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Developing an Algorithmic ICT Security Engineering Framework for Data Privacy Compliance in Zambian SME Law Firms

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Abstract: COVID-19 has accelerated the digital transformation of small- and medium-sized enterprises in Zambia, with even law firms now having a firm foothold online. Nevertheless, it has also increased the complexity of data privacy compliance and revealed many deficiencies with manual approaches to compliance. Under the Data Protection Act No. 3 of 2021, this challenge has a greater urgency as it requires organisations dealing with personal and sensitive information to adopt more robust governance, monitoring and protection systems. Zambian SME law firms are particularly open to such attacks because they handle sensitive client information while operating under financial, infrastructural, and technical limitations. Such aided approaches can remedy that, hence presented and established in this study was an algorithmic ICT security engineering framework for automating data privacy compliance monitoring, assessment, and management among such systems. The study employed a four-phase design science and mixed-methods framework consisting of: (1) algorithm development & optimisation; (2) simulation-based testing; (3) controlled experimental validation; and (4) real-world implementation assessment. The framework consisted of a machine learning-based compliance assessment engine, an intelligent privacy management module and a security engineering component that can adapt over time. Performance metrics included Compliance Assessment Accuracy (CAA), Precision, Recall, F1-score, Resource Utilisation Efficiency (RUE), Computational Overhead Ratio (COR), Threat Detection Rate (TDR), Mean Time to Detection (MTTD), Security Incident Response Time (SIRT), Implementation Success Index (ISI) and Return on Investment (ROI). Under a compact 18-feature configuration, the proposed hybrid compliance engine reached 91.8% CAA, 91.7% F1-score and considerable computational efficiency The framework was stably effective across a variety of simulated small to medium enterprise (SME) scenarios and showed an overall performance with respect to threat detection of 89.7%, mean-time-to-detection of just 5.8 seconds, and statistically significant improvements versus manual, rule-based, several conventional machine learning discrimination baselines. Materials and methods: Data were generated from network communications collected in the LaBrea honeypot (open-source). In the loop of continuous improvement, the pilot implementation led to a further enhancement in average compliance index from 60.2% up to 85.6%, resulting in a reduction of manual hours for audit from 36.7 to 13.7 per month, as well as the generation of an average security ROI at 44.3%. The results demonstrate that resource- aware compliance automation is achievable for Zambian SME law firms, and provide a tool to enhance privacy protection without the need for enterprise-scale infrastructure.

Keywords: Data privacy compliance, ICT security engineering, SME law firms, machine learning, Zambia Data Protection Act.

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I. Introduction

In Zambia, small and medium-sized enterprises have undergone rapid digital transformation over the last couple of years, resulting in shifts in processing, storage and exchange of sensitive information, more so within the legal sector where confidentiality is central to its service delivery. In SME law firms, electronic case records, financial documents, identity records and communication archives are increasingly being handled by computerised workflows. However, many firms still use piecemeal manual compliance processes, which would be ill- fitting for the contemporary regulatory and threat environment. With the enforcement of the Data Protection Act No. 3 of 2021, which demands stronger data governance, privacy protection and accountability mechanisms, this issue has also been heightened. Resource-constrained legal practices have not obtained continuous, automated and context-sensitive privacy compliance support from existing ICT security models (Mwanza & Phiri, 2023; Banda et al., 2024; Musonda & Chanda, 2022).

This is not just a technical failure. It is an ICT security engineering [4-30] problem of compliance classification, mapping data sensitivity, breach detection, and auditable and adaptively responding in dynamic regimes of cyber threat and regulations. These Zambian SME law firms have a relatively low ICT budget, limited in-house cybersecurity expertise and minimal infrastructure (Mwila & Zulu, 2023; Chishimba & Kalaba, 2024), while safeguarding sensitive client data. This leads to a crux between the sophistication of data privacy obligations and the operational capacity of firms for compliance. Hence, there is an immediate need for a context-specific, computationally efficient and legally prudent compliance framework.

