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AI-Enabled Audit Analytics for SME Financial Reporting and Anomaly Detection: A Risk-Based Framework for Early irregularity identification and Control Strengthening

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Abstract

Small and Medium Enterprises (SMEs) are susceptible to a "governance gap" due to weak controls and a high risk of financial fraud. This paper presents a Risk-Based Audit Analytics Framework to address this gap by combining AI-powered anomaly detection with transaction pattern analysis. By drawing on Shem & Mupa's (2024) research on business rescue and stakeholder engagement, and current research on the application of AI in fraud prevention (Adeboye, 2024; Antwi et al., 2024), the research explores how SMEs can use data science to identify unusual activity sooner than traditional audit processes.

We examine the use of Machine Learning (ML) in general ledger anomaly detection and Process Mining to assess internal controls (Duan et al., 2024). This framework builds on Mupa's "Enterprise Resilience" by suggesting that, to survive financial hardship, an SME must adopt a Sustainable Auditing model that offers real-time transparency (Pillai, 2025). By analyzing the use of AI in financial reporting and the ethical considerations of automated auditing (Murikah et al.2024), this study offers a scalable approach to enhancing controls in resource-limited settings. The article concludes that AI-powered analytics not only enhance efficiency but serve as a "digital buffer" for SME survival and community prosperity (Ayankoya et al., 2025).

Keywords: Unified Data Activation (UDA); Enterprise Resilience; SME Governance; AI-Enabled Auditing; Anomaly Detection; Process Mining; Sustainable Auditing; Internal Control Evaluation; Decision Intelligence; Digital Trust

1. Introduction: SME "Governance Paradox"

Small and Medium Enterprises (SMEs) play a crucial role as the lifeblood of the global economy, yet they are caught in a "Governance Paradox." According to Shem & Mupa (2024), in their groundbreaking work on business rescue, the strategic fulcrum for any organizational recovery or growth is the alignment of legal and strategic stakeholders. Yet this is often frustrated by a "governance gap" in smaller enterprises, resulting in disjointed internal controls and limited audit capacity. Whereas large firms have dedicated risk management units, SMEs may resort to manual control

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mechanisms and retrospective accounting. This poses a significant problem: the very firms that need to have sophisticated, real-time internal controls in place to sustain their operations through market shocks are least likely to have the infrastructure to adopt them.

Conventionally, auditing for SMEs has been compliance-driven and retrospective, a forensic exercise in financial health-checking rather than a preventative measure against irregularity. Conventional approaches involve annual audits that detect fraud, error, or business inefficiencies months after they have impacted the firm's financial performance. According to Adeboye (2024), for small firms to improve fraud prevention, they need to transform their accounting and auditing processes. Beyond reporting what has happened, businesses must be able to detect what is happening. This is where the shift to AI-powered audit analytics comes into play, turning the audit from a "one-off" to an "always-on" defense mechanism.

In Mupa & Shem's (2026) "Unified Data Activation" (UDA) approach, auditing needs to be viewed as an integrated part of the data ecosystem. For most SMEs, financial data is fragmented into separate general ledgers, payroll ledgers, and spreadsheets. Data activation with Artificial Intelligence enables what Ilori et al. (2024) term a "holistic risk assessment," in which micro variations in transaction patterns and anomalies, unseen by human auditors, can be identified (Yuan et al., 2025). By using Machine Learning (ML) to identify high-risk situations and high-risk SMEs, they can finally move from reactive to "predictive" control. This aligns with Mupa (2025), "Actuarial Implications of ESG Risk," in which the measure of success is the ability to assign a quantitative value to risk factors before they become a corporate disaster.

Additionally, the use of AI in general ledger anomaly detection (Putra & Chowanda, 2025) gives rise to "Sustainable Auditing". This makes the audit process an enabler of the business's future "Enterprise Resilience" by minimizing the "dwell time" of errors in financial reports through the adoption of AI in the preparation of financial statements. Awad et al. (2025) guarantee accuracy and compliance at the pace typically afforded only to multinational corporations. But, as warned by Murikah et al. (2024), this shift must be underpinned by ethical principles to prevent bias from entering the financial system. For local economies, SMEs adopting this risk-based framework is not just a technological advance; it is "digital trust" (Ayankoya et al., 2025). This trust serves as the infrastructure needed to attract investors and nurture risk-conscious development. This introduction sets the stage for a holistic framework that transforms auditing into a data-activated, early-warning system for the modern SME.

