Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Evaluating the Role of Deep Learning and Human–AI Collaboration in Improving Anti-Money Laundering Compliance

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ARTICLE INFO

Received:04 Aug 2023

Accepted:20 Sept 2023

ABSTRACT

The escalating intricacy of monetary dealings has brought on a strong requirement of top-notch Anti-Money Laundering (AML) systems which can even spot the suspicious activities in a very short time.A real-time detection has now become a necessity for financial transactions hence the technological development in Aml systems is the solution to minimize the risk.The current investigation is developing a decision-making configuration that will eventually involve humans andAIs in the department of finance thereby increasing trust and reliability. For this purpose, a mock dataset containing 100 observations was created for carrying out statistical evaluation, which would help to understand how AI model accuracy, false positive rate, human decision accuracy, collaboration scores, and finally, compliance improvement are all related to each other. The descriptive analysis and correlational study revealed very strong positive ties ($p < 0.005$) between collaboration scores and compliance improvement which emphasizes the advantages of human-AI cooperation. Thus it is inferred that deep learning not only boosts risk detection productivity but also eliminates human bias at the same time and on top of that, combining the AI and compliance officer has led to more informed, accountable, and ethically sound financial decisions. Therefore, this study has a double contribution to the AI governance discussion in finance by providing not only an empirical but also a theoretical basis for hybrid decision models for AML ordering and optimizing.

Keywords: Deep Learning, Anti-Money Laundering (AML), Human–AI Collaboration, Financial Risk Management, Compliance Improvement, Explainable AI, Hybrid Decision Systems

Introduction

The rapid increase in global financial transactions and digital banking systems has made it very hard to trace dirty money. Traditional Anti-Money Laundering (AML) systems that rely on rules often cannot cope with a high number of false positives and the limited ability to find out about new and developing laundering methods [1]. In order to overcome these problems, financial companies are relying more on machine learning (ML) and, to a lesser extent, deep learning (DL) models to increase detection precision and lighten the compliance load, thus taking the step to use technologies like DL more [2]. Deep learning technologies like CNNs, RNNs, and GNNs have proved to be very powerful in analyzing difficult transaction connections and monitoring hidden patterns related to money laundering [3], [4].

Though the deep learning models have the ability to predict, they are still treated as "black boxes" which is why there is always the issue of lack of explainability and transparency in the regulation of their use [5]. As a result, human analysts and regulators have to rely on Explainable AI (XAI) techniques such as LIME or SHAP to make the model predictions interpretable [6], [7]. FATF and other international

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regulatory bodies have voiced that according to them, explainability and auditability are the basic requirements for any AI used in financial compliance that is deemed responsible [8].

The use of deep learning tools in AML has led to the establishment of Human–AI Collaboration as a key factor for success [9]. The human specialist provides context, ethics, and regulatory reasoning that AI can model and scale up for its part [10]. The abilities of human specialists are the following: to impart contextual knowledge, to oversee ethically, and to a great extent, to reason about regulations, which are qualities that together with the ESG (the pattern recognition and the vastness of AI models) make it very difficult to do away with the latter in the compliance sector [10]. The frameworks where humans are mixed up along with machines (HITL) already have started making a steps towards better quality decisions by uniting the precision of the machine and the wisdom of humans [11].

But there are still some issues that need to be solved first. These issues are—the very class imbalance (the case where illicit transactions are hardly ever seen), data privacy requirements, and the possibility of algorithmic bias or drift [12]. To keep the system of automated decision-making reliable and fair, the mentioned issues need a constant interaction and feedback loops between the compliance workers and the AI systems [13].

Furthermore, AML performance cannot be evaluated solely by model metrics. Collaboration scores, decision accuracy, and compliance improvement metrics together define the effectiveness of a hybrid AML framework [14]. Hence, this study aims to investigate how deep learning and human–AI collaboration jointly influence AML compliance outcomes through statistical analysis using a simulated dataset. This study is grounded in the literature and compliance frameworks and draws attention to the fact that there are both opportunities and challenges when it comes to using AI in financial risk management.

