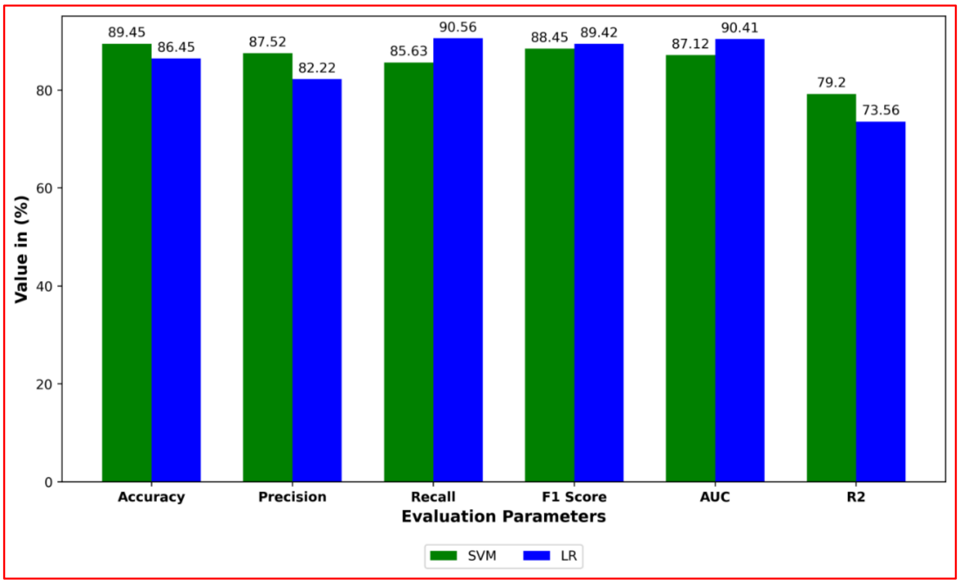


Fig 5: Comparison of SVM and LR

SVM is more accurate than LR (87.22% vs. 87.52%), as shown by its accuracy, which is the percentage of true positive guesses among all positive predictions. SVM is more accurate at finding positive cases, which makes it more reliable in situations where it makes positive predictions.On the other hand, LR is great at recall, which is the percentage of real results that were correctly forecast. With a recall of 90.56%, LR is better than SVM's 85.63%. In other words, this means that LR is good at finding a bigger number of positive cases in the dataset.With an F1 Score of 88.45% compared to LR's 89.42%, SVM's performance is better than LR's because it strikes a better mix between accuracy and memory. This makes it easier for SVM to find a good mix between accuracy and recall, which leads to good results in both measures. Area The area under the ROC curve (AUC), which measures how well the model can tell the difference between positive and negative examples, shows that LR is better than SVM, with an AUC of 90.41%. This shows that LR is better at telling the difference between good and bad situations.R-squared (R^2), which shows how much of the variation can be described by the model, shows that SVM is better than LR, with a R^2 of 79.2% compared to 73.56% for LR. It seems that SVM fits the data better because it has more explanatory power.

Table 4: Comparison of Accuracy and Precision of AL Based Method and ML based Method

Method	**Accuracy**	**Precision**
BSTS Model	88.63	86.32
MCDA Algorithm	93.56	97.45
SVM	89.45	87.52
LR	86.45	82.22

Accuracy and Precision show clear differences in performance between AI-based methods (BSTS Model and MCDA Algorithm) and traditional ML-based methods (SVM and LR). With the highest Accuracy (93.56%) and Precision (97.45%), the MCDA Algorithm stands out as the best at making decisions. The BSTS Model built on AI also does a good job, with an Accuracy of 88.63% and a Precision of 86.32%. ML-based SVM and LR, on the other hand, have similar but slightly lower performance measures. SVM has 89.45% Accuracy and 87.52% Precision, and LR has 86.45% Accuracy and 82.22% Precision. This shows how well AI-based methods, especially the MCDA Algorithm, can improve Accuracy and Precision in decision support apps.