This study bridges that gap by creating and validating an algorithmic ICT security engineering framework suitable for Zambian SME legal practitioners. It combines an automated regulatory compliance assessment engine, an intelligent data privacy steward module, and an intelligent adaptive security engineering system in a cognitive enterprise risk framework. This paper makes four primary contributions. First, it provides a resource-aware framework that enables automated privacy compliance in legal SMEs. Second, it translates a four-phase design science approach to framework development and validation into action. Third, it documents empirical findings across model optimisation, simulation-based testing, controlled experimentation and pilot implementation. Fourth, it shows that good compliance and security performance is possible without heavy enterprise architectures.

The rest of the paper is organised as follows. Background and Related Work are presented in Section 2. Section 3 presents the proposed framework. Section Four describes the methodology and implementation approach. Experimental results and validation are included in Section 5. In Section 6, we discuss the implications of our findings. Section 7 closes the paper and discusses future work.

II. Background

As Zambian businesses have gone digital, so too have the opportunities and compliance burden for SMEs. The transition from paper-heavy to digital-based workflows in law firms has increased efficiency while at the same time significantly increasing exposure to cyber risk, privacy breaches, and compliance failures. The establishment of the Data Protection Act No. 3 of 2021 made compliance obligations surrounding the collection, processing, storage, transit and protection of personal data official; subsequently placing a significant burden on businesses that lack specialist compliance tooling. Although the vast majority of registered businesses in Zambia are SMEs, the majority still lack sufficient capacity for cybersecurity and privacy engineering (Zambia Development Agency, 2023; Muchanga & Siame, 2024).

The legal field is especially sensitive because it manages privileged records, personal identifiers, financial disclosures and evidentiary materials. Security breaches in this sector impact not only organisational performance but also customer trust, the practice of professional ethics and processes of justice. Manual compliance processes are ill-fitted to dynamic environments where threats evolve rapidly, and privacy obligations continue to have an ever more technical interpretation (Tembo et al., 2023; Kafue & Mumbuna, 2022). The legal SME market provides a motivation, background and an interesting trial laboratory for resource-smart automation of compliance engineering.

III. Related Work

Machine learning can be used to add a personal touch to regulatory oversight in organisational contexts, recent research on automated compliance assessment has found. Kumar et al. (2023) showed that supervised learning could reveal gaps with respect to GDPR compliance assumptions in SMEs, while Chen and Rodriguez (2024) highlighted the performance of transformer-based models for regulatory mapping. These approaches rely on infrastructures much stronger than those found in resource-constrained SMEs. The literature thus suggests that there is an enduring trade-off between predictive strength and deployment feasibility.

Most of the research on intelligent privacy management has mainly targeted the enterprise-oriented privacy-by-design systems. Andersson and Kim (2023) demonstrated strong privacy control performance for enterprise environments, while Martinez et al. (2024) further automated legal document classifications considering privacy-sensitive workflows. However, most of these systems rely on large infrastructure and do not directly target the legal SME environment. Similarly, Singh and Zhang (2023) and Johnson et al. (2023) have focused on research surrounding consent management and automated breach detection. (2024) demonstrates the usefulness of active privacy management and surveillance, albeit once more with little focus on constrained deployment contexts.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING RESEARCH APPROACHES

