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# The Application of Artificial Intelligence and Big Data–Based Predictive Models in Accounting

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## Abstract

In today's data-driven and modern world, data is recognized as one of the most important informational resources that can be utilized in making intelligent and optimized decisions. The accounting profession, in the age of the information explosion, faces an unprecedented volume of financial and non-financial data. This study, employing a systematic literature review method, examines modern predictive models and their transformative applications across various areas of accounting. Predictive models are key tools in data science, capable of forecasting future events and simulating behaviors by using historical data and statistical or machine learning methods. These models are applied across numerous industries, including healthcare, business, finance, education, and even weather forecasting. The findings show that algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and particularly deep learning and Large Language Models (LLMs), demonstrate a high capacity for predicting bankruptcy, Financial Fraud Detection (FFD), credit risk, asset valuation, and even analyzing accounting texts. By utilizing big data (a combination of structured financial data, news, social media, etc.), these models have significantly enhanced the accuracy of traditional predictions. The conclusion of the paper indicates that integrating these technologies into auditing and reporting frameworks has become not only a competitive advantage but a necessity to ensure the reliability and timeliness of financial information.

**Keywords:** Predictive models, Artificial intelligence in accounting, Big data, Financial fraud, Machine learning.

## 1 | Introduction

Accounting, as the language of business, has traditionally relied on the analysis of historical data to inform decisions about the future. With the advent of Artificial Intelligence (AI) and Big Data technologies, the accounting paradigm is shifting from "historical reporting" toward "forward-looking insight generation."

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Advanced predictive models, with the capacity to process thousands of linear and nonlinear variables, enable the identification of complex patterns and the forecasting of financial events with unprecedented accuracy. This paper aims to provide a comprehensive review of the most significant predictive models and their practical applications within the accounting profession [1].

# 2 | Theoretical Foundations and Definition of Predictive Models

A predictive model is a mathematical or statistical framework that forecasts future outcomes or events using historical data and machine learning algorithms. The primary objective of these models is to transform raw data into actionable insights for future decision-making.

By identifying patterns, relationships, and trends within data, predictive models can generate estimates about future developments. Forecasts may take a numerical form (e.g., predicting the price of a commodity) or a categorical form (e.g., estimating the likelihood of a specific event, such as a customer purchasing a product).

In other words, predictive models enable businesses and organizations not only to analyze the past but also to anticipate the future. Overall, predictive models are considered key tools in data science for analysis and forecasting [2].

In data science, predictive models are regarded as key tools for analysis and forecasting. These models are employed to process and analyze large volumes of data, enabling organizations to use raw information to anticipate future patterns. Predictive models are typically applied in high-level decision-making processes within businesses and organizations. By leveraging historical data and employing advanced techniques such as machine learning, statistical analysis, and data mining, these models allow organizations to simulate future trends and behaviors.

Early studies in the field of financial forecasting primarily focused on simple statistical models, such as audit analysis using the Altman Z-Score [3]. With the advent of technology, Artificial Neural Network (ANN) models were employed for bankruptcy prediction, often demonstrating higher accuracy than linear models [4]. Over the past two decades, with the availability of big data, more complex models such as Random Forest and Gradient Boosting (XGBoost) have emerged as the new standard in research on Financial Fraud Detection (FFD) [5].

# 3 | Widely Used Predictive Models in Accounting and Finance

## 3.1 | Regression Models

These models are used to predict continuous (numerical) values.

I. Examples in accounting: Forecasting stock prices, predicting next month's sales, and projecting future cash flows.

II. Common models: Linear regression and logistic regression (for binary predictions, such as bankruptcy vs. non-bankruptcy) [6].

## 3.2 | Classification Models

These models are used to predict discrete labels, such as yes/no outcomes.

I. Examples in accounting: detecting financial fraud, predicting customer churn, and classifying financial documents.

II. Common models: decision trees, Support Vector Machines (SVM), and machine learning algorithms such as XGBoost [7].

## 3.3 | Neural Networks and Deep Learning

These models are designed to process complex, high-dimensional data, such as images and text. Examples in accounting: automated detection of fraudulent financial statements, sentiment analysis of management reports, and identification of anomalous patterns in transactions. Common models: Convolutional Neural Networks (CNN) for scanned documents and Recurrent Neural Networks (RNN).

## 3.4 | Time Series Models

These models are used to forecast future values based on past data arranged in chronological order. Examples in accounting: predicting seasonal sales, forecasting product demand, and projecting economic indicators that affect financial statements. Common models: ARIMA, Prophet, and Long Short-Term Memory (LSTM) networks.

## 3.5 | Decision Tree Models

These models are widely used for both classification and numerical prediction tasks. Decision trees split data into nodes, where different decisions are made based on specific features at each node. They are particularly well-suited for interpretable problems that require an explanation of the decision-making process. Examples in accounting, credit risk assessment, and identification of dissatisfied customers. In this section, the models are categorized according to the type of accounting problem.