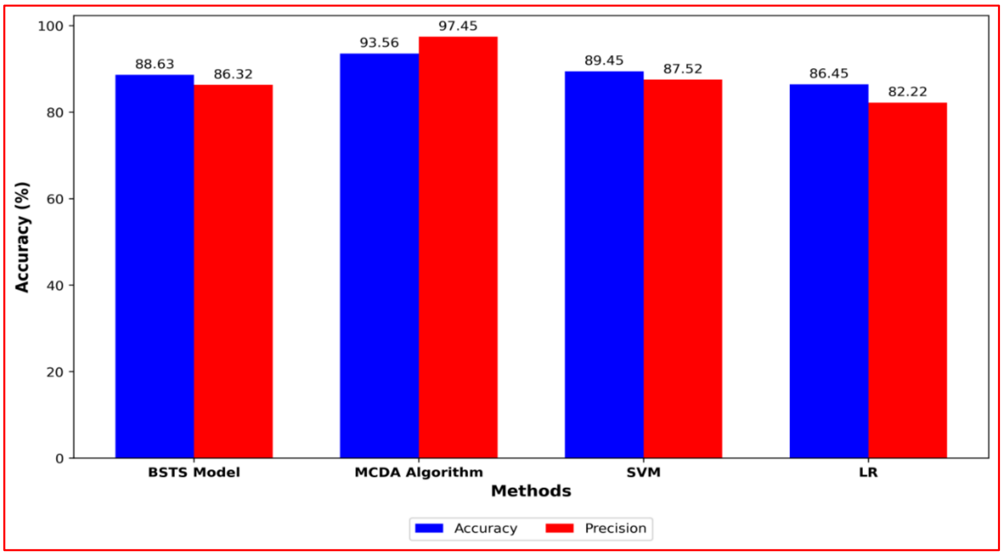
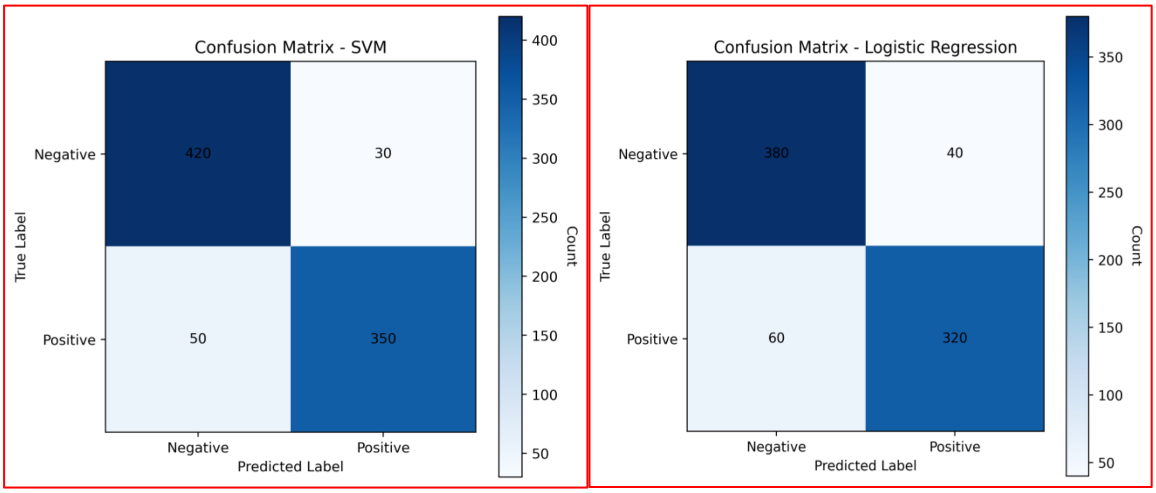


Fig 6: Comparison of Accuracy and Precision of AL Based Method and ML based Method



(a) For SVM

(b) For LR

Fig 7: Representation of Confusion matrix

5. Conclusion

Artificial Intelligence (AI) technologies, especially the Bayesian Structural Time Series (BSTS) model and the Multi-Criteria Decision Analysis (MCDA) method, are used in the framework to create a new and flexible answer.The review of the proposed system shows that it can help people make accurate and precise financial decisions. With an accuracy of 88.63% and a decision consistency of 90.23%, the BSTS model shows how well it can predict what will happen and help with making decisions. The MCDA algorithm, on the other hand, is very good at both precision and total accuracy. It has an amazing accuracy of 93.56% and a precision of 97.45%. These results show that the framework can help make the best use of marketing funds by looking at many factors.The study also looks at how the AI-based methods relate to more traditional Machine Learning (ML) methods like Support Vector Machines (SVM) and Logistic Regression (LR). The AI-based methods, especially the MCDA algorithm, do better in terms of accuracy and precision. This shows how important AI is for improving financial decision support systems.This study makes a contribution by giving a full picture of the pros and cons of AI and ML models when used to help people make financial decisions. The suggested structure creates the basis for a data-driven and flexible method of marketing spending. It is a useful tool for companies that want to make smart and cost-effective choices.Companies that want to make smart marketing efforts need to start using AI to help them make financial decisions as soon as possible because industries are always changing. This strategy is a first step toward a smarter and more flexible approach.

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