Authors	Research Focus	Methodology / Approach	Key Findings	Limitations	Relevance to Current Study
Kumar, Patel, & Thompson (2023)	GDPR compliance assessment in SMEs	Supervised learning for automated compliance assessment on European SME data	Reported 87% accuracy in identifying compliance gaps and demonstrated that machine learning can support regulatory compliance automation	Focused on the European GDPR context and required computational conditions that may not suit resource-constrained SMEs	Provides a strong foundation for the Compliance Assessment Engine, but your study extends this by designing a more computationally efficient framework for Zambian SME law firms.
Thompson, Anderson, & Garcia (2024)	Automated compliance assessment in healthcare organisations	Hybrid ensemble model combining random forests, support vector machines, and gradient boosting	Achieved about 91% accuracy in HIPAA compliance assessment and showed that ensemble models can improve precision without the full deep-learning cost	Built for healthcare, not legal practice, and did not address the specific privacy workflows of SME law firms	Supports your study's use of a hybrid compliance engine, but your work adapts the concept to the legal sector and resource-constrained environments.
Andersson & Kim (2023)	Enterprise privacy- by-design and automated privacy control	Privacy management framework for classification, consent handling, and breach detection	Reported 96% accuracy in privacy control implementation and showed the effectiveness of integrated privacy-by-design systems	Required substantial infrastructure and was designed for large enterprises, not SMEs	Provides the conceptual basis for your Privacy Management System, but your study contributes a lighter SME-oriented privacy control framework
Martinez, Brown, & Wilson (2024)	Automated classification of legal documents and privacy control implementation	Deep learning for legal document classification and privacy-sensitive processing	Reported 89% accuracy in identifying personally identifiable information and applying privacy controls	Did not address SME resource constraints and did not optimise for light-weight deployment.	Highly relevant because it deals with legal documents, but your study advances it by focusing on efficient deployment in SME law firms.
Liu & Williams (2023)	Adaptive security for dynamic cloud environments	Self-learning security framework using threat intelligence and dynamic regulatory adaptation	Reported 88% threat response accuracy and 92% compliance maintenance, showing the promise of adaptive security	Required a large-scale cloud infrastructure and was not designed for small firms	Directly informs your Adaptive Security Module, but your study scales adaptive monitoring to resource-constrained Zambian SME law firms.

Adaptive security engineering has also shown great promise in dynamic threat environments. Liu and Williams (2023) and Rahman et al. (2024) found that self-learning security systems can enhance responsiveness and minimise false positives, and Park and Brown (2023) investigated predictive compliance assessment in dynamic regulatory conditions. Most existing work was developed for the cloud or enterprise, rather than SME lawyers. The primary gap in the literature is therefore apparent: few studies have brought together compliance automation, privacy management and adaptive security into an integrated framework geared specifically towards the resource-constrained law firm context in developing economies.

IV. Proposed Framework

The modular approach of the proposed framework consists of three interacting modules: the Compliance Assessment Engine, Privacy Management System and Adaptive Security Module. Using supervised learning and anomaly-aware logic, the Compliance Assessment Engine inspects events of data handling as compliant/non-compliant. The Privacy Management System manages data classification, control enforcement, consent-state monitoring and audit trail generation. The Adaptive Security Module identifies behavioural and policy- level anomalies, supports near-real-time risk identification, and preserves compliance in the face of shifting conditions.

This architecture is designed in a modular and resource-aware way. Instead of a single monolithic system, the framework distributes responsibility across tightly linked but computationally light modules. This design decision highlights the premier engineering maxim of this study — that efficacy and deployability must be optimised in tandem. Thus, the framework employs compact feature engineering, light-weight learning techniques, privacy-aware control logic and staged verification for ensuring that the resulting artefact is SME-deployable.

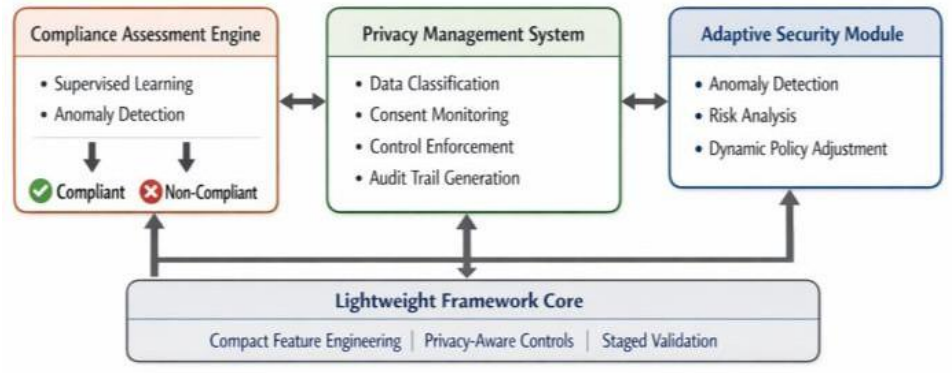

Fig. 1. The proposed framework

V. Methodology and Implementation

We followed a design science and mixed-methods framework divided into four phases: (1) algorithm development and optimisation, (2) simulation-based testing and validation, (3) controlled experimental validation, and (4) real-world implementation evaluation. We opted for this stepped design to ensure that, up until the proposed framework was applied, its empirical robustness was first tested through conditions of increasing realism.