2. Literature Review: AI-Ready Auditing and SME Disaster Preparedness

2.1. The Criticality of "Data Activation" in Small Business Auditing

One of the key principles underlying the Bridging Data Fragmentation research of Mupa & Shem (2026) is that data is only strategically valuable in an AI-ready environment when "activated". Traditionally, financial data in the SME sector has been "dormant" and sequestered in different digital ledgers, receipts, or accounting books. According to Antwi et al. (2024), the role of AI for detecting financial anomalies is to bridge siloed operational functions. Using computer-intelligent algorithms (Liu & Fu, 2024), SMEs can effectively convert a stream of independent transaction data into a single, high-speed intelligence stream.

This aligns with Mupa's "AfriDASH" approach, which views an audit as effective only when integrated with a platform that enables real-time visibility across business units. Lu & Wu (2015) also re-examine intelligent auditing from a data science perspective, noting that the ability to synthesize high-velocity transaction data is the key factor that distinguishes "Data-Driven" (new) firms from "Document-Driven" (old) firms. This enables an SME to see the chinks in its armor, which erode capital positioning.

Table 1 Dormant Data Vs. Activated Data in SME Auditing

Dimension	Dormant Data Environment	Activated Data Environment
Data Structure	Fragmented	Integrated
Audit Visibility	Limited	Real-Time
Decision-Making	Delayed	Immediate
Fraud Detection	Reactive	Predictive

Data Processing	Manual	AI-Driven
Business Intelligence	Weak	Continuous
Financial Monitoring	Periodic	Continuous
Operational Coordination	Siloed	Unified
Risk Awareness	Low	High
Enterprise Resilience	Vulnerable	Strengthened

2.2. Anomaly Detection and the "General Ledger" Frontier

This cutting-edge of auditing is General Ledger (GL) Anomaly Detection. Auditing has traditionally involved sampling - the review of a subset of transactions to determine the condition of the entire population. But as Putra and Chowanda (2025) show, GL anomaly detection using AI enables a 100% population review, which reveals irregularities that cannot be detected by sampling alone. This advancement is crucial for what is now known as "Sustainable Auditing" because it offers the sort of granularity seen only in the largest multinational enterprises. Pillai (2025) stresses that AI-based systems can detect anomalies in enterprise financial data streams in milliseconds, offering an early warning system vital for SMEs with limited cash flow and margins. This aligns with Mupa's (2025) strategic view of business rescue: the earlier the irregularity is detected, the greater the chance of a successful, stakeholder-driven rescue. Here, AI is not only a precision instrument, but also a life raft for enterprise survival.

Table 2 Traditional Auditing vs. AI General Ledger (GL) Anomaly Detection

Dimension	Traditional Audit Sampling	AI GL Anomaly Detection
Audit Coverage	Small Sample (<5%)	Full Population (100%)
Detection Speed	Slow	Real-Time/Milliseconds
Fraud Visibility	Limited	High Granularity
Risk Identification	Reactive	Predictive
Error Detection	Partial	Comprehensive
SME Protection	Weak	Strong
Data Processing	Manual	AI-Driven
Financial Monitoring	Periodic	Continuous
Enterprise Resilience	Vulnerable	Enhanced
Stakeholder Confidence	Moderate	High

2.3. Process Mining for Internal Control Evaluation

The research has not only moved beyond reviewing transactions to the complex field of Internal Control Evaluation (ICE), but also to the complex field of Internal Control Evaluation (ICE). Duan et al. (2024) suggest a sophisticated approach to Internal Control Evaluation (ICE) using Process Mining and Machine Learning. Within the need for speed of an SME, controls can be circumvented. Process mining makes "visible" the actual flow of financial transactions as opposed to the theoretical flow, thereby identifying "risky" gaps where fraud or process failure may occur. Ilori et al. (2024) claim that this offers a more holistic view of risk than traditional audit does. This is an application of Mupa (2025) "Actuarial Implications of ESG Risk" as it enables the firm to allocate "risk weights" to various processes. Through this process, management can understand which control points are most often circumvented and build the "firm's resilience" before the breach, turning the control point from a weakness into a strength.

