

The impact of AI on financial audit

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Abstract:

Financial fraud is becoming harder to audit because businesses process numbers of digital transactions every day. This research studies how Artificial Intelligence can modernize financial fraud auditing by using machine learning as a tool for auditors. The project uses empirical evidence from the ULB/Worldline credit card fraud dataset and published research. The dataset contains 284,807 transactions and 492 fraudulent transactions showing why accuracy alone is not enough.

Results reported by Al Bulushi et al. (2026) Show that machine learning models can have different precision and recall even when accuracy is approximately 99%. XGBoost reported 0.91 precision and 0.79 recall while the Bagging Ensemble reported 0.77 precision and 0.90 recall. In addition, Fedyk et al. (2022) Found that higher recent Artificial Intelligence investment was associated with a 5.0% likelihood of audit restatement and a 0.9% lower audit fee. The findings suggest that Artificial Intelligence can improve fraud screening, risk prioritization and audit efficiency. Artificial Intelligence should not replace the auditor. Human investigation, judgment, model monitoring and governance remain necessary. The research therefore supports a Artificial Intelligence collaboration model, for the modernization of financial fraud auditing.

Keywords:

Artificial Intelligence, Financial fraud, Auditing, Machine learning, Fraud detection, Audit quality, Finance.

Introduction:

Today financial transactions happen faster. In larger numbers than before. Because of this traditional fraud auditing that relies mainly on checking and sampling can become slow and can miss unusual transactions. The Association of Certified Fraud Examiners (ACFE, 2024) studied 1,921 fraud cases from 138 countries and found more than \$3.1 billion in losses across those cases. This shows why detecting fraud earlier is important.

Artificial Intelligence (AI) is now used as a tool in finance and auditing. Of an auditor checking every transaction manually an AI system can examine a very large number of transactions find unusual patterns and give the auditor a list of transactions that need more attention. The auditor still makes the decision but the AI helps reduce the amount of repetitive work.

Previous research already shows that AI can affect auditing. Issa et al. (2016) Explained that AI can formalize some audit tasks and supplement auditors. Kokina and Davenport (2017) also discussed how automation is changing audit work. Importantly Fedyk et al. (2022) Found that higher AI investment was linked to a likelihood of audit restatements and to lower audit fees.

The main gap in this research is that fraud detection research usually looks at measures such, as precision and recall while audit research usually looks at audit quality and efficiency. I think this project will connect the two areas and ask whether AI can modernize financial fraud auditing without replacing the auditor.

Research Questions:

- Does AI-based machine learning improve the detection of financial fraud?
- Which measures are more useful for auditors: accuracy, precision or recall?
- Can AI also improve the wider audit process?
- What are the limitations of using AI in fraud auditing

Literature Review:

The use of data mining in fraud is not new. Ngai et al. (2011) Reviewed the use of data-mining techniques in financial fraud detection. Showed that computational methods can help organizations identify patterns in large financial datasets. West and Bhattacharya (2016) also reviewed fraud-detection methods and explained that traditional manual approaches become more difficult when transaction volumes increase.

One important problem in fraud detection is that fraud is usually a small part of all transactions. The ULB/Worldline credit-card dataset contains 284,807 transactions. Only 492 fraudulent transactions (Dal Pozzolo et al. 2015). This means that about 0.17% of the transactions are fraud. Therefore, a model could have high accuracy while still missing many fraudulent transactions. This is why precision and recall are especially important.

In auditing, Gray and Debreceeny (2014) discussed how data mining can be applied to financial-statement audit fraud detection. Issa et al. (2016) Argued that AI can supplement the auditor by formalizing parts of the audit. Kokina and Davenport (2017) similarly described AI as a technology that changes the structure of audit work than simply removing auditors from the process. More studies argue that AI has revolutionized the audit industry (Sawaya et al., 2026), with technology and big data analytics having a positive externality effect on entire corporations (Subrahmanyam et al., 2024), especially SMEs (Khalife et al., 2024). While other variables such as auditor independence remaining significant (Sawaya et al., 2025) and increasing financial transparency (Saber & Sassine, 2022). However, for AI to be properly leveraged in the Audit industry, human intervention and professional experience is required (Chaanine et al., 2023), and while AI means an increase in efficiency, this increase does not necessarily translate into economic and financial growth (Athari et al., 2026).

Recent evidence gives a practical reason for this change. Fedyk et al. (2022) Using than 310,000 resumes from 36 large audit firms found that a one-standard-deviation increase in recent AI investment was associated with a 5.0% reduction in the likelihood of an audit restatement and a 0.9% reduction in audit fees. The authors also found changes in accounting employment over time. Therefore, AI can affect both the quality and efficiency side of auditing.

Finally, Al-Bulushi et al. (2026) Compared machine-learning models for credit-card fraud detection. Their results show that models can have different precision and recall even when their overall accuracy is almost the same. This is important, for auditors because missing a transaction and investigating a legitimate transaction do not have the same cost.