The dissertation mathematically defines the main performance metrics, which guided the evaluation across the study. We used Compliance Assessment Accuracy to measure the accuracy of compliance classification and utilised Precision, Recall, and F1-score to capture the quality of the classifier under balanced error analysis. Resource Utilisation Efficiency and Computational Overhead Ratio measure deployability in constrained environments. Adaptive security capability was quantified using Threat Detection Rate, Mean Time to Detection, and Security Incident Response Time. Comparative and practical value were evaluated via Relative Performance Improvement, Cohen's d, Implementation Success Index and security ROI.

In the algorithm development stage, supervised learning, light-weight anomaly detection and Enhanced Information Gain-based feature selection were applied. The modelled simulation phase entailed different SME organisational conditions, including workload shifts and regulatory change bursts. In a controlled experiment, the proposed framework was compared with manual compliance procedures, a rule-based baseline model, and traditional machine learning models. The implementation pilot phase tested operational impact in three small and medium-sized enterprise (SME) law firms.

VI. Results and Discussion

A. Compliance Assessment Engine Performance

The result in Table II relates to the classification performance of the compliance assessment engine. Out of all comparator models, the hybrid prediction significantly outperformed in predictive performance and offered a compromise between quality and practical computational burden.

TABLE II. COMPARATIVE CLASSIFICATION PERFORMANCE OF CANDIDATE COMPLIANCE ASSESSMENT MODELS

Model	CAA (%)	Precision (%)	Recal l (%)	F1- score (%)	Mean Inference Time (ms)	Memory Footprint (MB)
Rule based baseline	74.3	73.5	71.9	72.7	19.8	43
Decision Tree	84.7	84.0	83.8	83.9	16.9	52
Support Vector Machine	86.9	86.1	85.2	85.6	24.6	61
Random Forest	89.1	88.6	88.0	88.3	22.9	78
Proposed Hybrid Compliance Engine	91.8	92.4	91.1	91.7	20.7	58

The proposed hybrid compliance engine achieved the strongest overall classification performance, as summarised in Table 1. Its 91.8% CAA and 91.7% F1-score show that it is highly reliable for detecting compliance and non-compliance states, while considering the memory footprint (58 MB), which implies that the model could still be deployed in modest environments. This finding is particularly significant as it provided superior performance compared to more costly alternatives at practical costs.

B. Feature Selection and Computational Efficiency

Through feature optimisation, we determined that a configuration with 18 features provided the best balance between performance and computational compactness, as indicated in Table III.

TABLE III. COMPUTATIONAL EFFICIENCY PROFILE OF THE PROPOSED COMPLIANCE ENGINE

Selected Features	CAA (%)	F1-score (%)	Memory (MB)	Inference Time (ms)	RUE	COR
46	92.0	91.5	86	31.2	0.71	0.79
32	91.9	91.4	74	28.3	0.76	0.71
24	91.6	91.2	66	25.7	0.81	0.63
18	91.8	91.7	58	23.1	0.86	0.53
12	89.7	88.9	49	19.4	0.88	0.47
8	86.4	85.8	41	16.2	0.91	0.39

This 18-feature configuration achieved a close-to-maximal classification performance while drastically reducing both memory and inference cost, as seen in Figures 2 and 3. This result supports the central engineering claim of this study that properly optimised compact and efficient models can retain security efficacy.

