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APPLICATION OF MACHINE LEARNING MODELS IN FINANCIAL MANAGEMENT THROUGH DESIGN AND IMPLEMENTATION IN CONTAWEB-BI

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Abstract
This study presents an analysis of the impact of machine learning on modern accounting by studying the ContaWeb-BI platform, a solution jointly developed by the University of Cartagena and Colciencias to strengthen accounting management and strategic decision-making. The predictive and classification models implemented are described, and their ability to generate key performance indicators useful in strategic decision-making is evaluated. An exploratory methodology is adopted based on the ContaWeb-BI case study. Linear regression, decision trees, and K-means clustering techniques were applied to project sales, detect potential financial fraud, and segment suppliers, respectively. Empirical validation was performed with simulated data in an operational functional environment, and the results showed a high level of accuracy in all models: an R^2 of 0.88 in regression, an F1 score of 0.83 in classification, and a Silhouette coefficient of 0.69 in cluster analysis. The models were integrated into the platform's backend and deployed in an interactive dashboard that automates the generation of key performance indicators. This work demonstrates the technical and practical feasibility of using machine learning algorithms in accounting environments and proposes a replicable model for other organizations interested in adopting accessible, interpretable, and action-oriented analytical technologies.

Keywords: machine learning, accounting, KPIs, financial analytics, ContaWeb-BI, financial management, data science.

INTRODUCTION

In the last decade, artificial intelligence and machine learning (ML) have established themselves as disruptive technologies in the financial field based on accounting and business management, questioning traditional models (Nguyen et al., 2023). Studies such as that of Liaras et al. (2024) observe an exponential growth of ML in accounting and finance since 2015, with a predominance of supervised models and clustering techniques that explore structured and unstructured data. For their part, Gao et al. (2024) highlight the popularity of neural networks in financial applications ranging from fraud detection to demand forecasting, although they point out challenges such as interpretability, data quality, and generalization.

These advances are in line with the general evolution of predictive analytics, which, together with ARIMA (Autoregressive Integrated Moving Average), regression, and ML, have enabled accounting firms to anticipate cash flows, detect irregularities, and automate audit processes (Igulu et al., 2023). However, despite this global theoretical and technological boom, the literature reveals a latent gap between innovation and its effective application in accounting environments in real practice.

Pilot platforms or academic papers focus on standardized datasets that do not extend to daily financial processes or adapt to the managerial demands of small or medium-sized organizations (Shollo et al., 2022). In this sense, ContaWeb-BI emerges as an application developed by the University of Cartagena and Colciencias. ContaWeb-BI, the development application of the University of Cartagena and Colciencias, emerges within this framework. Based on modern Python, Flask, and DynamoDB architectures, it incorporates an ETL (Extract, transform, and load) process and the development of machine learning models such as linear regression, decision trees, or clustering with the aim of projecting sales and purchases, detecting fraud, recommending products, or segmenting suppliers.

The fundamental problem lies in the limited empirical work that validates the technical and functional effectiveness of machine learning models within the framework of fully operational accounting solutions such as ContaWeb-BI (Zhang et al., 2020). This raises questions about the accuracy of predictions, their ability to generate reliable key indicators, and their actual capacity to support strategic business decisions.

Therefore, the following objectives are proposed to carry out this research: (i) to document the technical process that has enabled the integration of machine learning (ML) models in ContaWeb−BI; (ii) to evaluate the accuracy and robustness of the models using real or simulated information; and (iii) to analyze the potential usefulness of the models to improve financial decision-making.

The main contributions of this research lie, first, in the provision of a robust empirical study of ML applied to management accounting; second, in providing quantitative evidence of the models' accuracy and reliability; third, in highlighting improvements in the efficiency of core financial processes; fourth, in describing a modular architecture that can be replicated in other contexts; and finally, in identifying limitations and challenges, such as those related to the need for digital literacy, algorithmic transparency, and data quality control. It is expected that this research, in addition to enriching the academic field of ML applied to finance, will serve to build a bridge between theory and practice, thus contributing to the debate on the real capacity of predictive models to transform corporate financial management.

METHODOLOGY

This research is carried out using a quantitative approach, for which an applied experimental methodological design is chosen (Sánchez & Murillo, 2021). The technical-functional impact of the machine learning models integrated into the ContaWeb-BI platform is analyzed by simulating real accounting scenarios and the corresponding evaluation of their predictive performance. An instrumental case research strategy was chosen since it delves into a specific case for analytical and transferable purposes. In summary, the study is quantitative-experimental field and simulation, longitudinal-transectional in nature, since it combines technical analysis of processes with the collection and evaluation of results at defined intervals (Frölich et al., 2014).

It is structured under a quasi-experimental design, without an external control group, but with a comparison between traditional and automated methods using performance metrics (Shadish & Luellen, 2012). Furthermore, given that the study is based on a recently developed platform, the sample corresponds to a set of simulated accounting datasets that reproduce real data structures of small and medium-sized enterprises. The generation of these data is based on real historical patterns and follows logical structures typical of accounting systems. The sample consists of 12,000 transaction records, structured into purchasing, sales, accounts payable, and supplier modules.