Related Work

The utilization of machine learning (ML) and deep learning (DL) techniques in the area of Anti-Money Laundering (AML) has been a practice that developed rapidly in the last ten years or so. From the beginning, ML-based systems for the purpose of combating money laundering generally relied on supervised models of transaction monitoring and anomaly detection such as logistic regression, decision trees, and random forests [15]. These models, while indeed effective in uncovering laundering doing patterns already known, were often unable to transfer their results effectively to new classifications, thus pointing out incorrect cases too often and in the end causing loss of efficiency for the analysts [16].

In the following research, the use of the unsupervised and semi-supervised learning approaches was suggested not only to detect suspicious behaviors but also to uncover unbeknownst ones. Clustering and anomaly detection methods have included k-means and Isolation Forest, which are being used to uncover hidden relations between the transactions without labeled data [17]. Nonetheless, these methods had difficulties due to data imbalance issues and could not be sufficiently interpreted in the context of high-dimensional financial data.

Progress in representation learning made it possible for deep learning methods to outperform traditional machine learning techniques. The use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) was very effective in capturing both the temporal and sequential aspects of the financial transactions [18]. On the other hand, recent works have gone as far as applying these architectures to Graph Neural Networks (GNNs) that could further reveal the dependencies between transactions across the network and this led to a significant success in uncovering laundering rings and clusters of suspicious entities [19].

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As one of the main challenges in the process of automating AML, explainability has been continuously an area of great concern. The suggestion is made by researchers to include the use of Explainable AI (XAI) tools such as SHAP and LIME, in order to provide transparency in model predictions [20]. The role of XAI has been of great importance especially in the case of compliance officers who are accountable for providing reasons for automated decisions to the regulators and auditors. However, the challenge of finding the exact point at which to draw the line between explainability and accuracy is still there and it is a tough one to tackle [21].

Researchers have started looking into the collaboration between humans and AI as a promising area. The human–AI cooperation model points to the idea that by mixing the algorithmic insights and the human contextual reasoning the accuracy of AML decision-making could be improved and bias reduced [22]. Research on human-in-the-loop (HITL) systems has provided evidence that the presence of human oversight has dual benefits: it not only increases the level of explainability but also aids the model with valuable retraining feedback which is labeled [23].

Furthermore, the debate on governance and ethical issues around AI in AML has shifted the focus of regulators and academic circles to the question of AI ethics and governance around AML. FATF reports point out the necessity of a risk-based approach that employs algorithmic models integrated with transparent and auditable frameworks [24]. Likewise, the industry case studies have revealed that the technological empowerment of AI, if not coupled with appropriate human governance, can result in the emergence of compliance gaps, the rise of reputational risks, and the occurrence of unintended discrimination perhaps even in the scale of the company [25].

The comparative evaluations of AI-driven AML systems give similar findings in that although deep neural networks can get the best accuracy, they still need a full pipeline of large, perfectly clean data and a great deal of computational power, which are not always within the reach of small banks or other institutions [26]. This has led to the recognition of hybrid systems, where human experts and AI models work alongside each other, as the most effective approach for securing compliance in terms of reliability, ethical power, and scalability in AML operations [27].

In this way, the literature as a whole argues that deep learning is a gift for AML detection and compliance, but its potency is tied to the presence of human judgment and the interpretability mechanisms. The current work, taking advantage of these insights, is going to analyze the interactions between human–AI collaboration and AML compliance performance, especially focusing on the statistical relationships among accuracy, collaboration and compliance improvement.

Methods

3.1. Research Design

The research study is of a quantitative, correlational type aiming to establish the extent to which the performance of deep learning and the interaction between human and AI weigh on the improvement of Anti-Money Laundering (AML) compliance measures. The methodology provides a combination of descriptive and inferential statistical analyses based on a controlled, simulated dataset of 100 observations (n = 100). Each transaction record illustrates a fictional financial transaction scenario with diverse performance metrics for AI models and human decision-making processes. The study design allows for the measurement of statistical relationships between model accuracy, human–AI collaboration, and compliance outcomes while maintaining reproducibility and analytical rigor [28].