2.4. Preventing Fraud and Its Economic Effect on Local Economies

The social and economic significance of auditing SMEs is critical. Ayankoya et al. (2025) propose a model for "Data-Driven Financial Optimization" to enhance efficiency and sustainability in local economies in the U.S. and worldwide. They find that SMEs adopting AI for improved financial controls are more likely to obtain credit and attract investors. This aligns with Adeboye's (2024) study of best accounting practices in small businesses, where he notes that fraud prevention is a critical factor in small business growth, sustainability, and trust. This is consistent with Mupa's (2025) research on Sustainable Budgeting, which finds that financial transparency is "the foundational infrastructure" for underserved communities. Without confidence in local business financial reports, capital is constrained, slowing financial growth. Thus, AI in auditing supports macroeconomic stability and ensures that the SME sector remains a source of growth, innovation, and jobs.

2.5. High-Risk Identification through Machine Learning

The underlying technology behind these audits may involve sophisticated adaptive Machine Learning processes. Yuan et al. (2025) outline an enterprise financial audit system based on "High Risk Identification". Their approach employs supervised learning to identify previous patterns of fraud and apply these to real-time data, "learning" the patterns of fraud. Awad et al. (2025) extend this to examining the use of AI in the preparation of financial statements, where they claim that compliance and accuracy are significantly improved when an algorithm removes the "human error" factor. But, as Meng (2024) cautions, adopting these models for small- and medium-sized accounting firms involves substantial training and a cultural shift. The research suggests that "Algorithm" is only as good as "Human Governance". For an SME, this means the auditor is shifting from a data miner to a data strategist who must analyze AI results in the context of the SME's risk.

Table 3 Machine Learning Risk Identification Vs. Traditional

Dimension	Traditional Auditing	ML-Based Risk Identification
Fraud Detection Method	Manual Review	AI Pattern Recognition
Detection Speed	Slow	Real-Time
Risk Identification	Reactive	Predictive
Data Processing Capacity	Limited	High-Volume Processing
Human Error Exposure	High	Reduced
Audit Scope	Sample-Based	Full Population
Learning Capability	Static	Adaptive & Self-Learning
Decision Support	Historical	Predictive Intelligence
SME Governance	Manual Oversight	AI-Assisted Governance
Auditor Role	Data Examiner	Strategic Risk Analyst

2.6. Ethical Implications and the Risk of Algorithmic Bias

As AI takes over the role of the auditor, there have been academic concerns about Ethics and Bias. Murikah et al. (2024) offer a systematic literature review of the ethical issues in AI-based auditing, arguing that if the algorithm is trained on "dirty data" or biased past data sets, it could discriminate against certain types of transactions or populations as "high risk," leading to unfair scrutiny or the refusal of services. This ethical aspect is discussed in Mupa (2025) regarding stakeholder engagement. Trustworthy audits are transparent and equitable, enabling investors, employees, and regulators to rely on them confidently. The "Black Box" characteristic of some AI models can compromise this, introducing a new source of institutional risk. As a result, the literature argues for "Explainable AI" (XAI) in auditing, where the "anomaly flag" is justified by a logical, data-driven explanation that a human auditor can verify. Ethics is not an optional consideration, but a key element of "Digital Trust," which Mupa claims is core to enterprise survival.

2.7. Decision Intelligence and Accuracy Enhancement

The end goal of AI-based auditing is to improve Corporate Performance through "Decision Intelligence." In Awad et al. (2025), we show that companies that rely on AI for financial monitoring report more accurately and achieve greater overall compliance with international reporting standards. This is not just about compliance and fines; it's about giving management a "clean bill of health." With complete trust in the accuracy of their financial data, management can be more ambitious and take more risks in their plans. Celestin & Mishra (2025) observe that AI-based analytics can improve forecasting accuracy, a key to SME planning. This echoes Mupa & Shem's (2026) "Unified Data Activation" theory. Once data is unified and audited through an intelligent audit, it ceases to be a historical record and becomes the driving force behind the enterprise's future "Resilience Engine."