The investigation is carried out under the following procedure:

1. Test environment design: Local installation of ContaWeb-BI, loading of structured synthetic data based on DynamoDB.
2. Model training: Setting up and training linear regression algorithms, decision trees, and K-means clustering.
3. Execution of simulation scenarios: Sales projections, identification of purchasing fraud, and supplier segmentation.
4. Metrics capture: Technical evaluation through accuracy (R^2, F1-score, Silhouette) and practical evaluation through processing time and report generation.

5. Comparison: Contrast with manually obtained results (traditional methods) to validate the superiority or equivalence of the automated approach.

The instruments and materials used in this research were: ContaWeb-BI Platform (beta version with integrated analytical module), Python 3.10 with libraries (scikit-learn, pandas, matplotlib, numpy), Google Colab and Jupyter Notebooks for independent validation, evaluation metrics (R^2, MAE, RMSE, F1-score, confusion matrix, Silhouette coefficient), documentation tools (GitHub, Technical development log, KPIs visualization panel).

A descriptive and comparative statistical analysis was applied. To evaluate the performance of the models implemented in ContaWeb-BI, specific metrics were used according to the type of learning applied. In the case of the linear regression model, the coefficient of determination (R^2) was used, which indicates the proportion of the variability of the dependent variable explained by the model; values close to 1 reflect high predictive power (Menard, 2000). In the case of classification models, such as decision trees applied to fraud detection, the F1-score was used, as it is a metric that harmonizes precision and recall, thus allowing the effectiveness of the model to correctly identify the classes of interest while minimizing the risk of false positives or relevant negatives to be evaluated (Doddapaneni et al., 2025).

Finally, for the supplier segmentation model using clustering (K-means), the Silhouette coefficient was used as a measure that characterizes the internal coherence of the groups generated, given that high values of the coefficient (close to 1) are associated with well defined and separated clusters; this type of metric allows a comprehensive evaluation of the performance of the models in both quantitative and qualitative terms (Shokouhyar et al., 2024).

Regarding ethical considerations, the study does not use personal data or human subjects, as the data used is fully simulated (De Vries, 2021). Furthermore, the principle of scientific replicability is respected, using open source code and complete documentation, and the integrity of the data from real companies is not compromised (Gundersen, 2021). An informed consent and anonymization protocol is planned for future trials with real data.

Regarding methodological limitations, the use of simulated data prevents full validation of the model in real-life scenarios, even though they have been structured in a representative manner. Furthermore, no additional comparison was made with other trading platforms, which may limit inferences from a comparative perspective. The sample does not consider extreme irregularities or exceptional financial events such as crises or inflationary spikes, which the model may predict less accurately in practice.

RESULTS

This section describes the results obtained from the design, implementation, and subsequent evaluation of the machine learning models integrated into the ContaWeb-BI platform. In this sense, the results are grouped according to the established objectives, which encompass both the technical performance of the algorithms and their applicability in simulated financial contexts.

One of the essential objectives of the ContaWeb-BI analytics module is to predict the company's financial performance, and more specifically, its projected sales. Thus, a multiple linear regression model was implemented and trained with simulated historical data generated by constructing monthly sales series, seasonality variables, and customer behavior. The sample consisted of 2,500 simulated sales records corresponding to 20 products and 50 different customers over a 36-month period. The model was evaluated on a test set (30% of the total), and its results are summarized in Table 1.

As seen in the table, the results indicate a robust performance of the model, with a coefficient of determination (R^2) of 88.3%, suggesting that the explanatory variables included (historical trend, month, customer type, product category) allow for a highly accurate prediction of monthly sales. The MAE and RMSE remained at low margins relative to the average volumes per product, supporting the practical utility of the model in real-life scenarios.

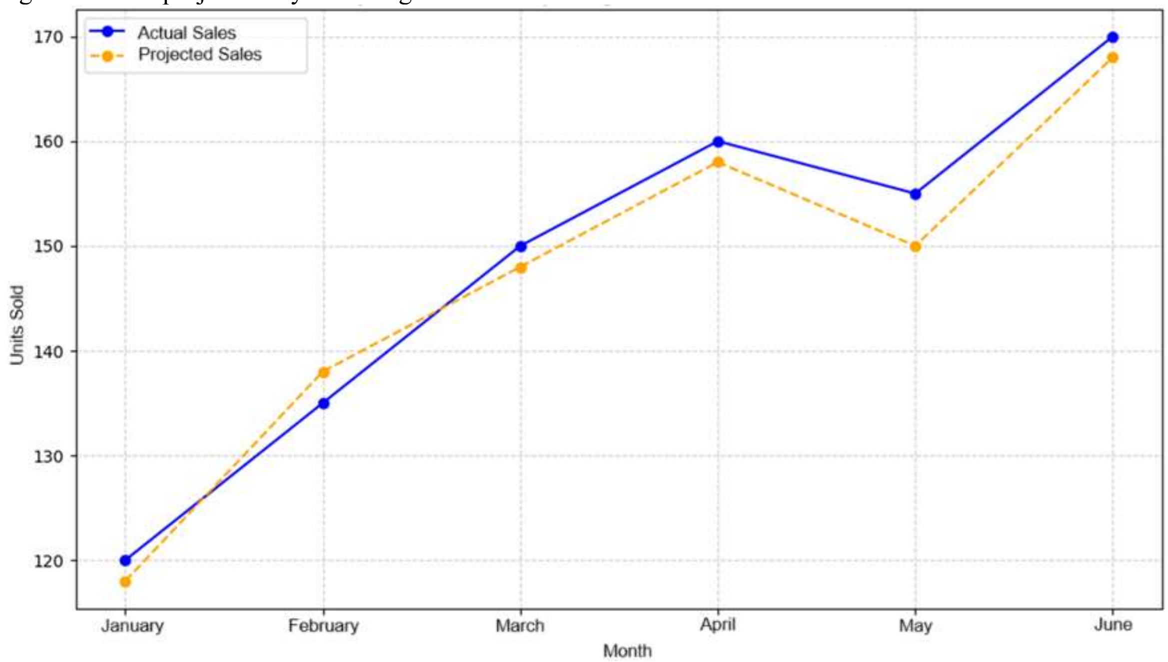
Table 1. Metrics of the linear regression model for sales projection