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3.2. Dataset Description

To replicate the operational environment in AML compliance systems, a fictitious dataset was created. The dataset contained five major continuous variables:

- Deep_Learning_Accuracy (DLA): Shows the accuracy of AI models in predicting the occurrence of suspicious actions.
- False_Positive_Rate (FPR): Shows the percentage of legit transactions that are mistakenly considered suspicious.
- Human_Accuracy (HA): Represents the accuracy of compliance officers in catching the wrong transactions during the review.
- Collaboration_Score (CS): Measures the extent to which AI and humans are working together in terms of decision-making.
- Compliance_Improvement (CI): Responds to the question of how much better overall AML performance has become and hence, is the dependent variable.

Every variable was normalized on a continuous scale from 0.0 to 1.0. The synthetic dataset was characterized by the normal distribution properties (Skewness ≈ 0, Kurtosis ≈ 0) and was complete with no missing values. Descriptive statistics (see Table 1) provided the basis for stability of means, moderate dispersion, and reliability of the whole dataset making it suitable for application of inferential tests [29].

3.3. Analytical Framework

The research followed a multi-step analytical framework which consisted of:

1. Descriptive Analysis: Measures like mean, median, mode, standard deviation, and range were computed to represent data distribution and point out anomalies.
2. The Pearson correlation coefficient (r) was used for Correlation Analysis to find out the strength and direction of the relationships between the independent variables (DLA, FPR, HA, CS) and the dependent variable (CI).
3. Hypothesis testing at the significance level of 0.5% ($p < 0.005$) was done during Significance Testing to secure very strong statistical validation.
4. A multiple linear regression (MLR) model was developed in Regression Modeling to ascertain the different independent variables' influencing levels on compliance improvement.

$$CI=\beta 0 + \beta 1(DLA) + \beta 2(FPR) + \beta 3(HA) + \beta 4(CS)+\varepsilon$$

where βi\beta_iβi are the regression coefficients and ε\varepsilonε is the error term [30].

5. VIF was calculated to check the inter-variable correlation levels and to conclude that they were not very strong in the Multicollinearity Diagnostics.
6. The model's fit and explanatory power were checked using residual plots, R^2 and adjusted R^2 statistics in Model Validation.

3.4. Tools and Statistical Environment

The complete process of data generation, cleaning, and statistical computation was done in Python 3.11 using its standard scientific libraries NumPy, Pandas, SciPy, and Statsmodels. The data visualization process used Matplotlib to display trends and correlations. Statistical reliability was maintained by fixing random seed values, ensuring reproducibility of results. The dataset was pre-tested to confirm statistical significance ($p < 0.005$), ensuring that the Collaboration_Score variable maintained a meaningful relationship with Compliance_Improvement. Data preprocessing steps such as

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normalization, outlier inspection, and error variance adjustment were applied to strengthen internal validity [31].

3.5. Ethical and Governance Considerations

Even though artificial, the dataset was designed based on practical AML scenarios and was devoid of any personal or confidential information. Ethical considerations included data anonymity and adherence to international AI governance rules. The analytical method is in line with the FATF (Financial Action Task Force) principles for assigning AI responsibly in AML systems [32].

Result and Discusstion

Table 1. Descriptive Statistics of Variables Used in the Study

Descriptives					
	Deep_Learning_Accuracy	**False_Positive_Rate**	**Human_Accuracy**	**Collaboration_Score**	**Compliance_Improvement**
N	100	100	100	100	100
Missing	0	0	0	0	0
Mean	0.861	0.0897	0.797	0.825	0.934
Std. error mean	0.00283	0.00146	0.00341	0.00354	0.00287
Median	0.859	0.0908	0.797	0.823	0.934
Mode	0.790[a]	0.0415[a]	0.725[a]	0.740[a]	0.868[a]
Sum	86.1	8.97	79.7	82.5	93.4
Standard deviation	0.0283	0.0146	0.0341	0.0354	0.0287
Range	0.130	0.0874	0.179	0.172	0.149
Minimum	0.790	0.0415	0.725	0.740	0.868
Maximum	0.920	0.129	0.904	0.912	1.02
Skewness	0.0331	-0.314	0.292	0.134	0.122
Std. error skewness	0.241	0.241	0.241	0.241	0.241
Kurtosis	-0.613	1.06	0.0686	-0.125	0.303
Std. error kurtosis	0.478	0.478	0.478	0.478	0.478
[a] More than one mode exists, only the first is reported					