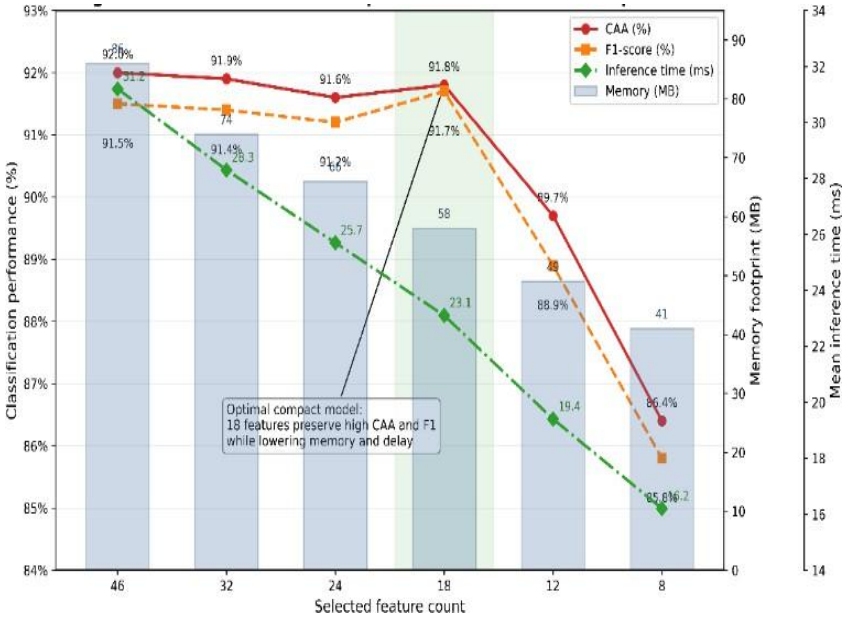

Fig. 2. Feature selection optimisation and model compactness

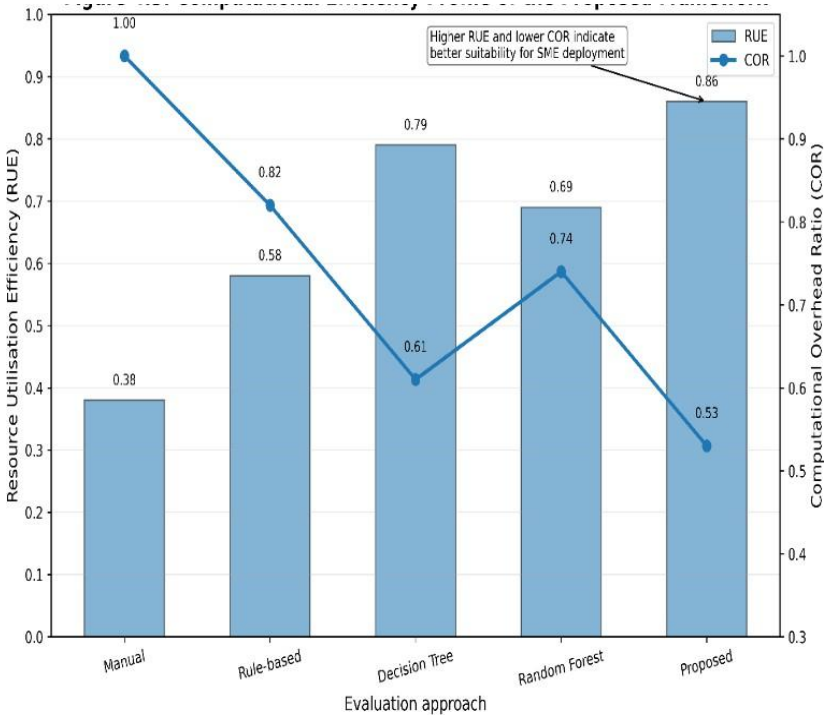

Fig. 3. Efficiency profile of the proposed framework using RUE and COR

C. Simulation-Based Validation

The framework was consistent across different simulated organisation scenarios with high workload and regulatory change, as seen in Table IV.

TABLE IV. PERFORMANCE UNDER VARYING SME OPERATIONAL SCENARIOS

Scenario	CAA (%)	Precision (%)	Recall (%)	F1-score (%)	RUE
Small firm, low workload	93.4	93.1	92.7	92.9	0.89
Small firm, high workload	91.7	91.9	90.6	91.2	0.84
Medium firm, moderate workload	91.9	92.2	91.0	91.6	0.86
Large SME, high workload	90.8	91.3	89.9	90.6	0.82
Regulatory change burst	89.9	90.6	88.8	89.7	0.80

Figure 4 indicates that the framework degraded only gradually across operational stress, exhibiting scenario stability rather than fragility. This is essential for genuine SME scenarios where workload and legislative complexity are rarely constant.