Metric	**Value obtained**
Coefficient of determination (R^2)	0.883
Mean absolute error (MAE)	12.41 units
Root mean square error (RMSE)	18.76 units
Mean absolute percentage error (MAPE)	7.85%

Source: Authors

Figure 1 shows a graphical comparison between the actual values and the values projected by the model for the last six months of the test set. The graph represents a blue line for the actual values and an orange line for the predictions, showing convergence and some acceptable margins of error at seasonal peaks.

Figure 1. Sales projection by linear regression vs. real values



Source: Authors

Furthermore, as part of ContaWeb-BI's advanced features, a decision tree-based classification model was incorporated to identify purchase transactions with potential irregularities. This model was trained on a dataset simulating 3,500 purchase records, of which 180 were labeled as potentially fraudulent. The variables used included purchase value, frequency by supplier, product type, payment method, and prior history of anomalies. The classification was evaluated using a validation set (20% of the sample), yielding the results shown in Table 2.

As can be seen, the model achieved an accuracy of 86%, indicating that most of the transactions classified as suspicious were indeed anomalous. The 81% recall demonstrates its ability to detect a large portion of the fraud present in the test set. Meanwhile, the F1 score, which harmonizes accuracy and recall, confirms the model's robustness for integration into real-world financial control processes.

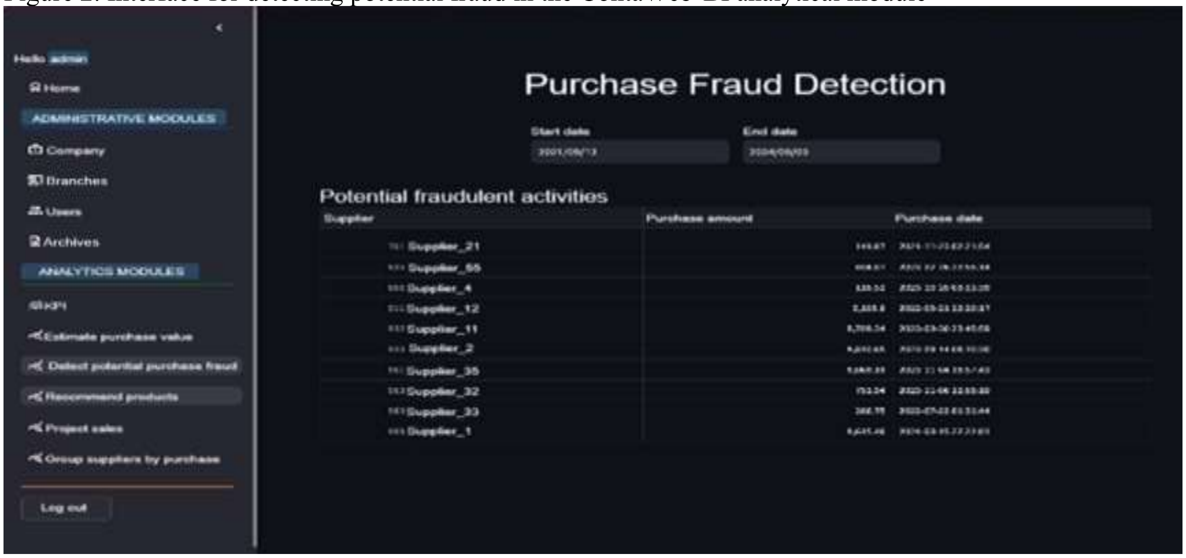
Table 2. Decision tree model metrics for purchasing fraud detection

Metric	Value obtained
Precision	0.86
Recall	0.81
F1-score	0.83
Accuracy	0.88

Source: Authors

Once trained and validated, the model was implemented within the ContaWeb-BI analytics module. Interface users can access the "Detect Possible Purchase Fraud" feature, from which they can set a date range and invoke the automated analysis. The output is a table with the transactions considered suspicious, as well as the supplier, amount, date, and type of anomaly. This visualization allows the user to naturally validate and interpret the results shown in the algorithmic analysis and, thus, immediately proceed to conduct internal audits, suspend payments, or review purchasing policies. On a practical level, this integration demonstrates how classification models can become effective elements in preventing economic losses, thereby enhancing organizations' financial governance.