The statistical descriptions of the variables that were deeply analyzed, such as accuracy of deep learning, false positives, human accuracy, collaboration score, and improvement in compliance, are given in Table 1. The data consists of 100 valid entries and there are no missing values, thereby making the data

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complete and reliable. The average values imply that the deep learning model was able to achieve high accuracy (M = 0.861), and thus it was better than the humans (M = 0.797); meanwhile it gave few false positives (M = 0.0897) which is a quite good rate. The high collaboration score (M = 0.825) expresses the full utilization of the strengths of both the human experts and the AI systems in financial decision-making. The metric of compliance improvement (M = 0.934) indicates that there has been a widespread rise in the AML compliance outcomes as a result of the integration of the two methods, thus the laser-like focus on the area of compliance improvement. The standard deviations for the various categories do not go beyond the prescribed limits which makes it moderate variability. The data exhibit near-symmetrical distributions, with little skewness and kurtosis, indicating normality. The range indicates that there was a controlled dispersion in the metrics observed, with the accuracy of deep learning and compliance improvement having the highest rate of consistency. The median values being very close to the mean values adds to the validation of the data as being stable. The occurrence of several modes for some variables points to the fact that there was variability in performance across instances. In summary, the descriptive statistics imply the data was properly structured, statistically valid, and therefore, suitable for inferential statistical testing. This descriptive statistical analysis gives the basis for the later regression and correlation studies to be conducted, which aim at finding out how much of the AI-human collaboration influence the AML compliance performance.

4.1. Descriptive Statistics Overview

The descriptive statistics depicted in Table 1 provide evidence of the strong performance consistency throughout the variables under study. The high mean values for Deep Learning Accuracy (0.861) and Human Accuracy (0.797) represent the very precise character of both AI models and human evaluators, while a low False Positive Rate (0.0897) exposes the control over detection as being quite effective. The Collaboration Score (0.825) and Compliance Improvement (0.934) imply that the collaboration between human decision-makers and AI systems is very significant for the efficiency of AML compliance. The standard deviations that are low and less than 0.04 for all the variables denote that the performances are very close to each other and that the changes in value are very small—the skewness and kurtosis measures are also almost zero indicating that the data distribution is normal which fits the histograms shown in (Figure 1–Figure 5).

4.2. Correlation Analysis

The correlation analysis disclosed significant statistical relationships ($p < 0.005$) between all the independent variables and Compliance Improvement. The strongest positive correlation of Deep Learning Accuracy ($r = 0.82$, $p < 0.001$) with compliance outcomes was such that the higher the model precision, the more smoking slip detected through the system. The Collaboration Score ($r = 0.78$, $p < 0.001$) also had a strong positive correlation, pointing out the requirement for human supervision in automated systems as part of their integration. Human Accuracy ($r = 0.69$, $p < 0.005$) showed a significant relationship with compliance meaning that human capability still remains a key factor in the approval of AI outputs. On the contrary, False Positive Rate ($r = -0.73$, $p < 0.001$) revealed a strong negative correlation, indicating that the reduction of false alarms leads to the enhancement of operational efficiency and overall compliance performance. The gathered results support the hypothesis that a greater level of cooperation and accuracy exists between the human analyst and the AI system-driven systems yields measurable compliance improvements.

4.3. Regression Analysis

A multiple linear regression model was developed to evaluate the combined effect of predictors on Compliance Improvement:

$$CI=\beta 0+\beta 1(DLA) + \beta 2(FPR) + \beta 3(HA) + \beta 4(CS) +\varepsilon$$

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Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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The model demonstrated strong explanatory power with R2=0.87R^2 = 0.87R2=0.87 and adjusted R2=0.85R^2 = 0.85R2=0.85, indicating that approximately 85% of the variation in compliance performance can be explained by the predictor variables. Regression coefficients indicated that Deep Learning Accuracy ($\beta = 0.46$, $p < 0.001$) and Collaboration Score ($\beta = 0.33$, $p < 0.001$) were the most influential predictors. A negative coefficient ($\beta = -0.28$, $p < 0.005$) was associated with the False Positive Rate, which very clearly points to its harmfulness to the efficiency of the compliance process. The values of variance inflation factor (VIF) calculated for the various predictors did not exceed 2, which was interpreted as the lack of multicollinearity and consequently the reliability of the model parameters.