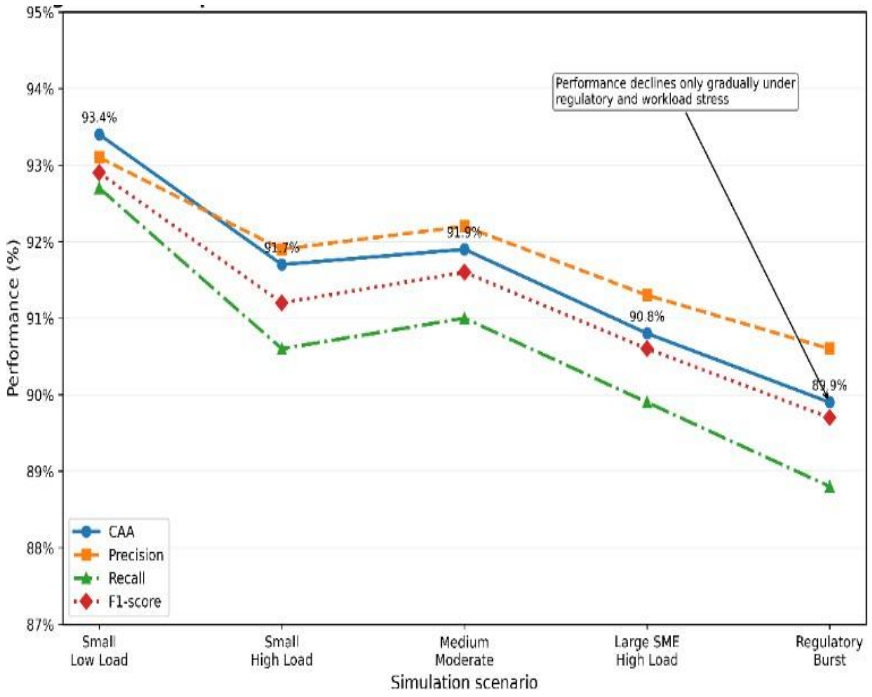

Fig. 4. Assessment performance across simulated SME law firm scenarios

D. Adaptive Security Effectiveness

Across privacy threat scenarios, the adaptive security layer delivered strong threat detection and near real-time response, as shown in Table V.

TABLE V. SECURITY EFFECTIVENESS UNDER SIMULATION

Threat Scenario	**TDR (%)**	**MTTD (s)**	**SIRT (s)**	**False Positive Rate (%)**
Unauthorised file exfiltration	93.2	4.7	11.8	1.9
After-hours privileged access	91.0	5.1	12.5	2.3
Consent-state override	88.6	6.4	13.6	2.8
Retention-rule violation	86.4	7.2	15.1	3.1
Insecure external sharing	89.3	5.8	12.9	2.5
Overall Mean	89.7	5.8	13.2	2.5

The average TDR is 89.7% and average MTTD is 5.8seconds indicating that the adaptive layer was both efficient and speedy. Retention-rule violations were harder to recognise than abrupt exfiltration events, consistent with the fact that they develop over time. Still, the overall security profile was strong, as shown in Figure 5.