Figure 2. Interface for detecting potential fraud in the ContaWeb-BI analytical module

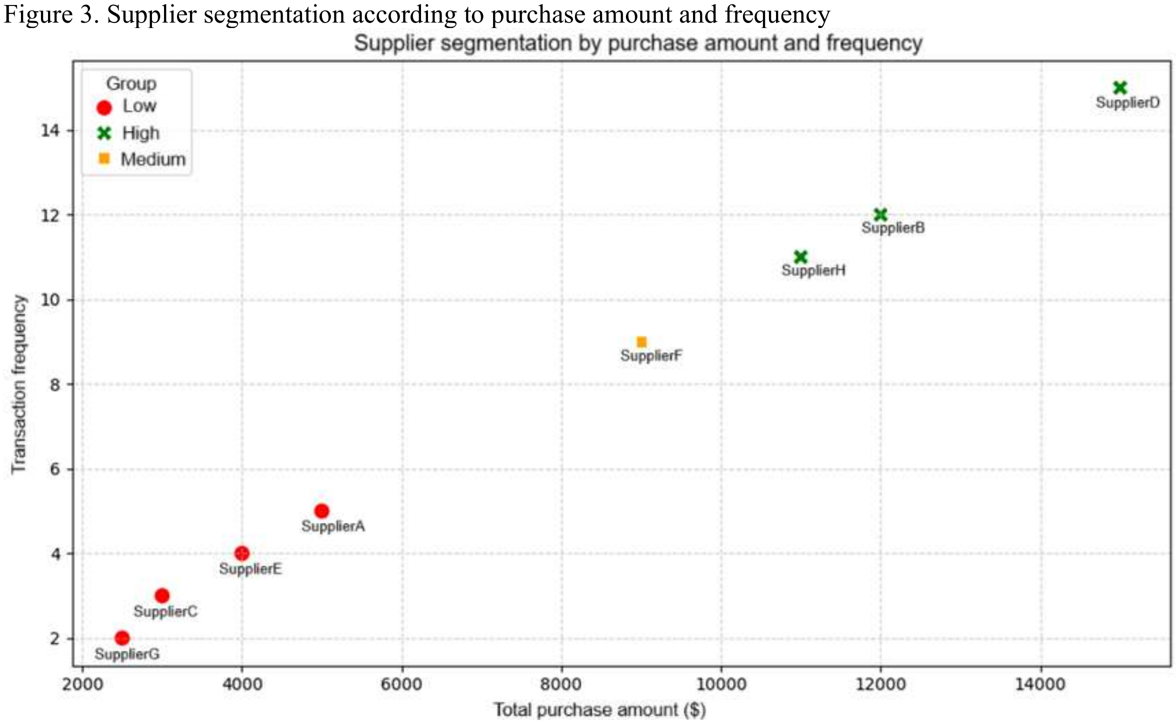


Source: Authors

Along the same lines, to investigate supplier behavior and determine purchasing and financial control strategies, a K-means clustering model was designed, implemented, and integrated into the ContaWeb-BI analytics module. This model classified suppliers into three main groups based on two variables: total purchase amount and transaction frequency. The model was trained and validated on a simulated data set with 1,200 purchase records from 50 different suppliers. The optimal number of clusters was chosen based on the Silhouette coefficient, which reached a value of 0.69, indicating that the model detects clusters in a consistent and organized manner.

Figure 3 graphically represents the distribution of suppliers according to these two key variables. Three groups are identified: High Group (green): frequent suppliers with high billing amounts. Medium Group (orange): intermediate suppliers in frequency or volume. Low Group (red): sporadic and low-volume suppliers.