2.8. Synthesis: The Risk-Based Framework for SME Survival

The amalgamation of Mupa et al. and these other 20 cross-disciplinary sources yields a simple conclusion: the future of SMEs will not be built on manual auditing. The "Governance Gap" is a structural threat that can only be bridged by the Risk-Based Framework proposed in this article. By combining Process Mining, GL Anomaly Detection, and Ethical AI Governance, SMEs can build a "defensive architecture" that is both robust and adaptive (Duan et al. 2024; Putra & Chowanda, 2025) & Murikah et al. 2024).

This review establishes that the "Service Cliff" for SMEs—the point at which they grow too large for manual oversight but remain too small for traditional enterprise audits—is the most dangerous phase of the business lifecycle. The application of Mupa's Resilience Theory suggests that AI is the "bridge" across this cliff. By automating the identification of irregularities and strengthening internal controls through data science, SMEs can achieve a level of financial reporting that commands the trust of the global market. As we move into the methodology section, we will detail how these theoretical threads are woven into a replicable, technical system for the modern, AI-empowered SME.

3. The Methodology: A Multi-layered AI-Audit Framework for SMEs

3.1. Data Integration and Normalization (The UDA Layer)

In line with Mupa's AfriDASH architecture, the first step in our methodology is to integrate SME data. Typically, SMEs have isolated payroll, inventory, and sales systems. Our approach uses Financial Big Data Management (Liu & Fu, 2024) to ingest these streams into a data lake. This involves extracting data from a variety of sources, such as QuickBooks, SAP FICO modules, and even simple Excel journals. We introduce a schema that enables capture and standardization of these data into machine-readable structure.

Table 4 Core Dataset Variables

Field Name	Description
Transaction ID	Unique transaction identifier
Source System	QuickBooks, SAP FICO, Excel
Account Code	General ledger account
Transaction Amount	Monetary value
Currency Code	Standardized currency
Vendor ID	Unified supplier identifier
Employee ID	Responsible employee
Transaction Timestamp	Date and time
Approval Status	Approved/Pending/Rejected
Branch ID	Business location
Entry Method	Manual/System-generated
Risk Tag	Initial risk classification

Once captured, the data is "normalized" (timestamped transactions, valuations in a single currency, unique vendor IDs across the entire landscape). This is a critical stage, as the success of AI in financial statement preparation, as described by Awad et al. (2025), depends on the quality of the initial data. Capturing governance variables help build stakeholder trust, sustainable auditing and ethical use of AI.

Table 5 Governance Variables

Variable	Description
Data Completeness	Percentage of missing values
Duplicate Record Rate	Frequency of duplicate entries
Timestamp Integrity	Accuracy of time records
Cross System Consistency	Alignment between systems
Data Lineage Status	Traceability of records
Access Control Level	User authorization quality
Audit Trail Availability	Presence of historical logs

We deploy scripts to cleanse data, removing duplicate transactions, inconsistencies in data formatting, or missing data elements, to provide a "clean" data set for further processing.

Table 6 Data Cleansing and Transformation Logs

Field	Description
Record ID	Original data record
Cleansing Action	Duplicate removal/format correction
Missing Value Action	Imputed/Removed
Currency Conversion Applied	Yes/No
Timestamp Adjustment	Standardization status
Validation Status	Passed/Failed
Processing Date	ETL execution time

Failure to complete this step would result in poor Anomaly Detection with high "False Positive" rates, which would reduce stakeholders' trust, as Mupa suggests, and would be critical to enterprise sustainability.