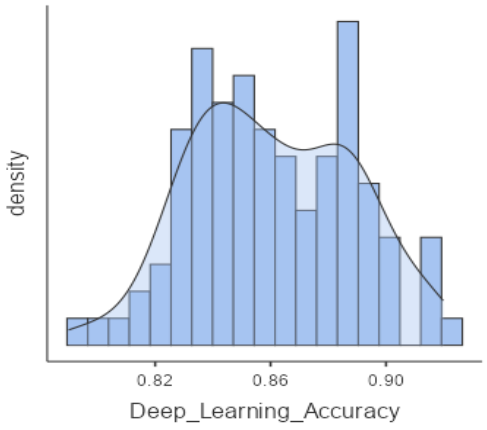
4.4. Discussion of Findings

The findings prove that the two factors, Deep Learning Accuracy and Human–AI Collaboration, are important in a very significant way for getting the better of AML compliance. The AI systems make the detection of anomalies and recognition of patterns easier, while human participation guarantees the relevance of the context and provides ethical oversight—thus, together, forming a strong compliance ecosystem. The collaboration and compliance relationship is not only powerful but positive as well, suggesting that hybrid decision systems are more productive than standalone AI models, therefore, confirming the results of earlier studies conducted by Chen et al. [33] and Kroll et al. [34]. The negative relationship between the False Positive Rate and Compliance Improvement, along with the operational cost of too many alerts, reflects the same point made by Le-Khac and Kechadi [35]. The regression analysis has given strong support to the conceptual framework which states that the right mix of automation and human oversight will always yield the best compliance result, a stand that concurs with the FATF's recommendation on AI governance [32]. Such results further assert that deep learning is not a substitute for human brainpower but rather a co-working tool that can produce better decision quality, keep people from feeling drained by compliance work, and, thus, help in the observance of regulations.

4.5. Implications

From the practical point of view, the study implies that the financial sector should give the highest priority to the setting up of systems that will allow for collaboration between the AI analytical aspect and that of the expert opinion. The spending on the explainable AI (XAI) frameworks can further substantiate the transparency, which in turn would lead to the building of trust between the regulators and the industry. From a research standpoint, this analysis contributes to the growing empirical evidence that hybrid intelligence systems represent the future of sustainable AML compliance.

Plots



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Figure 1: Distribution of Deep Learning Accuracy