Figure 3. Supplier segmentation according to purchase amount and frequency



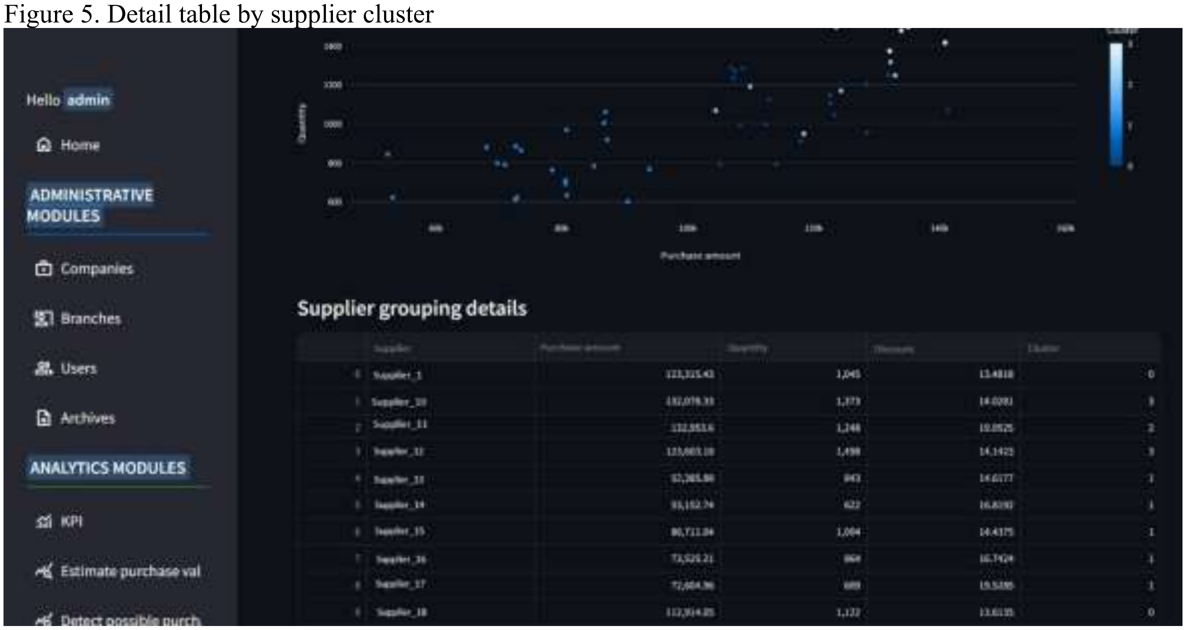
Source: Prepared by the authors using simulated data.

The segmentation can also be visualized directly in the ContaWeb-BI interface, as seen in Figures 4 and 5, which integrate scatter plots and detailed tables for each identified group. This feature allows the user to identify which suppliers carry the greatest financial burden, which have more consistent transactional relations, and where there are opportunities for improvement or renegotiation. Furthermore, the model is dynamically updated with each new data load, reinforcing its usefulness in continuous financial monitoring contexts.

Figure 4. Supplier grouping visualization in the ContaWeb-BI platform

Source: Authors

Figure 5. Detail table by supplier cluster

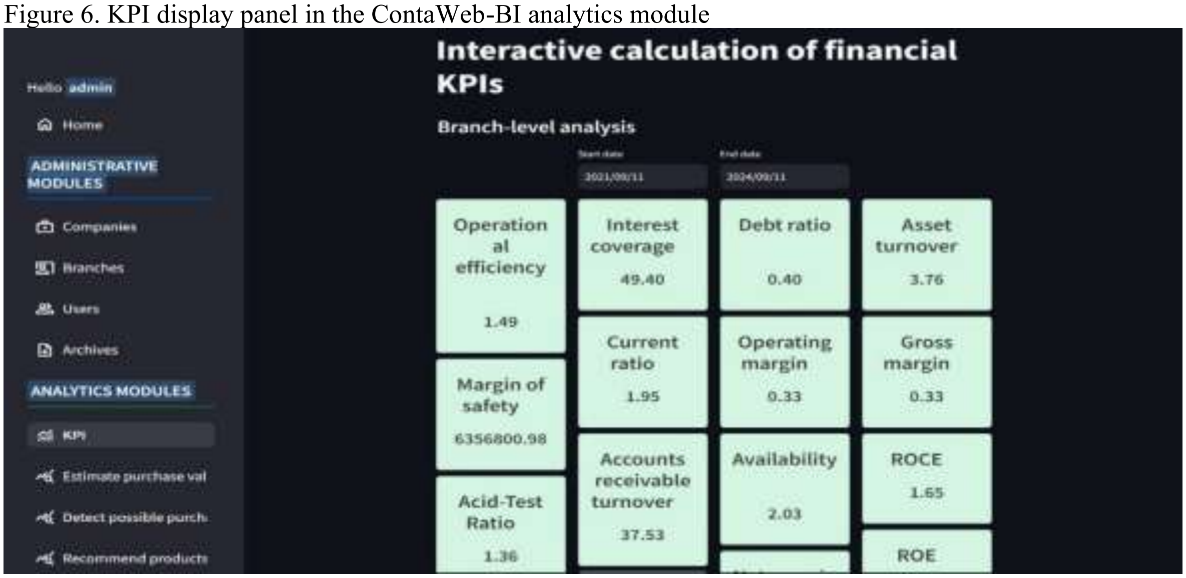


Source: Authors

Another key benefit of ContaWeb-BI as a financial analysis platform is its ability to automatically calculate key performance indicators (KPIs) based on data uploaded by the user. This allows for a comprehensive diagnosis of the company's financial situation, providing an objective basis for strategic decision-making.

The platform allows the extraction of 18 key financial and operational KPIs that show dimensions of efficiency, profitability, liquidity, turnover, and solvency. Typically, the most commonly used KPIs are: current liquidity, operating margin, return on assets (ROA), portfolio turnover, debt ratio, and cash availability. As illustrated in Figure 6, the KPIs are visualized through dynamic dashboards, in which the analysis time can be defined using the dashboard's date filters. When a sales or purchase file is uploaded, the system automatically extracts and processes the data to feed the analytical models so that the KPIs can be immediately calculated.