3.2. Machine Learning for Transactional Anomaly Detection

Phase two implements General Ledger (GL) Anomaly Detection, as discussed by Putra and Chowanda (2025). We develop an Unsupervised Machine Learning Model, in particular, the Isolation Forest algorithm. This model is selected for its effectiveness with High-Dimensional Data; it does not require a pre-classified "fraudulent" dataset, which is difficult to obtain in an SME environment. It finds anomalies based on the "path length" it takes to isolate a transaction in a tree-like model. Uncommon or unique transactions are isolated near the "root" of the tree, and are identified as potential anomalies.

Table 7 Dataset for capturing Anomalies and continuous auditing

Field Name	Description
Transaction ID	Unique transaction reference
Account Code	General ledger classification
Transaction Amount	Financial value
Transaction Date	Posting date
Transaction Time	Time of entry
User ID	Employee initiating transaction
Vendor ID	Supplier identifier

Approval Level	Authorization hierarchy
Payment Method	EFT, Cash, Cheque
Branch ID	Operational location
Currency Code	Standardized currency
Ledger Type	Payroll, Procurement, Sales
Transaction Status	Completed/Pending
Anomaly Score	Isolation Forest output
Risk Label	Normal/Suspicious

It considers 12 features for each transaction: the account's usage frequency, the transaction amount, the day of the week and time of day (e.g., weekend entries; late-night entries), and the user ID used to update the ledger. Any transaction that lies outside the three-standard-deviation "Resilience Zone" Mupa (2025) is automatically highlighted. This layer effectively replaces the classical auditor's sample (typically less than 5% of the data) with a population approach (100% of the data). The methodology's focus on reviewing the entire general ledger eliminates the "discovery lag" in detecting financial anomalies. It enables management to respond within days rather than wait for the annual audit report.

Table 8 Twelve (12) Features

Field Name	**Description**
Transaction ID	Unique transaction reference
Account Code	General ledger classification
Transaction Amount	Financial value
Transaction Date	Posting date
Transaction Time	Time of entry
User ID	Employee initiating transaction
Vendor ID	Supplier identifier
Approval Level	Authorization hierarchy
Payment Method	EFT, Cash, Cheque
Branch ID	Operational location
Currency Code	Standardized currency
Ledger Type	Payroll, Procurement, Sales
Transaction Status	Completed/Pending
Anomaly Score	Isolation Forest output
Risk Label	Normal/Suspicious

3.3. Internal Control Evaluation (ICE) using Process Mining

To overcome the "structural vulnerabilities" in SME governance, the methodology uses Process Mining as developed by Duan et al. (2024). This includes obtaining "event logs" from the SME's ERP or accounting system. These logs must include a Case ID (e.g., a specific Purchase Order ID), an Activity (e.g., "Invoice Received"), and a Timestamp.

Table 9 Core Event Log Variables

Field Name	Description
Case ID	Unique process instance (e.g., Purchase Order ID)
Activity Name	Specific business activity
Timestamp	Event execution time
User ID	Employee performing activity
Department ID	Business unit
Approval Level	Authorization hierarchy
Transaction Amount	Financial value
Process Status	Completed/Pending/Rejected
Vendor ID	Supplier involved
System Source	ERP/Accounting platform
Activity Duration	Time spent in process step
Exception Flag	Indicates process deviation

The AI system compares the "As-Is" process, which is the digital audit trail of how transactions flowed through the organization, with the "To-Be" process, or the firm's internal control policies. If there is a policy requiring clear "Segregation of Duties" so that different users must "Request" and "Approve" a payment, the process mining tool identifies all instances where this control was breached. It highlights "shadow processes" where users may have circumvented the formal process. This gives management an indication of the Internal Control Effectiveness and allows them to "Rescue" their business before it fails (Shem & Mupa, 2024).

Table 10 Process Mining Analytical Workflow

Stage	Function
Event Log Extraction	Capture operational records
Process Reconstruction	Rebuild workflow sequence
Conformance Analysis	Compare “As-Is” vs “To-Be”
Deviation Detection	Identify governance breaches
Risk Scoring	Assign control severity
Management Reporting	Dashboard visualization

3.4. Risk-Weighted Alerting and Stakeholder Reporting

In the fourth stage, Mupa (2025) Actuarial Risk Assessment is applied to the results. Anomalies may not always be fraud, but merely errors or special one-off transactions. To avoid "alert fatigue" and the consequent disregard for security measures, the approach has a Weighted Scoring System.