**Table 1. Classification of predictive model applications.**

| Application Area | Widely Used Predictive Models | Brief Description and Advantages |
|---|---|---|
| bankruptcy and credit risk prediction | Z-Score model (Altman)<br>ANN<br>SVM<br>XGBoost algorithm | ANN and XGBoost exhibit higher accuracy due to their ability to model complex nonlinear relationships among financial ratios. |
| FFD | Logistic regression<br>decision trees and random forests<br>deep neural networks (deep learning) | Random forest is highly popular due to its ability to reduce overfitting and handle high-dimensional data. Deep learning models can detect complex and hidden patterns of fraud. |
| Stock value and return prediction | ARIMA (for time series of prices)<br>LSTM<br>Transformers | LSTM is specifically designed for sequential data, such as stock prices, and incorporates both long-term and short-term memory. |
| Sentiment and text analysis of financial reports | Natural Language Processing (NLP)<br>language models such as BERT | These models can analyze stress, ambiguity, or positive/negative sentiment in management reports, financial statements, and news, and use this information to forecast future performance. |
| Cash flow and sales forecasting | Linear/multiple regression<br>time series models (prophet)<br>RNN | Integrating internal financial data with big data sources, such as economic indicators, enhances predictive accuracy. |

# 4 | The Role of Big Data in Empowering Predictive Models

Modern predictive models do not rely solely on structured accounting data, such as balance sheets. They leverage heterogeneous data sources to enhance accuracy, including: Textual data: annual reports, news articles, and social media analyses. Real-time data: online transactions and sensor data from the supply chain. Alternative data: weather information for forecasting seasonal product sales, traffic data for property valuation. This integrated approach has enabled the emergence of "predictive accounting [8].

# 5 | Advantages and Applications of Predictive Models

## 5.1 | Based on Existing Research, Predictive Models Enable Organizations

Mitigate risks (e.g., credit risk, fraud risk): accurate prediction of adverse events, such as declining demand, financial difficulties, or market fluctuations, can help companies proactively manage and prevent risks.

Identify new opportunities (e.g., emerging markets or consumption patterns): these models can assist in detecting potential opportunities, such as novel market demands or favorable industry trends.

Enhance productivity (through process and resource optimization): by forecasting demand, inventory levels, and future trends, firms can allocate their resources more efficiently, thereby achieving higher productivity.

Reduce costs (by preventing resource wastage and improving demand accuracy): accurate demand forecasting enables companies to avoid unnecessary expenditures and utilize resources more effectively [2].

## 5.2 | Practical Applications Include

Sales and demand forecasting: In numerous business contexts, predictive models are employed to forecast product sales and demand. These models enable companies to optimize inventory levels and mitigate the risks of both stockouts and excess inventory.

Stock price forecasting: in financial markets, predictive models assist analysts in simulating trends in stock and asset prices, thereby facilitating more informed decisions regarding buying and selling activities.

Individual and public health forecasting: within the healthcare domain, such models support the anticipation of disease trajectories and the identification of health risks. They also aid in projecting requirements for specific medications or therapeutic interventions.

Weather and climate forecasting: in atmospheric sciences, predictive models are utilized to forecast weather conditions and to anticipate natural disasters, including storms and floods.

Customer behavior analysis: in marketing and commerce, predictive models are applied to examine customer behavior and to forecast their future needs and preferences [9].

## 5.3 | Advantages of Various Predictive Modeling Approaches

Predictive models enable firms to enhance competitiveness, reduce costs, and improve overall performance. By providing a clearer understanding of market dynamics and competitors, these models support the development of effective strategies that help organizations achieve competitive advantage. Data-driven insights also allow firms to optimize existing products and services while better identifying and meeting customer needs.

Moreover, predictive analytics offers comprehensive knowledge of customer profiles and preferences, facilitating more informed decision-making. These models reduce the time, effort, and cost required for forecasting outcomes and help organizations anticipate external factors that may influence productivity and workflow. They also assist in identifying potential financial risks, improving inventory and resource management, detecting emerging market trends, and supporting workforce planning by analyzing employee behavior and turnover patterns.

# 6 | The Predictive Model Development Process (Six Stages)

Predictive modeling follows a structured process consisting of several key stages. First, the problem and prediction objectives are clearly defined. Relevant historical data are then collected from internal and external sources and prepared through data preprocessing, including cleaning, transformation, and integration. Next, important features that significantly influence predictions are selected. Machine learning algorithms are subsequently applied to train the model using the prepared dataset. Finally, the model is evaluated on new data to measure its performance using accuracy, sensitivity, and error metrics [10].

# 7 | Challenges and Practical Considerations in Predictive Modeling

Despite their numerous advantages, the implementation of predictive models presents several challenges. The effectiveness of these models depends heavily on data quality, as inaccurate or incomplete data can lead to unreliable predictions. Model performance may also become unstable in dynamic environments, such as during economic crises, where sudden changes reduce prediction accuracy. Furthermore, reliance on historical data can be problematic when future conditions differ significantly from past patterns.

Another major challenge relates to explainability, as complex models, particularly deep learning systems, often function as "black boxes," creating difficulties in meeting auditing requirements for transparency and accountability. Data bias represents an additional concern, since biased training data may result in unfair or misleading outcomes, especially in areas such as credit risk assessment. Moreover, the development and maintenance of predictive models require substantial financial investment and specialized expertise. Finally, ethical and privacy issues must be carefully addressed, ensuring compliance with data protection regulations such as the GDPR [11].

# 8 | Conclusion and Recommendations

AI and big data–based predictive models are transforming the role of accountants and auditors from mere recorders of events to strategic analysts and management advisors. These technologies have the potential to enhance efficiency, reduce risk, and generate new value for businesses. To ensure effective utilization, the following recommendations are proposed:

I. Training and empowerment of human resources: integrate data science and AI courses into accounting curricula.

II. Development of regulatory frameworks: professional organizations (e.g., auditing bodies and the FASB) should guide auditing and reporting for AI-based models.

III. Emphasis on interpretable models: prioritize models whose decision-making logic can be justified and explained.

IV. Interdisciplinary collaboration: form teams comprising accountants, data specialists, and software engineers [8].

# Conflict of Interest

The authors confirm that there are no financial or personal relationships that could have influenced the work reported in this paper.

# Data Availability

The datasets generated and analyzed during the current study are available in the article.

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