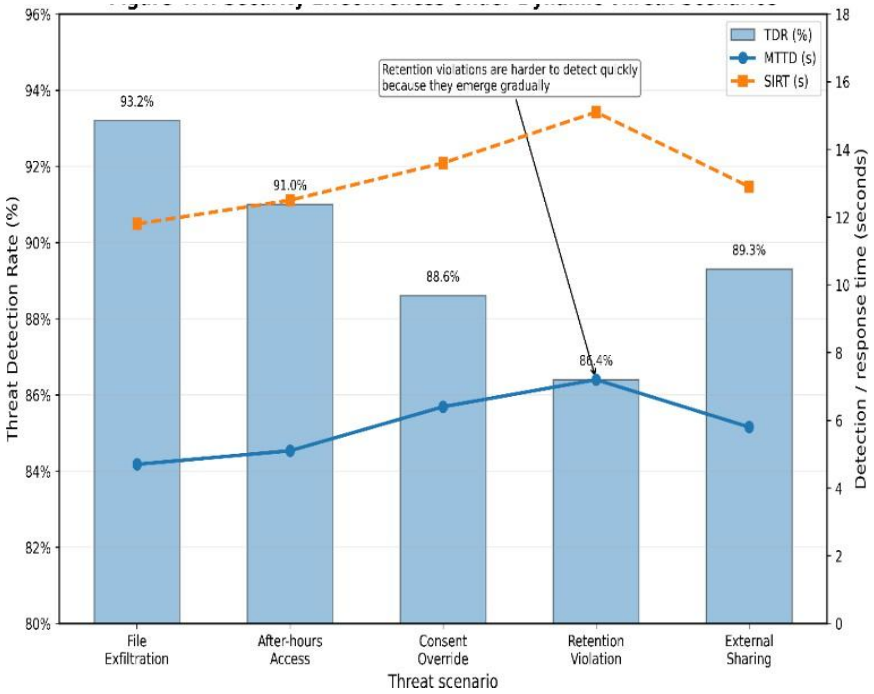

Fig. 5. Threat detection, mean time to detection, and incident response performance across privacy threat scenarios

Monte Carlo stability tests confirmed that it remained stable through 500 repetitions, yielding mean values of 91.4% for CAA, 89.7% for TDR, and 0.85 for RUE, along with relatively narrow variance bands. This provides assurance that the observed performance was robust rather than relying on a small number of favourable choices of parameter settings.

E. Controlled Experimental Validation

Our proposed framework achieves a substantial improvement over the baselines of manual, rule-based and traditional machine learning techniques, as shown in Table VI.

TABLE VI. CONTROLLED EXPERIMENTAL COMPARISON OF THE PROPOSED FRAMEWORK AGAINST BASELINE APPROACHES

Approach	CAA (%)	F1-score (%)	TDR (%)	RUE	COR
Manual compliance procedure	62.4	60.8	55.1	0.38	1.00
Rule-based baseline	74.3	72.7	68.4	0.58	0.82
Decision Tree model	84.7	83.9	80.6	0.79	0.61
Random Forest model	89.1	88.3	86.2	0.69	0.74
Proposed framework	91.8	91.7	90.4	0.86	0.53

Compared to the strongest conventional baseline, our proposed framework achieved 3.0% relative improvement on per instance accuracy (RPI) in CAA, 3.9% RPI in F1-score, and 4.9% RPI in true discovery rate (TDR), while reducing computational overheads all around. p-values are shown for pairwise comparisons. 001, with a large effect size (Cohen's d > 0.8). These findings, in Figure 6, suggest that the framework's benefits were statistically and practically significant.