High Risk (Score 8-10): Anomalies with cash-equivalent accounts, new vendor creations without proper approval, or transactions without a "Process Mining" equivalent.

Medium Risk (Score 5-7): Major control exceptions in procurement, or unexplained variances in inventory.

Low Risk (Score 1-4): Minor delays in entries, non-essential documentation, or minor variance in utilities.

These scores are summarised in a Strategic Audit Dashboard. This dashboard is intended for "Stakeholder Synergy," so that the business owner, external auditor, and board of directors can get a consolidated view of the company's risk profile. This is crucial for local economic and financial optimization, as Ayankoya et al. (2025) point out, because it provides the certified data required to access external funds and to demonstrate institutional resilience to investors.

Table 11 Strategic Audit Dashboard Metrics

Metric	Purpose
Enterprise Risk Index	Overall SME risk exposure
Fraud Exposure Score	Severity of detected anomalies
Control Effectiveness Index	Strength of internal controls
Financial Stability Score	Liquidity and resilience measure
Vendor Risk Map	Supplier-related risk analysis
Process Compliance Rate	Workflow and policy adherence
Open Critical Alerts	Number of unresolved high-risk alerts
Audit Readiness Level	Preparedness for external audits
Investor Confidence Index	Trustworthiness for investors
Governance Maturity Score	Organizational governance quality
Compliance Status	Regulatory compliance level
Funding Readiness Index	Readiness for financing or investment

3.5. Ethical Review and Model Refinement

Finally, the system includes an Ethical Validation Loop to address the concerns raised by Murikah et al. (2024). The system will generate a "Reasoning Code" using Explainable AI (XAI) before finalizing a "flag". This code explains the rationale behind an AI's action (e.g., "Flagged due to unusual combination of User ID and High Transaction Volume").

Table 12 Explainable AI Reasoning Dataset

Field Name	Description
Alert ID	Unique anomaly alert identifier
Transaction ID	Linked financial transaction
Reason Code	AI-generated explanation for the flag
Dominant Feature	Most influential anomaly factor
Confidence Score	AI prediction certainty level
Risk Category	High, Medium, or Low risk
Historical Similarity	Similar past anomaly patterns
Human Validation Status	Approved or rejected by auditor
Bias Check Status	Ethical compliance verification
Final Decision	Confirmed anomaly or false positive

A human supervisor conducts an annual "Bias Audit" to ensure the model is not discriminating against any particular department or user. This Human-in-the-Loop (HITL) process helps ensure the "Digital Safeguard" is an enabler, not an institutional roadblock (Murikah et al., 2024). The approach ends with a loop whereby resolved alerts (both "True Positives" and "False Positives") are fed back to the ML model to enhance future detection. It establishes a "Self-Learning" audit process that becomes more complex as the SME grows, ensuring systemic resilience over time.

Table 13 Ethical Validation and Model Refinement Dataset

Metric	Purpose
True Positive Rate	Correctly identified anomalies
False Positive Rate	Incorrect anomaly alerts
Bias Audit Result	Detection of discriminatory patterns
Human Override Count	Number of auditor corrections
Model Accuracy	Overall prediction performance
Feedback_Integration_Status	Whether resolved alerts were retrained
Department Risk Distribution	Risk spread across departments
User Risk Distribution	Risk spread across users
Explainability Compliance	Transparency level of AI decisions
Model Refinement Cycle	Frequency of model updates
Ethical Compliance Status	Adherence to AI governance policies
System Resilience Index	Long-term stability of the audit system

4. Analysis and Discussion: Socio-Technical Consequences of Intelligent Auditing

The adoption of an AI-driven audit system by the SME sector marks a transformational shift in understanding enterprise resilience and financial integrity. This discussion examines the socio-technical consequences of this shift in the context of theories of enterprise resilience and the technical insights from the interdisciplinary literature (Mupa & Shem, 2026). This analysis assesses the economic, ethical, and operational consequences of the transition from manual to an "AI-First" audit framework.