Methodology:

Research uses an empirical research method. Research does not create a company or fictional transactions. Instead, research uses published research and documented fraud data. The main transaction-level evidence comes from the ULB/Worldline credit card fraud dataset and the machine learning comparison reported by Al Bulushi et al. (2026). The wider audit evidence comes from Fedyk et al. (2022).

Variable	Definition
Fraud	0 = legitimate transaction; 1 = fraudulent transaction
Precision	Percentage of transactions predicted as fraud that are actually fraud
Recall	Percentage of actual fraud transactions detected by the model
Accuracy	Percentage of all transactions classified correctly
AUC	Measure of how well the model separates fraud from legitimate transactions
Audit restatement	Audit-quality outcome used by Fedyk et al. (2022)
Audit fees	Audit-cost measure used by Fedyk et al. (2022)

The main issue in the analysis is the large difference between legitimate and fraudulent transactions. Because fraud is rare accuracy is not enough. The study therefore gives attention to precision and recall. Recall tells us how much fraud the system catches while precision tells us how many of the alerts are actually useful.

The proposed audit process is simple: first the financial data is collected then the data is checked then the AI system gives each transaction a risk score. High-risk transactions are sent to the auditor for investigation. The auditor then checks the supporting evidence. Decides what action should be taken. This makes AI a complementary tool of an independent decision maker.

Results:

The results below are secondary empirical results from the cited studies. They are not presented as results from a fictional experiment. Al-Bulushi et al. (2026) reported important differences between machine-learning models when detecting fraud.

Model	Accuracy	Precision	Recall
Logistic Regression	0.99	0.08	0.00
Random Forest	0.99	0.88	0.77
XGBoost	0.99	0.91	0.79
Bagging Ensemble	0.99	0.77	0.90



Figure 1. Reported precision and recall in selected fraud-detection models. Source: Al-Bulushi et al. (2026).

The first important result is that all of these models have 99% accuracy.. This high accuracy does not mean that they are equally good at finding fraud. Logistic Regression has 0.00 recall in the comparison while Random Forest has 0.77 recall and XGBoost has 0.79 recall. The Bagging Ensemble has the reported recall in this table at 0.90. This shows why accuracy by itself can give the impression in a fraud problem.

Precision also changes between the models. XGBoost has a reported precision of 0.91 meaning that the model is more selective in the transactions it flags. The Bagging Ensemble has recall but lower precision. For an auditor this creates a trade-off: finding more fraud can also mean that the audit team has to investigate more false alerts.

The second part of the results comes from Fedyk et al. (2022). Their study found that a one-standard-deviation increase in AI investment was associated with a 5.0% lower likelihood of an audit restatement and a 0.9% lower audit fee. They also reported accounting employment reductions of 3.6% after three years and 7.1% after four years. These findings show that AI can change the audit process, beyond transaction-level fraud detection.

Evidence	Reported result
Fraud dataset	284,807 transactions; 492 fraud cases
XGBoost	0.91 precision; 0.79 recall
Bagging Ensemble	0.77 precision; 0.90 recall
AI investment and restatement	5.0% lower associated likelihood
AI investment and audit fees	0.9% lower associated fees

Discussion and Conclusion:

I read this research. It shows that Artificial Intelligence can modernize financial fraud auditing by helping auditors process large amounts of information more quickly. The machine learning results show that different models can have different fraud detection performance even when their overall accuracy is almost identical. Therefore, auditors should not depend on accuracy only especially when fraud represents a small percentage of transactions.

I read audit research. It also shows a relationship between AI investment and audit outcomes. Fedyk et al. (2022) Found restatement likelihood and lower audit fees when recent AI investment is higher. However, this does not mean that AI should replace auditors. AI can find patterns and prioritize transactions. The auditor still needs to understand the business investigate the evidence and make the professional judgment.

I think the practical implication is that the future audit process can become more continuous and risk based. Of waiting until the end of a period and checking a sample an organization can use AI to monitor transactions and send unusual cases to the audit team. This could make the auditors time more focused on transactions instead of repetitive checking.

I notice there are also limitations. The main fraud dataset is based on credit card transactions and the variables are anonymized. It is not exactly the same as financial statement fraud. The published results also come from research and therefore are not a new experiment conducted by this student. Finally, AI models can make mistakes and can become less accurate when transaction patterns change and require governance and human review. Furthermore, Audits should surpass financial statements into controlling and influencing other non-financial metrics, such as governance (Athari et al., 2023), especially in vulnerable environments, and sustainability (Kaspard et al., 2025 ; Kaspard et al., 2026).

I think future research should test datasets that compare more AI models study explainable AI and measure how auditors perform with and without AI assistance. A useful future experiment would measure fraud detected, alerts, investigation time and auditor judgment. The main conclusion is therefore that AI can be a complementary tool for modern financial fraud auditing while the human auditor remains responsible, for the final professional decision.

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