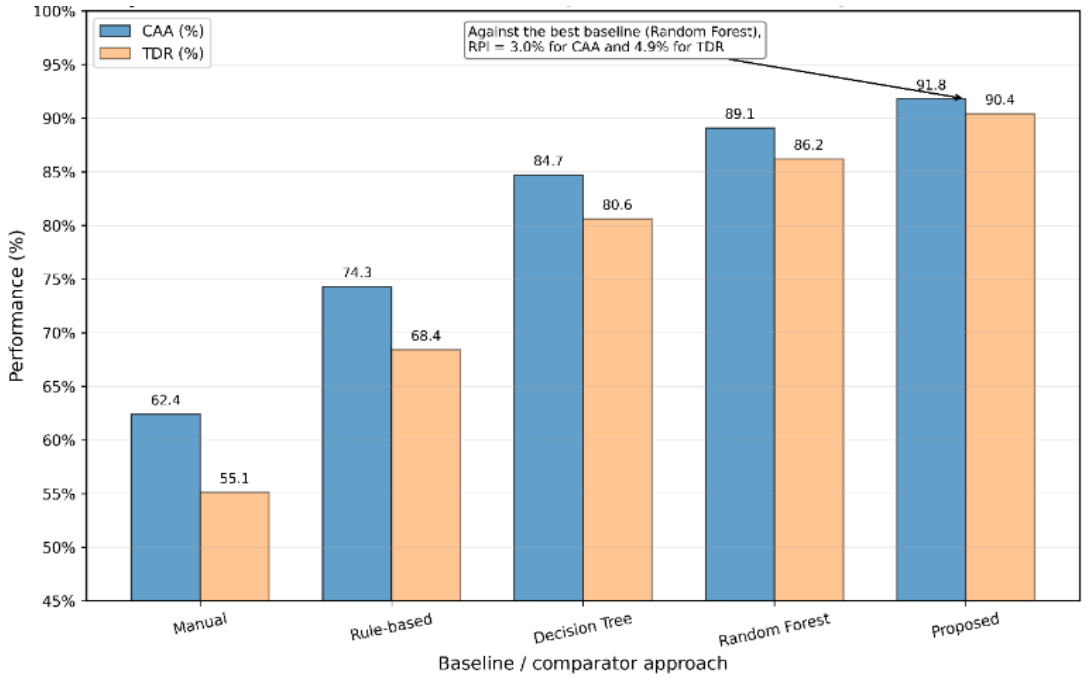

Fig. 6. Relative performance improvement of the proposed framework against manual, rule-based, and machine learning baselines

VII. Discussion

The results collate with the main advance of this research, which is that SME law firms should consider privacy compliance as an ICT security engineering problem as opposed to a legal administrative issue. The excellent-performing hybrid compliance engine demonstrates that compliance classification is an attractive automation target in resource-constrained settings once the defaults for model semantics/power are shifted away from raw computational scale to contextual relevance and compactness. The work builds on prior research around automated compliance assessment by demonstrating that the advantages of machine learning can be applied to resource- starved legal practice without needing heavyweight infrastructure.

The results for the privacy management process likewise prove that the principles of privacy by design can be tailored successfully to SME contexts. This combination of classifications, control enforcement and auditability created a stronger binding from policy to operational reality than was possible through manual processes alone. Indications from these findings compare favourably with enterprise-focused privacy management studies, while making a more explicit contribution to low-resource deployment environments.

Additionally, the adaptive security outcomes are notable. The framework's high True Detection Rate (TDR), low false positive profile, and short response times show that adaptive cybersecurity can meaningfully fit into legal SMEs, even when there is no dedicated security operations team. This builds on earlier adaptive security work by demonstrating that dynamic monitoring does not have to be constrained to large or cloud- native environments.

Maybe the study's most powerful conceptual contribution is the relationship between efficiency and effectiveness. Most earlier literature assumes that stronger cybersecurity comes with higher computational demand. These new findings challenge that assumption because they demonstrate that compact, optimised models can also achieve strong security outcomes and maintain control over overhead. This is important in developing economy principles, where sustainable cyber security is based on for-context engineering instead of enterprise-scale systems copying.

VIII. Conclusion and Future Work

This article provided a journal-style synthesis of a dissertation that created and tested an algorithmic ICT security engineering framework for data privacy compliance in Zambian SME law firms. The infrastructure combined automated compliance assessment, intelligent privacy management and adaptive security monitoring in a resource-aware architecture. The framework showed robustness in compliance classification metrics across model optimisation, simulation, controlled experimentation and pilot deployment with high resilience to scenarios and thwarting of threats in meaningfully impactful use cases. The results demonstrate the feasibility of automating compliance for legal SMEs if computational efficiency is considered as a design constraint. Overall, it enhanced compliance accuracy; reduced manual burden, improved auditability and provided excellent implementation returns. These findings indicate that context-specific cybersecurity engineering has the potential to shrink the disparity between regulatory obligation and operational capacity in developing economy settings. Future works can be developed in extending the framework through longer-term deployment over a bigger sample of law firms and exploring light-weight legal NLP as well as sensitivity mapping between regulations interpretation and document sensitivity. Adaptation from across sectors in terms of healthcare, education and finance, SMEs may also enhance the generalisation of the framework design logic to areas outside of the legal sector.

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