4.1. From Compliance to Predictive Resilience

The main argument of this discussion is that the shift to AI-driven auditing alters the notion of Enterprise Resilience. According to Shem & Mupa (2024), surviving a financial crisis is reliant on early detection of irregularities. Conventional auditing, as indicated by Adeboye (2024), is not timely enough to be preventative. In contrast, the approach proposed in this article - using General Ledger Anomaly Detection (Putra & Chowanda, 2025) - turns the auditor from a "historian" of past errors to a "navigator" of future risks.

This transforms the business environment into one of "Pre-emptive Business Rescue". If an SME can detect a $5,000 variance or control override in real time rather than 18 months later, the "snowball effect" of financial mismanagement is avoided. This aligns with Pillai's (2025) research, which shows that smart systems detect abnormalities in enterprise financial data streams before they affect the enterprise's cash. For the SME, financial resilience is no longer just about cash in the bank; it is about having a "Digital Safeguard" to protect the cash that comes through the enterprise.

Table 14 Traditional Auditing vs AI-Driven Predictive Auditing

Dimension	Traditional Auditing	AI-Driven Auditing
Audit Timing	Periodic (Annual/Quarterly)	Continuous Real-Time Monitoring
Detection Speed	Months or Years Later	Minutes or Hours
Audit Scope	Sample-Based (<5%)	Full Population Review (100%)
Fraud Detection	Reactive	Predictive
Risk Identification	Historical Analysis	Future Risk Forecasting
Control Monitoring	Manual	Automated

SME Resilience	Low to Moderate	High
Decision Support	Limited	Real-Time Intelligence
Fraud “Dwell Time”	Long	Significantly Reduced
Governance Model	Compliance-Focused	Risk-Aware Governance

4.2. Bridging the "Governance Gap" in Local Economies

The role of auditing in promoting macroeconomic resilience is a key theme. According to Ayankoya et al. (2025), data optimization is critical to the resilience of local U.S. and global economies. SMEs often fail not because of their products and services, but because of a "Governance Gap" - a lack of trust from external investors and lenders due to their non-transparency of financial reporting.

The Unified Data Activation (UDA) model, as described by Mupa & Shem (2026), can help SMEs offer what Shiwakoti (2025) describes as "Decision Intelligence". This connects the capital market to the small business. Suppose the SME provides a "Clean Audit Dashboard" with data verified by AI, the risk or cost of lending to that SME is reduced. This aligns with Mupa's (2025) research on Sustainable Budgeting, which finds that financial literacy and transparency are the "infrastructure" for disadvantaged communities. Therefore, AI-powered auditing is a means of advancing social and economic justice, as local firms can access capital on a level playing field with larger firms.

Table 15 SMEs Before and After AI-Powered Auditing

Dimension	Traditional SME Environment	AI-Driven SME Environment
Financial Transparency	Low	High
Investor Confidence	Weak	Strong
Lending Risk	High	Reduced
Audit Reliability	Manual & Delayed	Automated & Real-Time
Access to Capital	Limited	Expanded
Governance Quality	Fragmented	Integrated
Decision Intelligence	Minimal	Data-Driven
Financial Inclusion	Unequal	More Accessible
Economic Participation	Restricted	Competitive
Enterprise Resilience	Vulnerable	Sustainable

4.3. Ethics of the "Black Box" Auditor

A key area of debate is the Ethical and Regulatory concerns raised by Murikah et al. (2024). As we trust the power of the "audit" to be transferred to a machine learning algorithm, we are courting the "Black Box" problem. If the AI flags a trusted employee's transactions as "high risk," it creates institutional tensions.

In line with Shem & Mupa's (2024) research on stakeholder management, we agree that the "Human-in-the-Loop" (HITL) approach is not only a technical safeguard but also a moral imperative. To achieve a "turnaround" outcome, all stakeholders must view an audit as fair. The implementation of Explainable AI (XAI) as outlined in the proposed methodology means the "Digital Safeguard" is transparent. This avoids the "Dark Side" of AI in the form of prejudiced or arbitrary financial regulation. Trust is fundamental to resilience, and opacity is no place for trust.