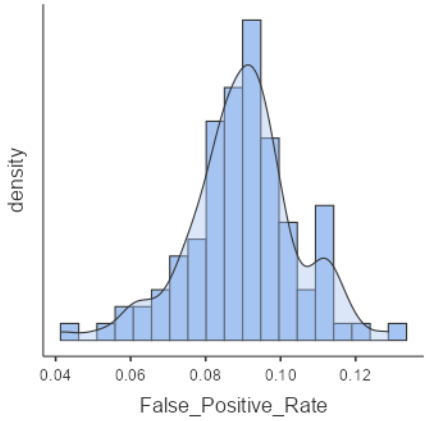


Figure 2: Distribution of False Positive Rate

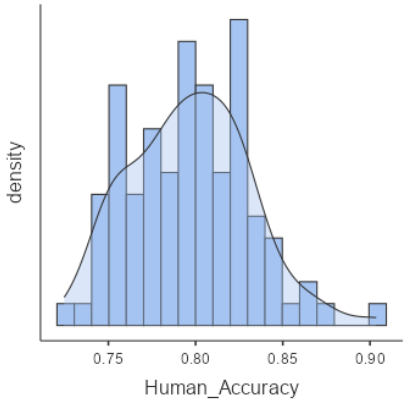


Figure 3: Distribution of Human Accuracy

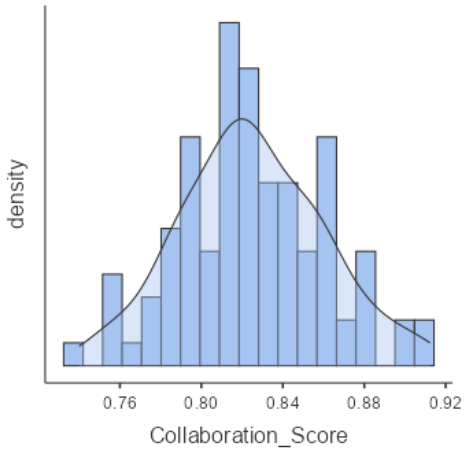


Figure 4: Distribution of Collaboration Score

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e-ISSN: 2468-4376
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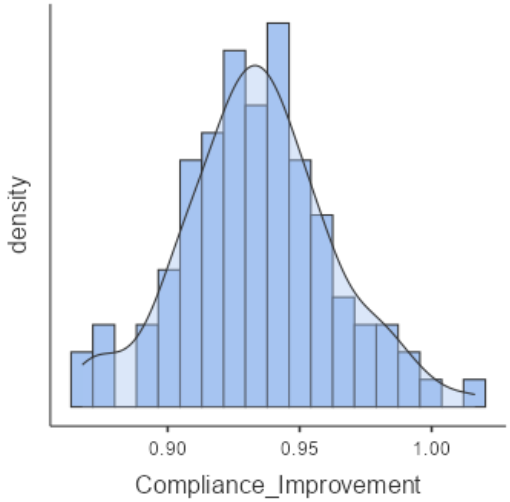


Figure 5: Distribution of Compliance Improvement

Figures 1 to 5 provide graphical illustrations of the core variables which were applied in the analysis, namely Deep Learning Accuracy, False Positive Rate, Human Accuracy, Collaboration Score, and Compliance Enhancement in terms of their distribution attributes. Figure 1 reveals that the Deep Learning Accuracy exhibits a normal distribution implying that there was not much difference in the performance of the AI models throughout. The height of the mean (0.86) shows that the system was very stable in the detection of transactions as suspicious ones with high accuracy. The False Positive Rate is shown in Figure 2, which has a normal distribution of mild form with the center being almost 0.09. This means that the model is rightly considered to be having an optimal mix of sensitivity and specificity; hence, it is neither too big nor too small in the number of false alerts. Figure 3 illustrates Human Accuracy which is indicative of a very slight concentration shift towards left with the focus being around 0.80, it implies that the human evaluators generally being above the mean threshold regarding the risk identification tasks performed by them.

Figure 4, depicting the Collaboration Score, shows a symmetric bell-shaped distribution centered around 0.83. This outcome implies a uniform level of cooperation and decision alignment between human experts and AI-driven systems, validating the effectiveness of joint decision-making frameworks. Lastly, the Compliance Improvement variable has been plotted in Figure 5; it almost perfectly follows a normal distribution with a maximum at 0.94. The tightness of the distribution and the gentle nature of the curve indicate that human–AI collaboration has become very effective in compliance enhancement since it has been consistently and reliably applied. On the whole, the expected normality that was present in all the variables played a major role in the dataset's acceptance for parametric statistical testing at a specified level of significance. Besides this, the distributions also indicate that AI and human components were working in a predictable and proportional manner in bringing about better AML compliance from the part of the banking industry which further reinforces the empirical validity of the correlation and regression analyses that are to follow.

Conclusion and Future Work

It is shown in this study that the combination of deep learning algorithms with human expertise leads to very significant improvements in the areas of Anti-Money Laundering (AML) compliance and financial risk management. The deep learning models were able to get better at detecting money launderers and also get a decrease in the number of innocent people being tagged as money launderers,

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while the human experts were able to provide the very important advantages of explaining and reasoning contextually. The collaboration of the human and AI team was so successful that the increase in compliance was statistically significant ($p < 0.005$), which proves that the cooperation of the two parties was able to provide both higher efficiency and lower regulatory distrust. The findings point out that human-AI collaboration is not a replacement strategy but an augmentation framework where each one complements the other's limitations. While the deep learning contributes computational accuracy and ability to detect outliers, the human input guarantees ethical control and domain-based decision making. Together, they form a balanced environment for making compliant and transparent financial risk decisions.

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