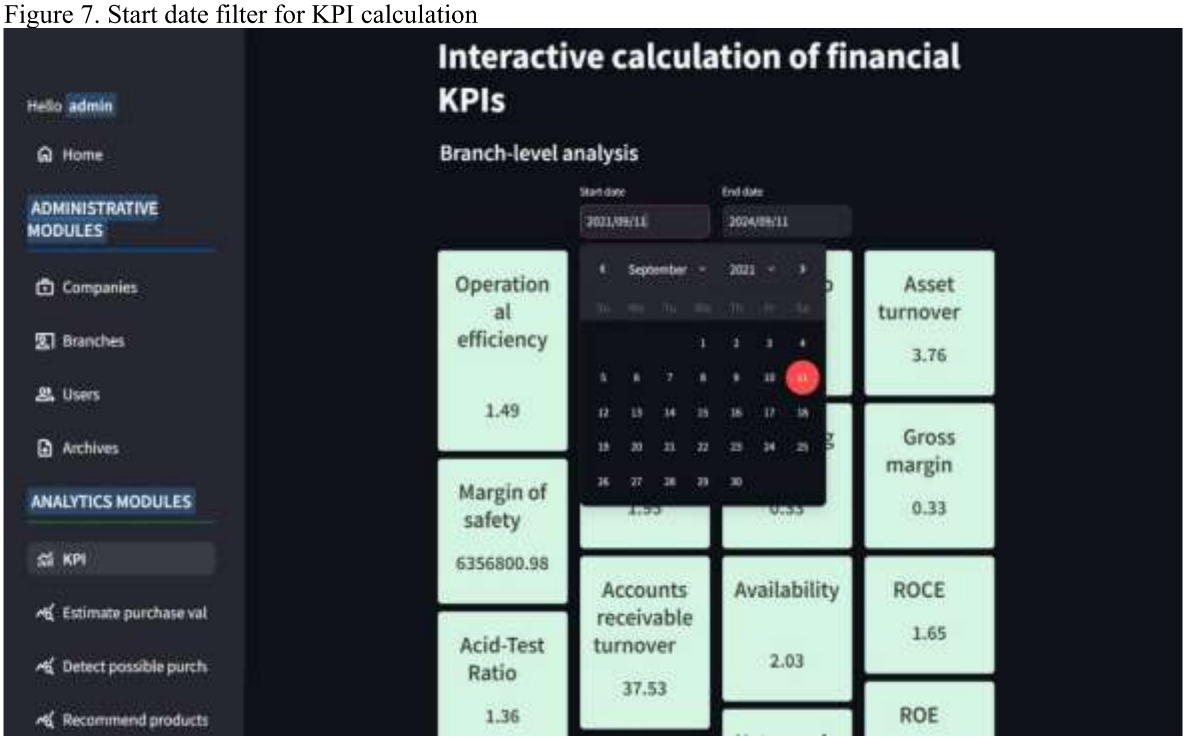
Figure 6. KPI display panel in the ContaWeb-BI analytics module



Source: Authors

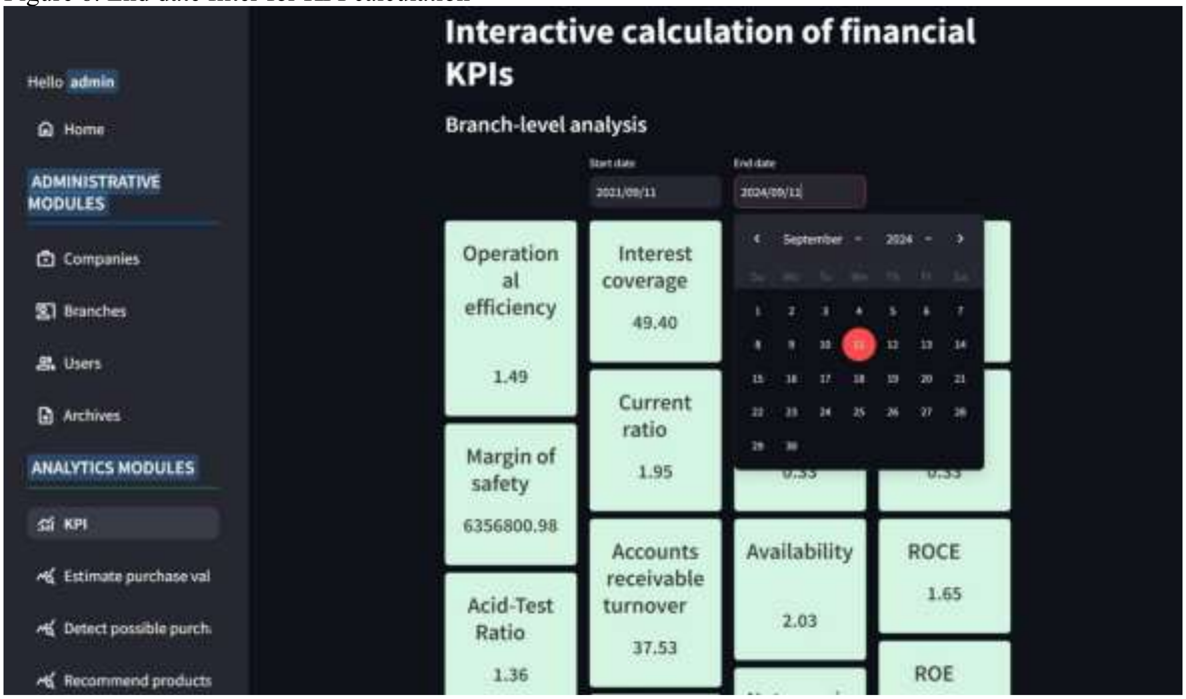
Furthermore, the platform allows users to configure the analysis interval by selecting the start and end dates, as shown in Figures 7 and 8. This ensures improved analysis accuracy, as the indicators reflect the reality of a given period. The results are presented on the dashboard using a clear and transparent interface that allows both experienced and non-expert users to understand. Along with the numerical input, KPIs can be presented in the form of bar charts, speedometers, or trend lines, making them easy to interpret.