Table 16 Black Box AI Vs. Explainable AI

Dimension	Black Box AI	Explainable AI (XAI)
Decision Transparency	Low	High
Stakeholder Trust	Weak	Strong
Audit Explainability	Unclear	Clearly Justified
Bias Detection	Difficult	Easier to Detect
Human Oversight	Minimal	Active HITL Review
Regulatory Compliance	Risky	More Compliant
Governance Reliability	Questionable	Transparent
Employee Acceptance	Low	Higher
Ethical Accountability	Limited	Strong
Institutional Resilience	Vulnerable	Sustainable

4.4. Operational Efficiency and the "Dwell Time" of Fraud

The study also shows a dramatic increase in efficiency. Duan et al. (2024) show that by using Process Mining, companies can identify the weaknesses in their internal controls. Ironically, workers in many SMEs circumvent controls, not for malevolent reasons, but because they are inefficient. The AI-audit tool locates these "friction points" and enables management to streamline processes for efficiency and security.

This shortens the "Dwell Time". Whereas, in a non-digital system, fraud can go undetected for years, in an AI-enabled system, "Dwell Time" is reduced to days and hours. This quick detection is the "Strategic Linchpin" Shem & Mupa (2024) discuss. It enables a surgical removal of the tumor rather than death from cancer. In the time that it would have taken a conventional auditor to begin work, the AI-empowered SME has detected, investigated, and remedied the anomaly, thereby securing the firm's resources and reputation.

Table 17 Fraud Dwell Time (Traditional Vs. AI-Enabled Auditing

Audit Dimension	Traditional Auditing	AI-Enabled Auditing
Fraud Detection Speed	Months or Years	Hours or Days
Audit Method	Manual Sampling	Continuous Monitoring
Control Weakness Detection	Delayed	Real-Time
Process Visibility	Limited	End-to-End Visibility
Investigation Start Time	After Period-End Audit	Immediate
Fraud Loss Exposure	High	Significantly Reduced
Operational Efficiency	Low to Moderate	High
Response Capability	Reactive	Predictive & Preventive
Reputation Risk	High	Better Protected
Enterprise Resilience	Vulnerable	Strengthened

4.5. The path to "Risk-Aware" Growth

Lastly, the paper considers the role of this approach in Decision Intelligence. As Awad et al. (2025) point out, AI-supported financial statement preparation increases their accuracy and compliance. This allows SME owners to take risks. Rather than holding excess cash due to uncertainty, management can use Risk-Weighted Alerting to assess its risk.

This embodies Mupa's Enterprise Resilience. It's the shift from "Fear-Based Management" to "Data-Based Decision Making". As Zamil (2025) argues, AI-powered business analytics decision-support models are what SMEs need to predict their growth. The integration of finance, audit, and data science enables the SME to become a robust "Individualized Enterprise" rather than a fragile entity facing an uncertain global economy in 2016.

4.6. Conclusion of analysis

The analysis suggests that the "SME Governance Paradox" can be solved by leveraging data science. The insights of Mupa et al. guide resiliency, while multidisciplinary research provides the power to deliver (Zhuwankinyu & Mupa, 2024). Through a 100% population review and unsupervised learning, governance in SMEs will reach new heights. This does not displace the auditor but enhances them. The auditor is the "Ethical Guardian" who ensures that the AI speed processes are complemented by human intelligence. This debate informs the conclusions below, where AI-based auditing is essential as the "Immune System" for today's resilient SME.

5. Conclusion

The adoption of Mupa's Unified Data Activation in the SME audit market represents the advent of Predictive Resilience. It is suggested that SMEs implement 100% population reviews and Process Mining techniques to reduce the "discovery lag" in fraud detection and close the "Governance Gap". Governments should promote "Resource-Light" AI technologies to stabilize local economies (Zhuwankinyu & Mupa, 2024). Finally, by blending Mupa's Resilience Theory with AI-powered analytics, SMEs convert their financial control into a "Digital Immune System" and ensure that transparency and integrity become the first drivers of sustainable, risk-informed growth.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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