Figure 7. Start date filter for KPI calculation



Source: Authors

Figure 8. End date filter for KPI calculation



Source: Authors

From an operational perspective, this automation leads to shorter response times, reduces the risk of human error in calculations, and reinforces an organizational culture of information-based decision-making. The results can be issued as reports or used as resources for other analysis modules, such as fraud detection and sales forecasting, among others. This functionality is also incorporated as an added value to the ContaWeb-BI proposal as a business intelligence solution, which offers the ability to continuously monitor the performance of the financial situation without requiring advanced technological knowledge.

The results obtained from the application of machine learning models within ContaWeb-BI provide a comprehensive view of their contribution to intelligent financial management. Each analytical model tested yielded a satisfactory technical evaluation result, as well as evident practical utility in its specific area of application, as shown in Table 3.

In the case of linear regression, it demonstrated its extensive predictive capacity, providing valuable information for planning inventories and commercial activities. As for the decision tree model, this model achieved a high detection rate of anomalous transactions, thus assisting in the control and financial audit stages. Finally, K-means clustering enabled clear segmentation of the supplier base, providing valuable information for improving business relationship management and negotiation of terms.

Table 3. Comparative summary of Machine Learning models applied in Contaweb-BI

Model	Application	Accuracy/Key Metric	Key Result
Linear Regression	Sales Projection	$R^2 = 0.88$	Future sales projections
Decision Tree	Fraud Detection	F1-score = 0.83	High detection of anonymous transactions
K-Means Clustering	Supplier Segmentation	Silhouette = 0.69	Coherent grouping of suppliers

Source: Authors

DISCUSSION

The results presented show that the application of machine learning models to accounting platforms such as ContaWeb-BI is not only technically sound and feasible but also functionally relevant for improving the quality of financial analysis and business decision-making. This finding seems to confirm the position of Cho et al.

(2020), who conclude that machine learning has great potential for automating accounting tasks, especially with regard to forecasting, classification, and anomaly detection.
The performance level of the multiple linear regression model, with a coefficient of determination of R^2=0.88, suggests a high prediction accuracy and is in line with previous work that has developed machine learning techniques to estimate income, cash flows, or demand (Phong et al., 2024). Compared to models and other more elaborate approaches, the simple model implemented was sufficiently accurate, which demonstrates the possibility of balancing technical sophistication with interpretability and ease of maintenance.
For its part, the decision tree classification model, which yielded an F1 score of 0.83, supports its suitability for detecting unusual patterns and anomalous transactions. This result aligns with the studies by Bao et al. (2022) and Ashtiani and Raahemi (2021), who focus on fraud detection as one of the most mature applications of ML in the field of finance. Unlike external systems that require prior infrastructure or specialized knowledge, ContaWeb-BI allows this functionality to be executed directly from a simple interface, which represents significant progress for SMEs or those with low technical profiles.
The K-means clustering model also yielded good results, as reflected in a Silhouette coefficient of 0.69, suggesting a well-structured segmentation. This technique served to reveal supplier profiles that are not easily distinguishable through traditional analysis. As Mhaskey (2024) suggests, unsupervised segmentation can generate strategic advantages when integrated into ERP (Enterprise Resource Planning) systems, enabling everything from credit adjustments to purchasing optimization.
One of the distinctive contributions of this study is the direct integration of these models into a functional accounting platform, rather than model-based literature or laboratory narratives. The modular design of ContaWeb-BI makes it possible to run these algorithms within a natural architecture, from data ingestion to results visualization, closing the full cycle of automated financial analysis. However, relevant limitations are also detected: the use of synthetic data, although replicable, fails to capture the complexity of real-life scenarios, especially in situations of high volatility or sophisticated fraud. The study did not include cross-validation with other more complex machine learning models, such as neural networks or XGBoost, or comparisons with commercial platforms, which can be explored in future research.
On a practical level, the findings show that platforms like ContaWeb-BI may be of potential interest to small and medium-sized businesses that require strategic support tools but lack the resources to hire expensive private alternatives. Similarly, the results demonstrate the need to increase the analytical literacy of accounting users so they can correctly interpret system outputs and thus help them make appropriate decisions.

CONCLUSIONS

The work presented in this article has allowed for corroborating that the use of machine learning models in accounting platforms such as ContaWeb-BI represents an adequate, accessible and functional response so that, when it comes to achieving strategic decision-making and economic management in the company, it can be useful, especially in small and medium-scale contexts.
The implementation of regression, classification, and clustering models successfully addressed three key problems: sales forecasting, the detection of possible fraud in purchases, and supplier segmentation. In each case, the models demonstrated solid technical performance and seamless integration into the platform's operational workflows, generating automated, visualizable, and actionable results for the end user.
The accuracy indicators obtained, such as the R^2 of 88% in the case of linear regression, the F1 score of 83% in classification, and the Silhouette coefficient of 0.69 in the case of clustering, confirm that it is possible to obtain reliable predictive and descriptive analyses without the need to resort to complex technological infrastructures or advanced knowledge in data science. Furthermore, ContaWeb-BI's modular design and user interface promote its use by non-expert users, reinforcing the value of this type of solution in environments where automation and the availability of real-time information are key to financial sustainability.
Among the study's main contributions are the practical validation of machine learning models in an operational accounting environment, the articulation of a complete analysis flow, from data loading to results visualization, and the proposal of a replicable system adaptable to different business contexts. In conclusion, ContaWeb-BI is a concrete example of how data science can be effectively introduced into accounting, representing a step toward analytical, automated, and intelligent accounting.

REFERENCES

1. Ashtiani, M., & Raahemi, B. (2021). Intelligent fraud detection in financial statements using machine learning and data mining: a systematic literature review. . *Ieee Access, 10*, 72504-72525.
2. Bao, Y., Hilary, G., & Ke, B. (2022). Artificial intelligence and fraud detection. . *Innovative Technology at the Interface of Finance and Operations: Volume I*, 223-247.
3. Cho, S., Vasarhelyi, M., Sun, T., & Zhang, C. (2020). Learning from machine learning in accounting and assurance. *Journal of Emerging Technologies in Accounting, 17(1)*, 1-10.
4. De Vries, K. (2021). A researcher's guide for using personal data and non-personal data surrogates: synthetic data and data of deceased people. . *De Lege*.
5. Doddapaneni, P., Sudhakar, S., & Vimala, S. (2025). Harmonizing Data Analysis and Model Selection for Superior IT Fraud Detection. . *In International Conference on Soft Computing and Pattern Recognition. Springer, Cham.*, 190-201.
6. Frölich, M., Landmann, A., Olapade, M., & Poppe, R. (2014). Non-experimental methodologies for quantitative analysis. *A practical guide to impact assessments in micro-insurance*, 111-129.
7. Gao, H., Kou, G., Liang, H., Zhang, H., Chao, X., Li, C., & Dong, Y. (2024). Machine learning in business and finance: a literature review and research opportunities. *Financial Innovation, 10(1), 86*.
8. Gundersen, O. (2021). The fundamental principles of reproducibility. *Philosophical Transactions of the Royal Society A, 379(2197)*, 20200210.
9. Igulu, K., Wisdom, D., Arowolo, M., & Singh, T. (2023). Computational Intelligence in Big Data Analytics. *In Computational Intelligence in Industry 4.0 and 5.0 Applications. Auerbach Publications*, 265-328.
10. Liaras, E., Nerantzidis, M., & Alexandridis, A. (2024). Machine learning in accounting and finance research: a literature review. *Review of Quantitative Finance and Accounting, 63(4)*, 1431-1471.
11. Menard, S. (2000). Coefficients of determination for multiple logistic regression analysis. . *The American Statistician, 54(1)*, 17-24.
12. Mhaskey, S. (2024). Integration of Artificial Intelligence (AI) in Enterprise Resource Planning (ERP) Systems: Opportunities, Challenges, and Implications. *Research Gate*.
13. Nguyen, D., Sermpinis, G., & Stasinakis, C. (2023). Big data, artificial intelligence and machine learning: A transformative symbiosis in favour of financial technology. *European Financial Management, 29(2)*, 517-548.
14. Phong, N., Tam, P., & Tung, N. (2024). Identifying Fraud Financial Reports Based on Signs of Income Management Using Machine Learning Technology: The Case of Listed Companies in Vietnam. *Journal of International Commerce, Economics and Policy, 15*, 2450013.
15. Sánchez, A., & Murillo, A. (2021). Enfoques metodológicos en la investigación histórica: cuantitativa, cualitativa y comparativa. . *Debates por la Historia, 9(2)*, 147-181.
16. Shadish, W., & Luellen, J. (2012). Quasi-experimental design. In Handbook of complementary methods in education research. *Routledge.*, 539-550.
17. Shokouhyar, S., Maghsoudi, M., Khanizadeh, S., & Jorfi, S. (2024). Analyzing supply chain technology trends through network analysis and clustering techniques: a patent-based study. *Annals of Operations Research, 341(1)*, 313-348.
18. Shollo, A., Hopf, K., Thiess, T., & Müller, O. (2022). Shifting ML value creation mechanisms: A process model of ML value creation. *The Journal of Strategic Information Systems, 31(3)*, 101734.
19. Zhang, J., Harman, M., Ma, L., & Liu, Y. (2020). Machine learning testing: Survey, landscapes and horizons. *IEEE Transactions on Software Engineering, 48(1)*, 1-36.